

## A FRAMEWORK FOR DRONE-BASED REMOTE BRIDGE STRUCTURAL HEALTH MONITORING

TOMMASO PANIGATI<sup>\*</sup>, STEFANO ZORZI<sup>†‡</sup>, PIER FRANCESCO GIORDANO<sup>\*</sup>,  
MARIA PINA LIMONGELLI<sup>\*</sup>, DOMENICO STRICCOLI<sup>†</sup> AND DANIELE  
ZONTA<sup>‡</sup>

<sup>\*</sup> Politecnico di Milano

Department of Architecture, Built environment and Construction engineering  
Piazza Leonardo da Vinci 32, 20133 Milano, Italy  
e-mail: [tommaso.panigati@polimi.it](mailto:tommaso.panigati@polimi.it), [pierfrancesco.giordano@polimi.it](mailto:pierfrancesco.giordano@polimi.it),  
[mariagiuseppina.limongelli@polimi.it](mailto:mariagiuseppina.limongelli@polimi.it)

<sup>†</sup> Polytechnic University of Bari

Department of Electrical and Information Engineering  
Via Orabona 4, 70125 Bari, Italy  
e-mail: [domenico.striccoli@poliba.it](mailto:domenico.striccoli@poliba.it)

<sup>‡</sup> Università di Trento

Department of Civil, Environmental and Mechanical Engineering  
Via Mesiano 77, 38123 Trento, Italy.  
e-mail: [stefano.zorzi@unitn.it](mailto:stefano.zorzi@unitn.it), [daniele.zonta@unitn.it](mailto:daniele.zonta@unitn.it)

**Key words:** Drone, Structural Health Monitoring, Bridge Inspection, Vision-based SHM, Machine learning

**Abstract.** The progressive aging of bridge networks raises the need for more frequent and effective structural inspections. Conventional inspection methods are often costly, labor-intensive, and potentially hazardous, especially in difficult-to-access areas. Drones are emerging as a promising alternative, enabling safer and more efficient data collection while providing high-resolution results. Their use can be extended to post-disaster assessments and large-scale surveys, with further potential offered by swarms equipped with Non-Destructive Testing (NDT) sensors. When integrated with machine learning techniques, drone-based inspections support agile and low-cost Structural Health Monitoring (SHM) procedures. In addition, the adoption of 5G-and-Beyond communication networks facilitates real-time, remote operations beyond visual line of sight (BVLOS), while immersive technologies such as virtual and augmented reality enhance operator awareness and data interpretation. This paper introduces a framework for remote bridge inspection that combines drones and virtual reality in a unified system, integrating autonomous mission planning, high-speed data transmission, real-time inspection, and decision-support tools. The approach aims to increase inspection frequency, reduce operational risks, and improve the reliability of infrastructure management.



## 1 INTRODUCTION

As bridge networks continue to age and deteriorate, ensuring structural integrity has become a growing concern for infrastructure managers. Regular and high-quality inspections are critical to detect early signs of damage and maintain safety standards [1], [2]. However, traditional bridge inspections are often costly, labor-intensive, and pose significant risks to personnel, especially in hard-to-reach or hazardous areas.

Unmanned aerial vehicles (UAVs), commonly known as drones, have emerged as a promising solution for structural inspections, enabling comprehensive data collection while minimizing operational risks [3], [4]. Recent research shows that drone-based inspections can significantly reduce fieldwork time - up to 75% compared to conventional methods - while still delivering high-resolution results [5],[6]. Moreover, drones are increasingly being used in post-disaster scenarios or following critical events, such as earthquakes or collisions, to rapidly assess structural safety [7]. The use of drone swarms, equipped with both visual and Non-Destructive Testing (NDT) sensors, further expands the potential for large-scale, detailed, and rapid inspections [8]. The integration of drones with machine learning techniques paves the way for agile, low-cost and unmanned Structural Health Monitoring (SHM) inspection and data elaboration procedure [9]. Furthermore, the same fleet of drones can be used, beyond bridge monitoring, for different scopes, such as road traffic management [10], pavement health monitoring [11] and wildfire prevention [12]. Thus, for a public operator, the return on the drone investment can be maximized through economies of scope.

As drone technologies evolve, the prospect of fully remote, real-time inspections becomes increasingly viable. Emerging tools such as 5G-and-Beyond (5GB) communication networks enable low-latency data transmission and remote control capabilities, essential for Beyond Visual Line Of Sight (BVLOS) operations [13]. At the same time, immersive technologies like Virtual Reality (VR) and Augmented Reality (AR) are being explored to enhance the situational awareness of remote operators and facilitate data interpretation [14], [15].

This paper presents a comprehensive framework for remote bridge inspection using drones and VR. The proposed approach allows an operator, located at a mission control center, to deploy, monitor, and interact with a drone - or a swarm of drones - in a completely remote manner. The framework integrates autonomous mission planning, high-speed data transmission, real-time inspection capabilities, and decision support tools into a unified system, aiming to increase inspection frequency, reduce operational risks, and ultimately enhance the reliability of infrastructure asset management. This manuscript is structured as follows: in section 2, the framework is described in detail. In section 3, the main physical and virtual components are described. Section 4 deals with data management, including data transmission, data collection, data elaboration, data usage for decision support and data visualization. Section 5 concludes the paper by presenting the missing gaps to enable the full implementation of the framework.

## 2 A FRAMEWORK FOR VIRTUAL REALITY REMOTE BRIDGE INSPECTION

The proposed framework enables the execution of fully remote bridge inspections through the integration of drone technology, VR environments, and advanced data analytics. Within this environment, a human operator - such as an infrastructure engineer or network manager - remains physically located at a mission control center, from which all operations are planned, executed, and monitored.

**Mission scheduling.** The operator initiates an inspection mission remotely via a graphical interface, selecting either a scheduled routine or an on-demand inspection. On-demand missions may be triggered by anomalous data from fixed SHM sensors, reports of vehicular impacts, or

extreme environmental events such as earthquakes or floods.

**Drone swarm navigation.** Once a bridge monitoring mission is activated, a swarm of drones is deployed from strategically located docking stations. These docking stations serve as logistical hubs, enabling autonomous takeoff, landing, recharging, and payload swapping. Their placement is optimized to minimize travel times across the monitored bridge network. The mission control office does not need to be co-located with the docking stations, as communication between operators and drones is facilitated through low-latency, high-bandwidth 5G networks. Drones autonomously navigate to the target bridge using GNSS-based positioning systems, possibly supplemented by SLAM (Simultaneous Localization and Mapping) or visual-inertial odometry in environments where GPS is denied (e.g., under bridges or inside tunnels). During transit and inspection phases, the operator has the option to switch to manual control—particularly in Beyond Visual Line Of Sight (BVLOS) conditions—via a VR interface. This immersive interface enhances situational awareness and is especially valuable for precision maneuvers, such as close-up inspections of critical areas or follow-up investigations triggered by initial findings.

**Drone-based bridge inspection.** Upon reaching the inspection site, the drone follows a predefined flight path designed to maximize data acquisition efficiency. The path can be tailored to the scope of the mission: it may cover the entire structure for general condition assessment (e.g., photogrammetric survey) or target specific elements identified in earlier inspections as potential failure zones. The route is optimized to balance energy consumption, regulatory compliance (e.g., no-fly zones), and full surface coverage. During the inspection, drones collect multimodal data using both vision-based and contact-based sensing technologies. Lightweight drones (<250g) typically capture high-resolution images and videos for visual inspections and dynamic identification. Heavier drones (<25kg, remaining within the “open category” of EASA regulations) can carry contact-based sensors for NDT, such as ultrasonic probes, ground penetrating radar or vibrational sensors, maintaining stable contact with structural elements when required.

**Data management.** Collected data are transmitted in real time to the mission control center via the 5G network. While cloud-based or edge computing platforms can support on-board preprocessing (e.g., lightweight Convolutional Neural Networks (CNNs) for real-time damage detection), the primary dataset is stored either locally or in cloud infrastructure for post-processing. The operator can dynamically adapt the inspection plan during the mission—for instance, zooming in on a suspicious area after observing real-time imagery—thus combining automation with expert human judgment. The gathered data are processed to extract quantitative information on bridge health (for instance natural frequencies from videos and crack extension from photos) and inserted into the bridge digital twin. Here, drone-based gathered data integrates the outcomes of other SHM sources (fixed sensors, inSAR, etc.) and contribute to the risk-based assessment of bridge safety. In this way, an effective decision-support tool is provided to network operators, who can decide for preventive maintenance or bridge closure in emergency situations, and arrange further drone-based bridge inspections through the mission control office. The use of VR extends beyond real-time control. Post-inspection, the VR environment serves as a data visualization and decision-support interface, where engineers can interact with 3D reconstructions, review annotated damage locations, and simulate maintenance scenarios. Ultimately, the framework promotes a shift from reactive to proactive bridge management, allowing more frequent, safer, and cost-effective inspections across distributed infrastructure networks.

### 3 COMPONENTS OF THE FRAMEWORK

In this section the mission setting is presented, describing each component involved in the framework presented in Section 2. The setup for drone-based remote bridge inspection is composed of different units, both physical and virtual, as shown in Figure 1:

**Decision maker:** it is the person or the unit in the company responsible for decisions related to the bridge operation. Based on the outcomes from data gathered from both traditional sensors and drone-based inspection, the decision maker is required to take decisions: do nothing, close the bridge, restrict access to the bridge, plan preventive or corrective maintenance, ask for additional inspections. The decision making process should be risk-based and data driven. Further details on data elaboration for decision making are given in Section 4.

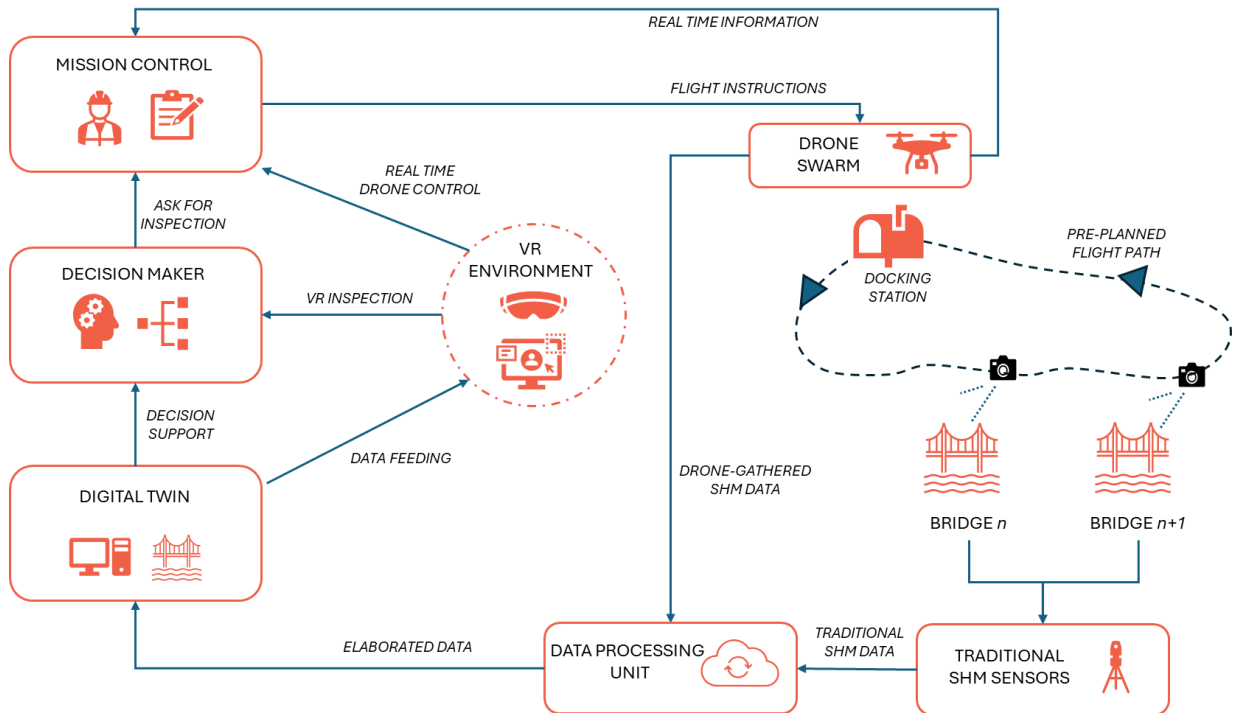


Figure 1: framework for remote drone-based bridge inspection

**Mission control unit:** It is the central hub for planning, supervising, and interacting with inspection missions. Here, the operator interfaces with the drone fleet through a control system equipped with real-time monitoring dashboards and a VR interface. The VR interface can support immersive teleoperation in BVLOS conditions and might enhance situational awareness during manual inspections [16]. Data exchange with the drones is performed via 5G cellular networks, ensuring low-latency communication and high-throughput streaming for HD video and sensor feeds. The mission control unit also manages scheduling for both routine and event-triggered inspections, supporting flexible operational modes. The mission planning involves the selection of the location, timing and path of the inspection, of the data to be gathered, and on which kind of equipment should be used. Inspection can be pre-scheduled or on-demand. In the first case, they are repeated in time with predefined fixed frequency (for instance, every 3 or 6 months), while in the second case, missions are sent when a specific inspection is required, for instance after an exceptional event. The path planning should be carefully carried out in order to maximize the effectiveness of data gathering. Firstly, the most efficient path between the docking station and the bridge must be selected, complying with

regulatory requirements, such as no-fly zones. Secondly, the drone path around the bridge should be designed in order to minimize energy consumption and ensure full coverage of the parts to be inspected. In order to accomplish an effective image collection, the path should also include location and orientation of the image acquisition points. Example of path planning algorithms are shown in [6], considering a single drone, and in [17], using a swarm of drones.

**Drone docking station:** It is a specialized platform designed for long-term automated drone operations. Drone docking station permits autonomous landing, recharging, data transfer, and payload swapping of drones. It is designated to store drones when not operating, protecting them from environmental conditions. Since it is positioned in the location that minimizes travel distance along the bridge network, its position may not coincide with the mission control unit. There might also be more than one location for the drone docking station [18], exactly as road maintenance equipment is deployed in multiple hubs.

**Drone swarm:** One or more drones are deployed for data gathering. Although using a single drone for every inspection is simpler, the usage of multiple drones is sometimes necessary. For instance, where different sensors have to be used, the operator can decide to send contemporaneously two or more drones carrying different sensors. Another example arises when simultaneous data acquisition at multiple locations is required, such as during modal analysis of long-span bridges, where capturing the dynamic response across several points is necessary for accurate identification of mode shapes [19]. Drones are also specialized for different tasks. Lightweight drones (<250g) perform vision-based inspections, and heavy drones, weighing <25 kg, will carry heavier sensors to perform contact-based data collection. In order to fly in BVLOS conditions, the drone must be capable of autonomous navigation, eventually integrated by SLAM method (Simultaneous Localization and Mapping) [20] or visual-inertial odometry [21] to operate in GPS-denied environments like tunnels, bridges, or indoor structures.

**Computing and data storage unit:** It is the physical infrastructure that has to perform computation on gathered data, and to store results and raw data when required. As the computational burden is sometimes heavy and the data dimension is significant, this physical location of this unit may not coincide with the mission control unit, but instead computation and storage can be made in a specialized third-party cloud computing infrastructure. Particular attention may be posed on edge computing and cloud computing approaches [22], [23], for instance in real-time damage detection on-board of drones [8], to reduce data transmission and computational demand at the center of the network.

**VR environment:** Its usage is twofold, both online (for real-time operations) and offline (for ex-post bridge inspections). In the first case, the VR environment can be used by the mission control unit for real-time drone controlling, whenever it is required to control the drone in First Person View (FPV) mode, for instance when a particular defect is seen on the bridge. In the second case, the VR environment is provided with visual and technical information to serve as a base for decision support [14]. The VR system hardware may include a Head-Mounted Display (HMD) and a VR controller or hand-tracking system to enhance the user experience and the effectiveness of the remote inspection.

**Digital twin:** It is the central data repository and reasoning engine of the framework. It aggregates visual, dynamic, and material-related data from drones and fixed sensors. Data is structured for integration with BIM models and supports analytics including structural simulations, degradation modeling, and probabilistic safety assessment. Thus, the twin evolves from a static database to a predictive system supporting condition-based maintenance. Further discussion is reported in the part on *integration on decision support* within Section 4.

#### 4 DATA MANAGEMENT

As depicted in Figure 2, this section presents data management from different perspectives (Data transmission and security, data collection, data processing, data integration in decision support, data visualization). Each of them is presented in the next subsections.

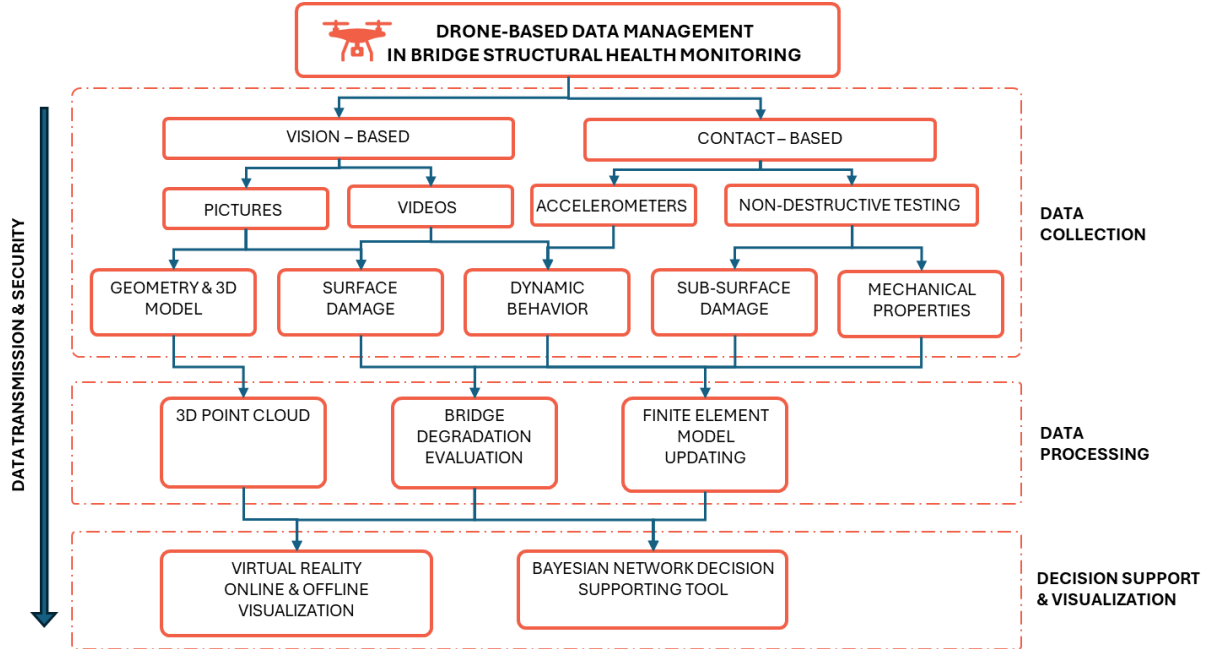


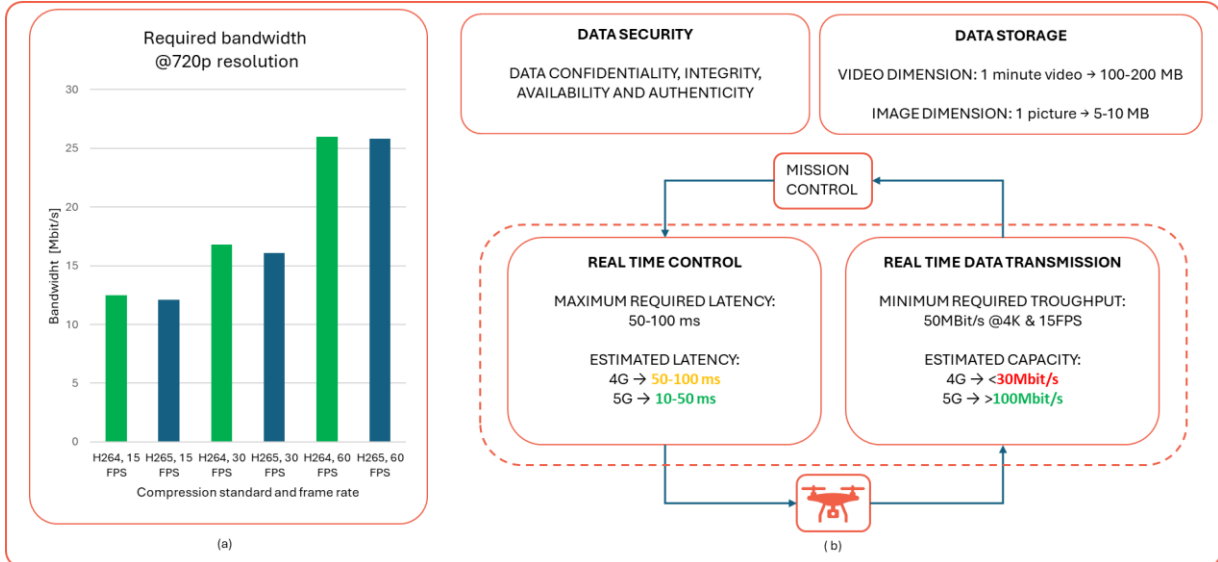
Figure 2: synoptic view of drone-based data management

##### *Data transmission and security*

To perform drone-based remote virtual bridge inspection, it is necessary to establish well-defined communication protocols through the wireless medium. In the proposed framework, communication between drones and the mission control unit is performed through the cellular network, preferentially using the 5G network. In recent years, the rapid growth of 5G-and-Beyond (5GB) cellular networks has paved the way for interesting applications using drones, concerning also the formation of swarm of drones [13]. A short experiment was carried out to measure the bandwidth required to transmit 720p video in real time from a drone in H264 and H265 video compression standards, as presented in Figure 3(a). Given that the average measured bandwidth is in the order of 20-30 Mbit/s, and it is expected to increase with high resolution videos, the usage of 4G network is typically insufficient for data transmission, as shown in figure 3(b). Furthermore, also maximum latency requirements suggest the usage of 5G networks. Results are aligned with Makropoulos et al. [24]. However, a noticeable discrepancy is often observed between the maximum declared network capacity and the actual bandwidth measured during drone operations. In practice, real throughput is affected by factors such as network congestion, distance from the base station, obstacles or bridge geometry causing signal attenuation, and environmental conditions. Given these limitations, the implementation in the framework of an Internet-of-drones approach presents some advantages: capability to extend wireless coverage areas, or ability to reach places inaccessible to humans, improve of reliability, connectivity and throughput, and delay reduction [25].

Since sensitive information - such as GPS coordinates, structural imagery, and health condition data - is exchanged between the drones and the mission control unit, ensuring data security is critical. The system must address core requirements including confidentiality, to restrict access

to authorized parties; integrity, to prevent data tampering during transmission or storage; and availability, to guarantee uninterrupted access to mission-critical information. Additionally, authenticity must be ensured to verify the identity of both drones and control systems, while privacy preservation is necessary to protect mission-sensitive or personally identifiable information from unauthorized disclosure.



**Figure 3:** (a) measured bandwidth in a real-world experiment. (b) bandwidth and latency requirements for drone-based remote bridge inspection with real-time transmission

### Data collection

Drone swarms might be composed of different drone models, each specialized in different tasks. Lightweight drones (<250g) perform vision-based inspections, and heavier drones (<25kg, from now called *payload-carrying* drones) can carry heavier sensors to perform contact-based NDT data collection. Specifically, vision-based inspections, performed using lightweight drones, gather images for surface damage identification and videos for dynamic monitoring. The usage of images is twofold: firstly, photos with various levels of detail can be used for assessing the presence of surface damage (cracks, spalling, efflorescence, etc.). Depending on the level of detail required during inspection planning, images should be captured at distances ranging from 3 to 15 m, with closer distances for inspection of critical details. Moreover, georeferenced images covering the whole bridge can be used as a base for a photogrammetric model. Typically, to cover a full bridge, hundreds of pictures are required depending on the complexity of the bridge. Contextually to photo gathering, drones can record videos of the bridge to capture its dynamic behavior. Typically, videos can fruitfully capture the first natural frequencies of slender bridges, such as pedestrian bridges, and medium span (>50m) concrete/steel bridges [26]. Video should be taken at distances of 5-10 meters while at least one significant load (i.e. a truck or a train) is passing on the bridge, to achieve sufficient excitation amplitude. Complementary, payload-carrying drones are in charge of carrying non-destructive testing. If vision-based dynamic identification cannot be performed, as an alternative the operator can deploy a drone capable of keeping a traditional accelerometer in contact with the structure – while the drone is hovering in position – to extract dynamic data. The usage of drone swarms helps in sampling multiple points contemporaneously. Furthermore, payload-carrying drones, currently at an early stage of development, should be designed as multi-tool platforms

capable of supporting a variety of NDT sensors for sub-surface damage evaluation. For instance, ultrasonic sensors can be mounted on the drone, with the scope of assessing the state of health of prestressing cables.

### ***Data processing***

The vast amount of data gathered within the inspection phase should be processed and elaborated, not only to extract useful information, but also to discard and eliminate unnecessary data, to save storing space. Data processing can be performed either in a physical infrastructure that might coincide with the mission control office, or that can be a third-party cloud computing infrastructure. Moreover, in some cases the possibility of partial information processing on-board of the drone can be contemplated, for instance in the case of lightweight convolutional neural networks for damage detection [8]. With regard to the photogrammetric usage for images, georeferenced images can be inserted into task-specific software that reconstruct a 3D photogrammetric model, whose precision can reach sub-centimetric levels. The primary usage of photogrammetric models is to serve as a basis for a 3D reconstruction integrated with BIM, that can be used for instance for geometric control of the structure and as a basis for damage localization.

Concerning images for surface damage identification, the processing involves the phases of:

- Damage detection – automatic recognition of defects on raw images, identifying pixels or regions of interest that deviate from expected patterns.
- Damage classification – distinguishing between different types of defects (e.g., cracks, spalling, efflorescence), often using machine learning or deep learning models.
- Damage localization – assigning each detected defect to a specific position within the 3D point cloud or digital twin of the structure.
- Damage severity evaluation – assessing the extension, width, depth, or intensity of the detected defect to quantify its criticality and prioritize interventions.

Videos can be used for dynamic identification through the usage of computer vision. The process essentially involves several stages for extracting the time histories of displacements, as highlighted in [4]. Once the reconstruction is performed, the original video can be destroyed to save storage space, as the dimension of the video is in the order of 100-200MB for every minute recorded, depending on resolution and frame rate. Data from NDT sensors can be elaborated to gather insights on the condition of materials and single element of the bridge; for instance, data gathered from ultrasonic sensors can be used to assess the integrity of prestressing cables, through a map of the subsurface of the bridge.

### ***Integration on decision-support***

The integration of the elaborated data into the bridge management and decision support process is the most challenging step, as it has a strict connection with the decision-making process.

The integration of drone-based inspection is straightforward in standard procedures for bridge management. An example is here reported for the *Guidelines for risk classification and management, safety assessment and monitoring of existing bridges* [27] provided by Italian regulatory bodies. The guideline involves a multi-level approach for bridge safety assessment, each of increasing complexity. Drone-based remote inspections support several levels of assessment. At Level 1, aerial imagery and 3D point clouds streamline the compilation of defect sheets and enable automated detection, classification, and localization of damage (§3; §4.2–§4.3). At Level 2, VR-assisted inspections can complement or partly replace on-site surveys (§7.4.1), giving easier access to hard-to-reach areas and allowing more frequent checks at lower cost. For instrumental testing, drones can perform periodic or event-based dynamic identification (§7.6.2) and deploy contact-based NDT sensors to enhance understanding of

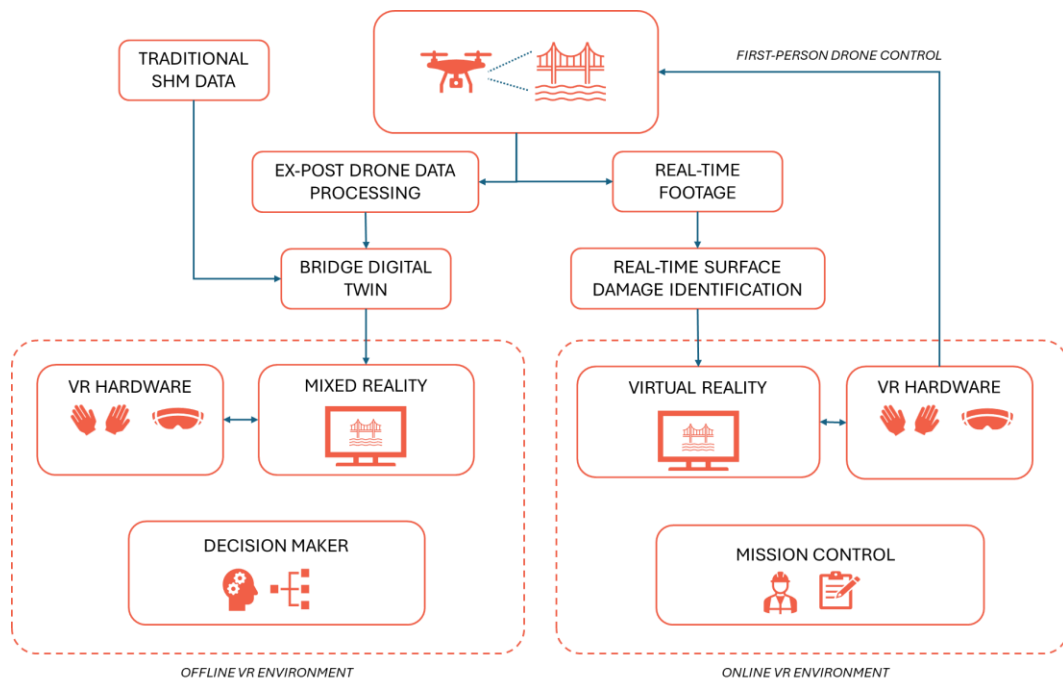
structural health in extraordinary inspections (§7.4.2). The drone-gathered information can also have a quantitative usage. For instance, vibrational data can feed finite element models of the bridge, such as in [6], where the georeferenced point cloud is compared with a Finite Element Model to assess the geometrical discrepancies under thermal loading conditions. The dynamic parameters can continuously update a physic-based digital twin composed of a Finite Element Model of the structure. A Bayesian network, capable of supporting decision-making, can be fed by drone-gathered data altogether with traditional SHM data [1]. Furthermore, within the network, the quality of the information and its influence on the decision-making process can be assessed through reliability-based metrics [2]. Whenever machine learning algorithms are employed to perform automated decisions, knowledge sharing can be applied by means of transfer learning techniques [28] or population-based approaches [29].

**Data visualization**

As illustrated in Figure 4, two complementary approaches for data visualization within a VR environment can be envisioned.

The first is an offline VR environment, where the digital twin of the bridge is embedded in a 3D visualization platform and provided to the decision-maker to enhance situational awareness of structural conditions [30]. A representative example is presented in [15], which combines augmented reality with computer vision for automatic fatigue crack detection and localization. In that work, holograms of cracks are overlaid during on-site visual inspection, while detection results are delivered in near real time. This concept can be extended to fully remote inspections, integrating real-time surface damage detection with immersive visualization tools that support decision-making.

The second is an online VR environment, designed for the mission control center to improve real-time drone operations by providing the operator with a first-person perspective. In this setup, real-time information such as surface damage detection can be superimposed on the VR visualization, enabling the operator to better interpret local bridge conditions and dynamically adjust the inspection strategy to focus on areas of concern [22].



**Figure 4:** VR application in offline and online environments for bridge SHM

## 5 CONCLUSION AND MISSING GAPS

This work presented a framework for remote drone-based bridge inspection, dealing with multidisciplinary topics, such as inspection planning, data transmission, data collection, data elaboration and decision-making. Although the proposed framework presents the potential of drone-based remote bridge inspection, several technological and operational gaps must be addressed before achieving full implementation.

- Data collection and analysis. Novel approaches for integrating vision-based, remote sensing, and NDT data are required, including improved algorithms for vision-based vibrational analysis, automated surface damage detection using vision-based approaches, and extraction of NDT data from drone-borne sensors.
- Decision support integration. Robust decision-support systems should be developed to combine heterogeneous data coming from drones and traditional sensors into actionable insights. Bayesian networks represent a promising approach, provided that uncertainty in drone-derived data is better quantified.
- VR environment. The development of immersive, task-oriented VR interfaces will improve quality and speed, both for real-time operations and for post-inspection data visualization.
- Mission planning. Path planning, event management, and systematization of mission setup must be refined, ensuring resilience to unforeseen conditions and maximizing inspection efficiency.
- Battery endurance. Current drone batteries provide flight times of less than 40 minutes, which is insufficient for long-range inspections between docking stations and bridges. Endurance of at least two hours will be required for continuous and efficient operations.
- Contact-based drones. At present, solutions for contact-based dynamic measurement remain at very low technology readiness levels (TRL 1–2). Advances are needed in both drone technology and monitoring techniques to ensure stable contact during hovering, while mitigating drone-induced vibrations in sensors.
- Regulatory framework. The widespread adoption of remote inspections requires authorization for BVLOS flights and operational clearance in restricted areas, particularly when bridges are located within sensitive zones.
- Cost–benefit evaluation. A systematic comparison between drone-based and traditional inspections is needed to quantify economic viability, assess advantages, drawbacks, costs and uncertainties, and evaluate risk reduction.

Addressing these gaps will require parallel advances in drone hardware, sensing technologies, data analytics, and regulatory frameworks. Only through such integrated progress can the proposed framework evolve into a fully operational tool for reliable, safe, and cost-effective bridge inspection and management.

## REFERENCES

- [1] E. Tubaldi, F. Turchetti, E. Ozer, J. Fayaz, P. Gehl, and C. Galasso, “A Bayesian network-based probabilistic framework for updating aftershock risk of bridges,” *Earthq Eng Struct Dyn*, vol. 51, no. 10, 2022, doi: 10.1002/eqe.3698.

- [2] Stefano Zorzi, Marco Broccardo, Daniel Tonelli, and Daniele Zonta, “Reliability-based metrics for structural health monitoring information quality assessment,” *Struct Health Monit*, p. 14759217241265956, Aug. 2024, doi: 10.1177/14759217241265956.
- [3] S. Feroz and S. A. Dabous, “Uav-based remote sensing applications for bridge condition assessment,” *Remote Sens (Basel)*, vol. 13, no. 9, 2021, doi: 10.3390/rs13091809.
- [4] T. Panigati *et al.*, “Drone-based bridge inspections: Current practices and future directions,” *Autom Constr*, vol. 173, p. 106101, May 2025, doi: 10.1016/J.AUTCON.2025.106101.
- [5] S. Perez Jimeno, J. Capa Salinas, J. A. Perez Caicedo, and M. A. Rojas Manzano, “An integrated framework for non-destructive evaluation of bridges using UAS: a case study,” *Journal of Building Pathology and Rehabilitation*, vol. 8, no. 2, 2023, doi: 10.1007/s41024-023-00299-x.
- [6] G. Morgenthal *et al.*, “Framework for automated UAS-based structural condition assessment of bridges,” *Autom Constr*, vol. 97, 2019, doi: 10.1016/j.autcon.2018.10.006.
- [7] D. C. Nguyen, T. Q. Nguyen, R. Jin, C. H. Jeon, and C. S. Shim, “BIM-based mixed-reality application for bridge inspection and maintenance,” *Construction Innovation*, vol. 22, no. 3, 2022, doi: 10.1108/CI-04-2021-0069.
- [8] S. Jiang, Y. Cheng, and J. Zhang, “Vision-guided unmanned aerial system for rapid multiple-type damage detection and localization,” *Struct Health Monit*, vol. 22, no. 1, pp. 319–337, 2023, doi: 10.1177/14759217221084878.
- [9] Y. J. Cha, R. Ali, J. Lewis, and O. Büyüköztürk, “Deep learning-based structural health monitoring,” 2024. doi: 10.1016/j.autcon.2024.105328.
- [10] G. Kopsiaftis *et al.*, “IKAROS: a UAV-based integrated system for monitoring road defects and managing vehicle traffic and emergencies on road transport networks,” in *Proceedings of the 17th International Conference on Pervasive Technologies Related to Assistive Environments*, in PETRA '24. New York, NY, USA: Association for Computing Machinery, 2024, pp. 463–465. doi: 10.1145/3652037.3663950.
- [11] T. Askarzadeh, R. Bridgelall, and D. Tolliver, “Drones for Road Condition Monitoring: Applications and Benefits,” *Journal of Transportation Engineering, Part B: Pavements*, vol. 151, Sep. 2025, doi: 10.1061/JPEODX.PVENG-1559.
- [12] S. C. Okoro, A. Lopez, and A. Unuriode, “A Synergistic Approach to Wildfire Prevention and Management Using AI, ML, and 5G Technology in the United States,” 2024. [Online]. Available: <https://arxiv.org/abs/2403.14657>
- [13] M. K. Banafaa *et al.*, “A Comprehensive Survey on 5G-and-Beyond Networks With UAVs: Applications, Emerging Technologies, Regulatory Aspects, Research Trends and Challenges,” *IEEE Access*, vol. 12, 2024, doi: 10.1109/ACCESS.2023.3349208.
- [14] F. Luleci, L. Li, J. Chi, D. Reiners, C. Cruz-Neira, and F. N. Catbas, “Structural health monitoring of a foot bridge in virtual reality environment,” in *Procedia Structural Integrity*, 2021. doi: 10.1016/j.prostr.2022.01.060.
- [15] A. Mohammadkhorasani *et al.*, “Augmented reality-computer vision combination for automatic fatigue crack detection and localization,” *Comput Ind*, vol. 149, 2023, doi: 10.1016/j.compind.2023.103936.
- [16] D. Mourtzis, J. Angelopoulos, and N. Panopoulos, “Unmanned Aerial Vehicle (UAV) path planning and control assisted by Augmented Reality (AR): the case of indoor drones,” *Int J Prod Res*, vol. 62, no. 9, pp. 3361–3382, 2024, doi: 10.1080/00207543.2023.2232470.

- [17] M. Bolognini, L. Fagiano, and M. P. Limongelli, “A fault-tolerant automatic mission planner for a fleet of aerial vehicles,” *Control Eng Pract*, vol. 135, 2023, doi: 10.1016/j.conengprac.2023.105501.
- [18] A. Avi, G. Quaranta, and A. Valentini, “AI-assisted Design of UAV Docking Station Network for Dual Use Purposes,” in *34th Congress of the International Council of the Aeronautical Sciences (ICAS2024)*, 2024.
- [19] M. Bolognini, G. Izzo, D. Marchisotti, L. Fagiano, M. P. Limongelli, and E. Zappa, “Vision-based modal analysis of built environment structures with multiple drones,” *Autom Constr*, vol. 143, 2022, doi: 10.1016/j.autcon.2022.104550.
- [20] C. Friess, V. Niculescu, T. Polonelli, M. Magno, and L. Benini, “Fully Onboard SLAM for Distributed Mapping With a Swarm of Nano-Drones,” *IEEE Internet Things J*, 2024, doi: 10.1109/JIOT.2024.3367451.
- [21] J. Kühne, M. Magno, and L. Benini, “Low Latency Visual Inertial Odometry With On-Sensor Accelerated Optical Flow for Resource-Constrained UAVs,” *IEEE Sens J*, vol. 25, no. 5, pp. 7838–7847, 2025, doi: 10.1109/JSEN.2024.3406948.
- [22] M. Zakaria, E. Karaaslan, and F. N. Catbas, “Advanced bridge visual inspection using real-time machine learning in edge devices,” *Advances in Bridge Engineering*, vol. 3, no. 1, 2022, doi: 10.1186/s43251-022-00073-y.
- [23] P. McEnroe, S. Wang, and M. Liyanage, “A Survey on the Convergence of Edge Computing and AI for UAVs: Opportunities and Challenges,” *IEEE Internet Things J*, vol. 9, Sep. 2022, doi: 10.1109/JIOT.2022.3176400.
- [24] G. Makropoulos *et al.*, “Field Trial of UAV flight with Communication and Control through 5G cellular network,” in *2021 IEEE International Mediterranean Conference on Communications and Networking, MeditCom 2021*, 2021. doi: 10.1109/MeditCom49071.2021.9647620.
- [25] P. Boccadoro, D. Striccoli, and L. A. Grieco, “An extensive survey on the Internet of Drones,” *Ad Hoc Networks*, vol. 122, 2021, doi: 10.1016/j.adhoc.2021.102600.
- [26] T. Panigati, P. F. Giordano, D. Tonelli, M. P. Limongelli, and D. Zonta, “Perspectives on vision-based bridge vibrational monitoring by drones,” in *13th International Conference on Structural Health Monitoring of Intelligent InfrastructureAt: Graz, Austria*, Graz, 2025.
- [27] “Italian Ministry of Infrastructures and Transportations. D. M. 01 July 2022. Linee Guida per la classificazione e gestione del rischio, la valutazione della sicurezza ed il monitoraggio dei ponti esistenti. 2022.”
- [28] E. Morleo, M. P. Limongelli, A. Piscini, and E. Troielli, “A Transfer Learning approach for damage identification in operational viaducts,” in *proceedings of the 13th International Conference on Structural Health Monitoring of Intelligent Infrastructure*, Graz, 2025. doi: :10.3217/978-3-99161-057-1-136.
- [29] S. Quqa *et al.*, “Regional-scale bridge health monitoring: survey of current methods and roadmap for future opportunities under changing climate,” *Struct Health Monit*, vol. 24, pp. 2309–2337, Oct. 2025, doi: 10.1177/14759217241310525.
- [30] F. Luleci and F. N. Catbas, “Bringing site to the office: Decision-making in infrastructure management through virtual reality,” *Autom Constr*, vol. 166, p. 105675, 2024, doi: <https://doi.org/10.1016/j.autcon.2024.105675>.