Reducing risks and time of inspection of critical infrastructures by means of light small-size drones

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Abstract: Unmanned Aerial Vehicles (UAVs) or drones are increasingly popular for inspecting critical infrastructure for potential damage. This is especially true in areas where human access is dangerous or impossible, and the inspection process could be lengthy or inaccurate.

Although UAV technologies can overcome many challenges of manned inspections, factors such as long flight permitting times and high vehicle and service costs often deter their adoption. Furthermore, while UAVs reduce risks associated with human inspections, they also introduce new ones. These include air risks from potential collisions with other manned aircraft and ground risks such as impacts on the surrounding population. Additionally, there are potential increases in service costs and social concerns due to the operation of a novel technology often linked to military actions.

The paper addresses the raised questions and proposes solutions involving small drones equipped with RGB cameras and Artificial Intelligence (AI) algorithms. This combination enables the processing of data captured from the drones to generate valuable insights for assessing potentially damaged structures. For example, information such as recomposed images for visual inspection, intelligent 3D reconstructions of affected areas, pattern recognition of damaged zones and the location of anomalies is made available to infrastructure analysts. Furthermore, data elaborations could provide approximate but reliable estimation of representative damage indicators. These qualitative assessments, coupled with the location of damage, enable the selection of more precise investigation techniques and the formulation of appropriate remediation and corrective measures.

Small drones offer several advantages. They are less invasive, quiet, and lightweight, minimising air and ground risks and typically requiring low capital expenditure. Furthermore, applicable regulations often permit exceptions for these UAVs. While lightweight drones can be affected by weather conditions like wind and rain, well-defined missions, appropriate flight planning, and experienced pilot supervision can mitigate these issues. The paper delves into these aspects, highlighting strengths and weaknesses of this novel inspection technique.

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) or drones are increasingly popular for inspecting critical infrastructure for potential damage. This is especially true in areas where human access is dangerous or impossible, and the inspection process could be lengthy or inaccurate.

They provide a versatile and efficient way to collect and monitor data, performing detailed inspections and even detecting superficial damage. This information can then be integrated into broader management systems for improved maintenance and decision-making. Drones can store a large amount of data, including high-quality videos and images, on memory cards. This data can be post-processed in the office or delivered directly to a ground/fly station via a wireless communication system.

Recent technological advances in drones, particularly the availability of small-size and low-weight sensors, offer the potential for more efficient, potentially cheaper and safer drone-based damage detection. Being unmanned, drones also benefit from optimisation methods for determining suitable and safe flight paths. Drones can easily access hard-to-reach areas, rapidly collect a large number of images and enhance operator safety [1].

While UAVs reduce risks associated with human inspections, they also introduce new ones. These include air risks from potential collisions with other manned aircraft and ground risks such as impacts on the surrounding population. For these reasons, there are limitations about their operations, particularly regarding regulations. Drones often cannot fly over restricted areas where they might pose a hazard, especially with their size growing. Furthermore, drone application depends on specific requirements, geography, ambient conditions, regulations governing drone flights and mission design, possibly impacting service costs. Additionally, a large deployment of this novel technology may raise social concerns due to its association with military actions.

The European Union's regulation of Unmanned Aircraft Systems [2, 3], primarily governed by the European Union Aviation Safety Agency, has harmonised rules across Member States [4, 5]. However, it still faces several hurdles. By 2026, these challenges include navigating complex operational categories, complying with technical standards and managing fragmentation in local implementation.

Small drones offer several advantages. They are less invasive, quiet, and lightweight, minimising air and ground risks and typically requiring low capital expenditure. Furthermore, applicable regulations often permit exceptions for these UAVs. While light drones can be affected by weather conditions like wind and rain, well-defined missions, appropriate flight planning, and experienced pilot supervision can mitigate these issues.

The following Sections discuss these aspects and propose solutions involving small drones equipped with RGB cameras and AI algorithms. This combination allows to process the data captured by the drone during its flight and generate valuable insights for assessing potentially damaged structures, such as recomposed images for visual inspection, smart 3D reconstructions of affected areas, pattern recognition of damaged zones, and location of anomalies, estimation of representative damage indicators. This information, coupled with the location of damage, enables the selection of more precise investigation techniques and the formulation of appropriate remediation and corrective measures.

More precisely, Section 2 introduces the proposed methodological approach, constrained by an evolving and incomplete regulatory framework but also encouraged by the potential of small drone technology to capture valuable data and the power of artificial intelligence to dig in them to extract information for early damage detection. Section 3 presents an example of application related to a decarbonisation solution. Section 4 discusses the advantages and limitations of utilising small-size drones in conjunction with AI techniques for infrastructure inspection, highlighting reduced risk, capital expenditure and operational costs. Section 5 will conclude the paper.

2. METHODOLOGY

A thorough inspection of critical infrastructures is essential for detecting potential damages. This technical process, crucial for preventing accidents, involves a systematic and sensory analysis typically performed by technicians. While these inspections could pose risks to workers, they also incur high costs and require significant time. In contrast, drones offer a more efficient and safer alternative. They can capture high-resolution images and videos, simplify damage identification and enable rapid maintenance interventions in the event of accidents. They can be deployed across multiple structures potentially covering entire infrastructure networks and their mobility and modularity make them easy to deploy and reuse on different applications. Equipped with sensors near the critical structure drones enable thorough inspections of hazardous areas and hard-to-reach locations significantly reducing risks for human operators, including falls, unstable environments and exposure to dangerous conditions. Furthermore, drones offer faster inspections than traditional methods and are resilient to external factors affecting traditional monitoring systems, operating effectively even during vandalism, power outages theft or tampering.

The use of drones for professional activities is a relatively recent phenomenon but is now widespread globally. To regulate this mid-air traffic in a manner that does not introduce unacceptable risks to the population, the current air traffic and the environment, an international effort is underway to create a regulatory framework as consistent as possible among different countries.

2.1. Evolving Regulatory Framework

The European Union (EU) has established a unified regulatory framework for Unmanned Aerial Systems (UAS) operations for the safe operation of civil drones in Europe. The drone Regulation (EU) 2019/947 [2] and Regulation (EU) 2019/945 [3] classify civil drone operations into three categories: "open", "specific" and "certified". The 'open' category permits operations without direct supervision or prior approval. In contrast, the 'specific' category requires a formal approval process utilising a risk-based approach. The specific operations risk assessment (SORA) is a key method employed within this category [8]. The "certified" category imposes even stricter safety standards, mirroring those in manned aviation. Due to the high safety and regulatory hurdles, certification is challenging and reserved for the most complex and high-risk operations. Two main types of operations are considered: Visual Line of Sight (VLOS) and Beyond Visual Line of Sight (BVLOS). In the open category only VLOS operations are currently permitted.

The European Union Aviation Safety Agency (EASA) is an independent and neutral body, ensuring confidence in safe air operations in Europe and world-wide by proposing and formulating rules, standards, and guidance; by certifying aircraft, parts, and equipment; and by approving and overseeing organisations in all aviation domains. EASA is in charge of preparing and updating the acceptable means of compliance (AMC) and guidance material (GM) related to the EC regulations 2019/947 and 2019/945. The AMC adopt a risk-based that is centered on the specifications of the civil drone, its weight, and the operation it is intended to conduct.
EASA published the SORA [9] as an Acceptable mean of compliance to Article 11 to Regulation (EU) 2019/947. Further to that, the SORA methodology was developed as an international standard by the Joint Authorities for Rulemaking on Unmanned Systems (JARUS) [10]. As outlined in [9], SORA employs a holistic safety risk management process to assess the risks associated with a specific operation and then establishes proportionate requirements to ensure a Target Level of Safety (TLOS) is achieved. This includes evaluating ground and air risks based on the drone's size and weight and the geographical location of the operations. The TLOS is defined for people on ground and aircraft uninvolved in the operation and is commensurate with existing manned aviation safety standards for these stakeholders, precisely:

a. For ground risk: $< 10^{-6}$ fatalities per hour
b. For air risk:
    - $< 10^{-7}$ mid-air collisions/flight hour for operations occurring in uncontrolled airspace or
    - $< 10^{-9}$ mid-air collisions/flight hour for operations occurring in controlled airspace.

Within the 'specific' category, different operations have varying levels of inherent risk and therefore require demonstrating differing levels of control to meet the TLOS. To achieve this, the SORA has developed the Specific Assurance and Integrity Levels (SAIL) which maps the maximum allowable loss of control rate to operational, organisational, personnel, design and manufacturing risk controls. These controls, when implemented correctly at the required level, ensure an operation meets the TLOS.

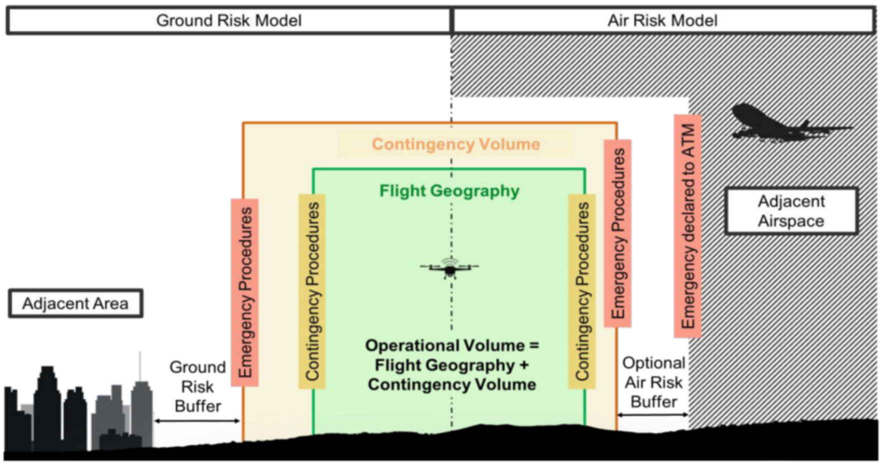
The SORA considers two states of operation: in control and loss of control. The SAIL score is inversely proportional to the acceptable loss of control rate required to meet safety objectives. Six levels are defined, with a higher SAIL score indicating greater integrity (i.e., how good the mitigation/objective is at reducing risk) and assurance (i.e., the degree of certainty with which the level of integrity is ensured) of operational safety objectives. Therefore, as SAIL increases, requirements for the entire flight operations (technology, operation, maintenance and training) also increase and directly affect the cost of operation. For example, SAIL IV requires the UAV to receive a design verification report (DVR) and SAIL V and VI a type certificate issued by EASA [11].

Mitigation measures such as strategic flight path planning, operational handling and technical solutions can significantly reduce risks. Based on the final risk assessment, a specific assurance integrity level (SAIL) is defined.

The main SORA process is applied to an operational volume and the associated ground risk buffer (ref. Figure 1). The operational volume is defined as the volume in which the operation is intended to take place safely. It is made up of the flight geography where the planned operations are carried out and the contingency volume. To protect the adjacent area and airspace the UAS operation should be contained within the operational volume. The Ground Risk Buffer (GRB) is a designated area surrounding the operational volume intended to contain a drone in the event of a loss of control, minimizing risk to third parties on the ground. It acts as a safety perimeter to ensure that if a drone leaves its planned, controlled airspace, its final crash location is limited to this protected buffer area.

For normal operations, the UAV shall only operate inside the flight geography. The contingency volume surrounds the flight geography. The outer limit of the contingency volume is equivalent to the outer limit of the operational volume. Entry into this volume is always considered an abnormal situation and requires the execution of appropriate contingency procedures to return the UA to the flight geography.

Figure 1: Graphical Representation of SORA Semantic Model (Courtesy of JARUS, [10])



The SORA uses the operational airspace as the baseline to evaluate the intrinsic risk of mid-air collision with manned aircraft and for determining the air risk class (ARC). The ARC may be modified/lowered by applying strategic and tactical mitigation means. An example of strategic mitigations to reduce collision risk may be by operating during certain times or within certain boundaries. After applying strategic mitigations, any residual risk of mid-air collision is addressed by means of tactical mitigations. Tactical Mitigation Performance Requirements (TMPR) are defined as the required performance standards for measures taken after takeoff to detect and avoid potential mid-air collisions with other aircraft. Depending on the residual risk of mid-air collision, Tactical Mitigation Performance Requirements may vary. There are two classifications of Tactical Mitigations within the SORA, namely:

1. VLOS, whereby a pilot and/or observer use human vision to detect aircraft and take action to remain well clear and avoid collisions from other aircraft.
2. BVLOS, whereby an alternate means of mitigation to human vision, as in machine or machine assistance, is applied to remain well clear and avoid collisions from other aircraft.

Four Air Collision Class are defined (ARC-a, -b, -c -d) with associated Tactical Mitigation Performance Requirements levels (no, low, medium, high). For VLOS and for ARC-a no tactical mitigation performance requirements are requested.

The footprint of the operational volume plus the ground risk buffer is the area used to determine the Ground Risk Class (GRC). The intrinsic GRC is a simplified metric providing a conservative starting value for the unmitigated ground risk an operation poses to persons within the operational volume and ground risk buffer on the condition of a failure. It is assumed that people within the defined area is uniformly distributed and fully exposed to the risk. The appropriate size of the ground risk buffer is based on the individual risk of an operation and is driven by the flight characteristics of the UA and the identified containment requirements of the SORA.

A UA weighing less than or equal to 250 g and having a maximum speed less than or equal to 25 m/s is considered to have an intrinsic GRC of 1 regardless of population density. It follows that the size of the ground risk buffer and the adjacent area do not influence the GRC level, and the determination of containment requirements is therefore not requested. Concerning the Air Risk, as stated before, if the UAV is operated in VLOS or has a final ARC-a classification, it does not have to comply to tactical mitigation requirements. Therefore, the resulting SAIL level for the 250g-25m/s drone could be 1 if the operator proves that the strategic mitigation measures are able to keep the UAV within ARC-a class. Air-SORA strategic mitigation encompasses both operational restrictions such as boundary, chronology and time of exposure, and mitigations by common structures including common flight rules and common airspace structure.

In the current evolving regulatory framework, flying small-size drones in the open category is the safer, faster and more cost-effective method for conducting inspections and collecting aerial data for damage detection. However, some structures are located in areas with flight restrictions. In these situations, following the permitting process for flight authorisation is facilitated if the UAV technical characteristics and flight geography do not introduce relevant air and ground risks. Indeed, the SORA analysis can be conducted more easily as in many operational scenarios the SAIL level can be lowered to 1 (ARC-a, GRC=1) with less restrictive requirements for the entire flight operations.

2.2. Methodological Approach for Small-Size UAV Inspections of Critical Infrastructures

AI-powered damage detection in drone inspections integrates unmanned aerial systems with artificial intelligence to automatically identify, classify and assess damage to infrastructure. Drones are remotely piloted or, where authorised, fly autonomously over facilities to capture high-resolution imagery and video of assets such as power lines, pipelines, bridges, wind turbines, solar farms and industrial buildings. This modernises inspection practices providing a large volume of data for automated image analysis and machine learning.

Data capture typically involves drones capable of collecting high-resolution data using multiple sensor types [12]. These include RGB cameras for detailed visual imaging, thermographic cameras for detecting temperature anomalies, LiDAR sensors for precise 3D mapping and multispectral and hyperspectral cameras for specialised applications. High-resolution RGB cameras are now lightweight, reasonably priced and can be embedded in small and cost-effective drones, while other sensor types, primarily reserved for specialised activities, are more expensive and heavier and necessitate dedicated hardware. These are typically installed on sized drones that require restrictive flight authorisations.

The process of AI-based damage detection in drone inspections is conducted in several stages:
- Obtain the operational authorisation for the geographical area of interest
- Define the operational volume and the flight geography for the inspection mission
- Prepare the automatic flight plan for the inspection with sensors installed on the drone
- Fly the drone according to the flight plan for data capture and recording
- Transmit or download the data for processing
- Process the data for damage detection.

To provide a smart, economic, and accessible instrument to inspectors, this paper suggests possible solutions utilising small drones equipped with RGB cameras and AI algorithms to process the data they capture and enable the assessment of potentially damaged structures providing recomposed images for visual inspection, a 3D reconstruction of significant affected areas, pattern recognition and location of identified anomalies.

The key challenge of automated techniques is developing defect detection algorithms that are accurate and repeatable [13]. Several attempts have been made, categorised into those using traditional image processing techniques and those using AI techniques. Traditional techniques utilise image features such as convexity or signal intensity, which achieve high accuracy in test data but fail to generalise effectively and require continuous tuning. In contrast, AI algorithms using computer vision and machine learning have shown promising results in defect detection [14].

High-resolution imagery and video of critical infrastructures captured by drones remotely piloted can be analysed by existing AI models trained to detect typical damage patterns. By utilising machine learning and advanced image processing techniques, AI systems can detect and classify damage with high accuracy. After anomalies detection and image segmentation using Machine Learning (ML) techniques, the image segments are processed by deep learning algorithms. Common architectures include convolutional neural networks (CNNs) and models such as YOLO (You Only Look Once) and Mask R-CNN.

The primary challenge of machine learning algorithms is the requirement of a large amount of data. For CNNs this can be in the thousands, particularly if a model is not pre-trained. Consequently, these models must be trained on thousands of annotated examples to recognise anomalies such as cracks, material fatigue, corrosion, rust formation, surface defects, spalling, deformations and structural anomalies, insulation damage in electrical systems, vegetation encroachment at critical locations and abnormal vegetation growth behaviour. Detected defects are then classified by type and severity assisted by AI algorithms. For example, the possible output of crack detection includes crack number, length and width. This assessment and the location of damage facilitate the selection of more precise investigation techniques and the definition of the most appropriate remediation and corrective measures. This enables rapid, objective and scalable inspections that complement or replace manual visual checks, improving maintenance planning, reducing failure risk and lowering costs. Based on the results of the inspections, repair urgency and maintenance priorities can be determined according to the extent and progression of damage, safety relevance, probability of failure and compliance requirements.

The post-processing of the images captured during inspection can be typically carried out in four stages:

1. *Orthomosaic generation*: Individual RGB frames are stitched into georeferenced maps of the entire site using photogrammetry software (Pix4D, DroneDeploy or Agisoft Metashape). The construction of an orthomosaic is particularly useful for identifying the position of damage when a comprehensive image of the analysed point cannot be obtained through digital photographs. Although the process is time-consuming it facilitates the production of damage maps and maintenance activities.
2. *Anomaly detection and segmentation*: A machine learning model identifies individual anomalies and their boundaries within the orthomosaic. This is typically a segmentation task and architectures such as U-Net or Mask R-CNN can be employed.
3. *Defect recognition and classification*: A second model, such as a multi-task model, classifies each damage for defect types and severity. This process involves CNNs pretrained on a large dataset for recognising and classifying a series of defects. The classifiers are a combination of these CNNs that can be retrained using transfer learning for more focused analysis. By combining the results of different classifiers, the challenge of small datasets for defect classes can be effectively addressed. Real-time object detection frameworks built on CNNs such as YOLO variants are particularly suited for this purpose due to their speed and accuracy balance. YOLO is particularly well-suited for simultaneously detecting multiple objects.
4. *Maintenance intervention planning*: Detected anomalies can be transmitted as maintenance requests with defect class, severity and location, ready for prompt or scheduled intervention.

2.3. Basics for Flight Planning

The initial task of infrastructure inspection by drones involves flying over and capturing detailed visual images according to predefined flight plans.
When planning a drone flight path several key criteria must be addressed to comply with mission objectives and local regulations. These include ensuring collision-free flight, achieving full coverage of the structure to inspect, obtaining images of sufficient quality for feature detection and 3D reconstruction and minimising data volume by optimising the number of images and devising efficient flight routes.

To optimise flight speed, the plan should maintain a balance between flying fast enough for battery saving and slow enough to ensure high-quality image collection. First the drone speed must be aligned with the camera's capability to capture images at specified intervals. This interval is influenced by the required overlap between images which should range from 60% to 90% according to various studies. Second the flight speed should be coherent with the camera's photo interval which is the time required to save captured images. During this period the camera cannot take additional pictures so flying the drone too quickly could result in the loss of important data. Lastly exposure time should be adequate as the camera's shutter speed is affected by daylight settings and any movement during an open shutter can result in blurred images due to the larger area of light captured.

The timing of the flight plays a fundamental role to achieve high-quality inspection results. Shadow occlusion, daylight and solar radiation can cause overexposure during image acquisition affecting the emissivity of materials and resulting in false positives or exaggerated readings.

3. APPLICATIONS

3.1. Application Areas of AI-Powered Damage Detection by UAV

AI-powered damage detection by means of drones can be used in the energy, infrastructure, telecommunications, and industrial sectors to monitor and detect damage in various structures and equipment.

Table 1: Application Sectors

Sector	Structures and equipment	Damage
Energy Sector	- Power lines and high-voltage pylons - Wind turbines - Solar farms - Substations	- insulator damage, corrosion, vegetation risks - blade cracks, erosion, structural defects - thermographic detection of defective modules, hot spots, shading - monitoring transformers and electrical components
Infrastructure and Construction	- Bridges - Building façades - Roads and motorways - Tunnels and underpasses	- cracks, concrete spalling, corrosion on steel members - high-rise and industrial structure inspections - automatic detection of potholes and surface damage - structural condition monitoring
Telecommunications	- Mobile masts - Inventory management	- inspection of antennas, cables, and fixings - automatic capture of installed components
Industry and Facilities	- Pipelines - Refineries and chemical plants - Power stations	- corrosion detection and leak monitoring - tanks, pipelines, and process facilities - boilers, cooling towers, and chimneys

3.x. Example: SMR and Hydrogen System Integration Options

The sector integration solutions offer advantageous applications for infrastructure aerial inspections by small-size drones. These new concepts are designed to interconnect energy-intensive sectors such as industry, transportation and heating with the power-generation sector to create a more efficient, sustainable and integrated energy system. Within this configuration each sector is linked to at least one other and their interfaces become highly relevant as new risks may arise that require management by actors of different nature and operational objectives.

An example is provided by the NuScale concept of Small Modular Reactor (SMR) integration for hydrogen and ammonia production [15]. The proposed model is a distributed hub utilising small modular reactors. The NuScale-powered plant has a small land mass of approximately 40 acres is approved for off-grid operation and has a site boundary Emergency Planning Zone (EPZ) which allows proximity to industrial users. The site boundary EPZ provides separation between nuclear and commercial plants. The industrial facility could be a petrochemical plant or a hydrogen generating plant. Hydrogen is generated without producing carbon emissions. The solution suggests coupling the SMR facility to a state-of-the-art system of solid oxide electrolysis cells (SOEC) to readily produce commercial-scale quantities of hydrogen in a carbon-free and highly reliable and efficient manner.

According to NuScale, a regulatory base already exists for establishing jurisdictional boundaries between a nuclear plant and non-nuclear industrial facilities collocated at the same site. It suggests that energy-conversion systems located within the nuclear-protected area boundary are integral to the nuclear facility and those operated by the nuclear facility control room should be considered part of the nuclear facility. Nuclear safety analysis, including probabilistic risk assessment (PRA), is required for all nuclear and industrial systems of the nuclear facility in relation to potential missiles security issues flooding and any other impacts that may influence systems structures and components (SSC) that perform a nuclear safety function.

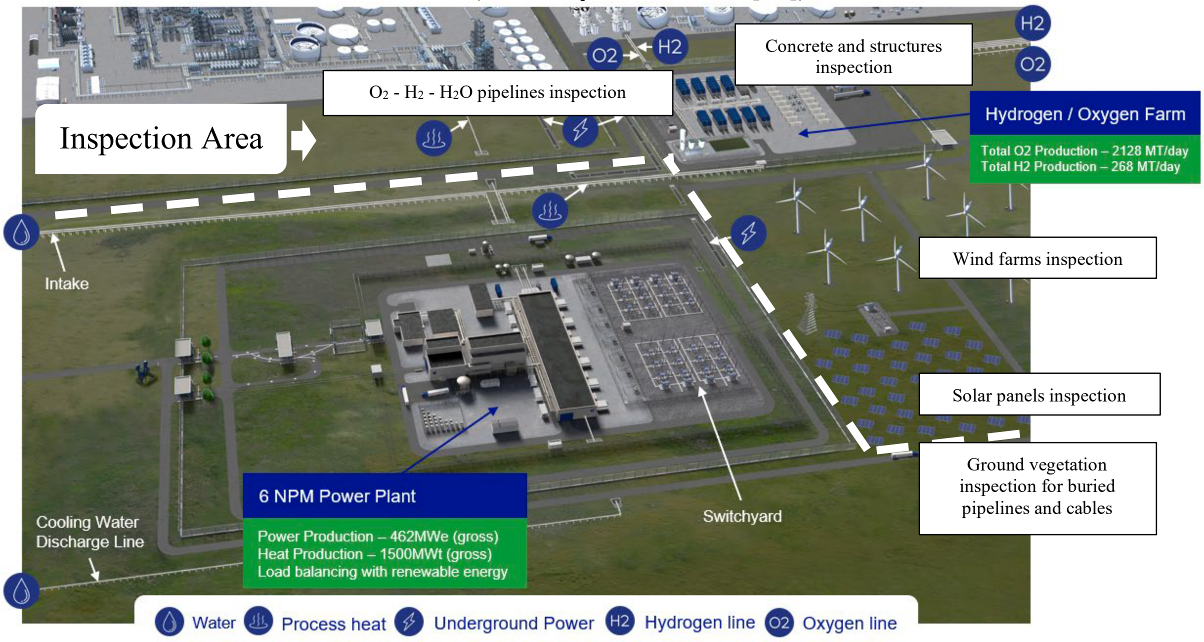
Energy-conversion systems located outside the protected area boundary and separated from the nuclear facility by a transfer system with appropriate interface criteria could be excluded from the nuclear facility scope.

Figure 2 illustrates a 6-module power plant supplying electric power and steam to a hydrogen plant located at the top right corner. A minimum safe distance between the plants is maintained. The image includes a “stand-off” distance between the power plant and the hydrogen production facility. The NuScale Reactor building has significant overpressure capability (5 psi=0.3447 bar) and could be safely located in as little as 150 m from the hydrogen production facility based on hydrogen hazards analysis. The risk of hydrogen detonation is a significant concern when collocating a nuclear power station (NPP) with hydrogen generation or utilisation facilities. The pressure caused by these detonations was used to determine a safety distance to avoid damage to the most vulnerable component in the switchyard: the transmission tower, located within the nuclear facility [16].

Inspection of critical infrastructures located at the interface and outside the nuclear facility is of paramount importance to prevent occurrence of undesired events. Drones can cover a large area in a short time, significantly reducing the time required for inspection compared to sending personnel to walk through the integrated site. Experts previously plan drone routes based on the layout of the infrastructures located outside the nuclear facility, such as hydrogen generating plant, wind farm, solar panel farm, pipelines, for aerial scanning. Even if operated in sensible areas, small-size drones pose negligible air and ground risk, and it is expected that they could obtain a permit for operation by the competent authorities through the submission of an application in the specific category supported by SORA analysis.

Once the permit is obtained, the drone operator prepares the plan for the specific mission to be accomplished after having examined the geography and the local characteristics of the operational area and following the basics for flight planning provided in paragraph 2.3. The drone performs the plan by flying over and capturing detailed visual images. The collected images are then analysed with various processing technologies to identify damaged structures and to provide instructions for maintenance intervention, as explained in Section 2.

Figure 2: Flight operation boundaries for small drones and inspection types. Conceptual Layout of a 6 NPM Power Plant Integrated with an SOEC Hydrogen Production Plant (Courtesy of NuScale, [15])



A good practice to perform high quality UAV-based inspections is to validate the methodology by developing a standardised and replicable research protocol. This protocol should enable the identification of damage through the collection, treatment, processing and technical analysis of recorded data.

4. DISCUSSION

As shown in the previous Sections, AI-powered drone inspection presents several advantages. Some limitations also exist and further research and development in certain areas is still necessary.

The main advantages can be summarized as follows:
- *Efficiency gains and time savings*: Manual inspections can take hours or days, whereas AI-powered drone inspections can analyse the same area in a shorter timeframe. This reduces the time to repair as damage can be notified to the maintenance team earlier.
- *Enhanced safety*: Drone inspections eliminate the need to send personnel to dangerous locations or hard-to-reach areas significantly reducing accident risk and supporting HSE (Health, Safety, Environment) standards.
- *Cost reduction*: Automated inspections, particularly with small-size drones, can reduce overall costs by lowering personnel demand, avoiding asset downtime, enabling early detection anticipating costly failures and optimising maintenance planning.
- *Precision and objectivity*: AI provides reproducible and objective results without the need for repetitive tasks. Furthermore, it utilises the recorded data to retrain models and enhance the precision of anomaly detection.
- *Scalability*: The approach is scalable across various typologies of facilities and sites..

Inspection planning is crucial to ensure cost-effectiveness, efficacy and data quality. A primary requirement for the advantages listed above to be effective is the development of an inspection protocol that experienced professionals apply during the drone mission to obtain high-quality images and data that are key inputs to data processing. To achieve this, a rigorous and informed flight plan must be prepared, either for automatic or manual operations.

Inspections conducted with drones are limited to external operations and the UAVs have a restricted flight endurance. Typical flight times for small-size UAVs range from 30 minutes to two hours. Furthermore, these UAVs are susceptible to adverse weather conditions such as strong winds, rain and light variations which can compromise flight stability and image quality. Image processing also requires appropriate overlays for the construction of visual resources to avoid flaws and occlusions. This can be hindered by the geometric complexity of the studied objects, surrounding obstacles and the potential for bird strikes. Another critical factor is the pilots' handling skills and experience as they must ensure the drone follows the automatic flight plan. They must also be prepared to take command in unexpected situations to maintain a steady and continuous trajectory and ensure the accuracy of the collected data.

Regarding data analysis, AI models typically require a considerable amount of time to process information, and the computational capacity must be pre-set to ensure timely results.

A few suggestions are made to overcome these limitations:

- The UAV's stability properties to withstand wind gusts must be known in advance and the flight inspection should be possibly planned when weather conditions are favourable. The UAVs should also be waterproof for rain events.
- Flights should be automated with an adequate percentage of image overlay (75–80%) to eliminate flaws and occlusions.
- Adequate computing capacity of the equipment used for image processing is necessary to avoid long processing times.
- Pilots need to undertake thorough and continuous training and development, along with frequent updates to keep pace with advances in UAV technology.
- Potential adverse weather conditions in the geographical area of interest should be identified and directions establishing landing, take-off and eventual flight postponement criteria should be provided.
- - AI models must be selected to balance complexity and computational time to achieve the desired precision of the results.

Future challenges include enhancing surface damage detection algorithms for greater precision and reduced computational load. While visual inspection technologies are mature, further progress in information technology is expected to lead to fully automated inspections utilising AI for damage recognition. Further research is therefore required to achieve a full and effective deployment of UAV-based inspections. The most relevant areas are:

- *Regulatory framework*: Authorisation processes should be simplified, and further studies should demonstrate that high safety levels are assured for air and ground risks. This will also facilitate the spread of BVLOS operations [17] to optimise flight planning and execution.
- *AI models*: Data bases should be enriched with new open data. AI models should be specifically trained for damage detection, recognition and classification to reduce computing time.
- *Hardware*: Advancements in hardware to enhance battery performance and reduce equipment weight, such as high-precision sensors, are necessary for the installation of these systems on small-size UAVs. Dedicated equipment should be designed to elaborate and transmit data in real-time.
- *Data processing and transmission*: A key aspect of drone inspections is transmitting high volumes of data in real-time. Reliable and high-bandwidth communication networks are essential for remotely driven drone-based monitoring enabling the transmission of images and video streams to remote locations. Communication technologies such as enhanced transmission and remote-control capabilities require further improvement to significantly expand drone applications.

5. CONCLUSION

The combination of drone technology with AI transforms infrastructure inspection into a data-driven, efficient process with high safety and compliance standards. Key advantages of AI-powered damage detection include automated, precise detection across large image datasets, reduced inspection times and personnel requirements, improved documentation and traceability via digital reports, seamless integration with asset management and maintenance systems and the enablement of predictive maintenance through early anomaly detection.

UAVs can minimise inspection time and cost by delivering speed, precision and scalability beyond manual methods. Integration with existing systems makes AI-powered drone inspections a key capability for critical infrastructure management.

The discussion about advantages and limitations shows that the use of drones for automated surface damage detection is a promising field that will gain increasing importance as hardware, communication and procedures improve. Among the benefits of using drones for such inspections are the ability to access hard-to-reach areas with ease, the rapid collection of a large amount of data and the enhanced safety conditions provided for the operator. The limitations concern particularly regulatory aspects, as drones often cannot fly over restricted areas where they might be a hazard and the environmental conditions.

Employing small-size drones offer several advantages. They are less intrusive, operate quietly and are lightweight, thereby minimising air and ground risks and typically requiring low capital expenditure. Furthermore, applicable regulations often permit exceptions for these types of UAV. The known disadvantages of operating light drones, such as the influence of weather conditions particularly wind and rain, can be successfully mitigated by well-defined missions, appropriate flight planning and supervision by experienced pilots.

Future challenges include simplifying authorisation processes while maintaining high safety levels for air and ground risks; improving surface damage detection algorithms and enriching data bases to increase their capability of detecting with precision a wide range of defects; reducing computational burden; improving hardware by enhancing battery performance, reducing equipment weight, designing real-time data processing equipment for installation on small UAVs; improving communication technologies for real-time data transmission.

AI-powered damage detection is evolving towards predictive analytics by forecasting failures before they occur; autonomous inspections by fully automated drone with BVLOS (Beyond Visual Line of Sight) operations; real-time monitoring by continuous surveillance of critical assets; and self-learning systems with AI models that improve continuously with new data.

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