# Final report

## 1. Project details

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| **Project title** | PACMAN |
| **File no.** | 64021-2072 |
| **Name of the funding scheme** | EUDP |
| **Project managing company / institution** | Semco Maritime A/S |
| **CVR number** (central business register) | 25490762 |
| **Project partners** | IPU, Aalborg Universitet, MM Survey, Energy Cluster Denmark and Trefor |
| **Submission date** | 09 March 2026 |

## 2. Summary

*Describe the objectives of the project, the obtained results and how they will be utilized in the future, both in English and in Danish. The summary will be published on www.eudp.dk and www.energiforskning.dk.*

### Project summary:


**The purpose of the project**

*The PACMAN project addressed the need for efficient corrosion management by developing and demonstrating a predictive technology that reduces the need for manual inspections through automated image analysis and decision support.*

**Results, conclusions and perspective**

*The PACMAN project demonstrated how predictive corrosion management can streamline inspection and maintenance of critical infrastructure. The project developed and tested a solution based on:*

- *Automatic positioning and tagging of inspection images*
- *Enhanced image capture using advanced camera technology*
- *Machine learning for visual corrosion detection in 2D images*
- *Transfer of 2D findings to a 3D model for better overview and planning*

- *Classification of corrosion findings by severity*

*The demonstration was initially conducted on both onshore and offshore facilities and concluded with a full-scale demonstration on an onshore plant featuring process technology.*

*The main results included a significant reduction in required manual labour hours, improved detection accuracy, and the establishment of a decision support platform for maintenance.*

*The results are expected to be used in future inspection strategies for offshore wind farms, transformer stations, and oil platforms, with the potential for substantial cost savings and increased operational reliability.*

*The technology is expected to reduce costs, improve safety, and provide a stronger foundation for proactive maintenance, contributing to a more sustainable and cost-effective operation of energy infrastructure.*

## Projektresumé

**Formålet med projektet**

*PACMAN-projektet adresserede behovet for effektiv korrosionshåndtering ved at udvikle og demonstrere en prædiktiv teknologi, der reducerer behovet for manuelle inspektioner via automatiseret billedanalyse og beslutningsstøtte.*

**Resultater, konklusioner og perspektiv**

*PACMAN-projektet demonstrerede, hvordan prædiktiv korrosionshåndtering kan effektivisere inspektion og vedligehold på kritiske infrastrukturer. Projektet udviklede og afprøvede en løsning baseret på:*

- *Automatisk positionering og tagging af inspektionsbilleder*
- *Forbedret billedoptagelse med avanceret kamerateknologi*
- *Maskinlæring til visuel korrosionsdetektion i 2D-billeder*
- *Overførsel af 2D-fund til en 3D-model for bedre oversigt og planlægning*
- *Klassificering af korrosionsfund efter alvorlighedsgrad*

*Demonstrationen blev først udført på landbaserede og offshore baserede faciliteter og afsluttet med en fuldskala demonstration på et landbaseret anlæg med proces teknologi.*

*De vigtigste resultater var en betydelig reduktion i nødvendige manuelle timer, forbedret detektionsnøjagtighed og etablering af en beslutningsstøtteplatform til vedligehold.*

*Resultaterne forventes anvendt i fremtidige inspektionsstrategier for offshore vindmølleparker, transformerstationer og olieplatforme, med potentiale for væsentlige besparelser og højere driftssikkerhed.*

*Teknologien forventes at reducere omkostninger, øge sikkerheden og give et bedre grundlag for proaktiv vedligeholdelse, hvilket bidrager til en mere bæredygtig og omkostningseffektiv drift af energiinfrastruktur.*

# 3. Project objectives

The project aims to revolutionize corrosion management in offshore and energy infrastructure by developing a fully digital, predictive, and sustainable system. The project's overarching objective is to drastically reduce manual labour, increase inspection efficiency, and extend asset lifetimes through a combination of advanced imaging, machine learning, and 3D spatial mapping technologies.

## 3.1 Strategic Goals

- **Digitalization of Corrosion Management:** Transform the current manual, paper-based, and subjective inspection process into a fully digital workflow - from data acquisition to repair and quality control.
- **Predictive Maintenance:** Enable early detection and severity classification of corrosion to prioritize maintenance actions and reduce unnecessary offshore trips.
- **Sustainability:** Reduce $CO_2$ emissions by minimizing offshore travel, eliminating printed documentation, and extending asset lifetimes.
- **Commercial Viability:** Develop a scalable, modular system that can be deployed across offshore wind farms, oil & gas platforms, and other steel-based infrastructure.

## 3.2 Technical Objectives

The following technical objectives outline the core innovations and capabilities that the project seeks to deliver.

- **Automated Spatial Tagging of Visual Data**
  Develop a robust positioning module capable of tagging every image with precise spatial metadata (location, orientation, timestamp). This enables accurate localization of corrosion findings and supports integration with 3D representations of the asset.
- **Enhanced Corrosion Detection through Multimodal Imaging**
  Integrate and benchmark RGB, multispectral, and hyperspectral imaging technologies to enhance the detection of corrosion, particularly in early stages.
- **3D Spatial Modelling of Offshore Assets**
  Establish a local 3D representation of the inspection site. This model serves as the spatial framework for projecting corrosion findings and contextualizing them within the asset's structure.
- **Machine Learning for Corrosion Identification and Classification**
  Develop deep learning models for automated corrosion detection and segmentation in 2D images. These models will be trained using both real and synthetically generated data to improve robustness and generalizability.
- **Synthetic Data Generation for Model Training**
  Create synthetic datasets using generative models to supplement real-world data. This will reduce the dependency on costly and time-consuming manual data collection and labelling.
- **Projection of Corrosion Findings into 3D Space**
  Combine spatial tagging and machine learning outputs to map corrosion findings directly into the 3D representation of the asset. This enables intuitive visualization, historical tracking, and spatial analysis of corrosion development.
- **Context-Aware Severity Classification**
  Implement object recognition within the 3D model to associate corrosion findings with specific components (e.g., pressure pipes, structural beams). Use this context to classify the severity of corrosion and prioritize maintenance actions.

- **System Integration and Field Validation**
  Integrate all components into a cohesive software platform. Validate the system through staged field tests - first onshore and then offshore - demonstrating usability, robustness, and efficiency in real-world conditions.

### 3.3 Impact

PACMAN transforms corrosion management by making it faster, more reliable, and more sustainable. The system reduces the need for manual work and offshore travel, helping to lower operational costs and environmental impact. It improves safety by limiting time spent in hazardous environments and enhances decision-making through better data quality and traceability. By supporting predictive maintenance, PACMAN helps extend the lifetime of offshore assets and ensures more efficient use of resources across the energy sector.

## 4. Project implementation

The project evolved steadily but encountered several external and technical challenges along the way. Early stages were impacted by extended delivery times and increased hardware costs due to global supply chain issues caused by the COVID-19 pandemic and resulting inflationary pressures. Additionally, key development activities relied heavily on computational resources, which proved to be more limited than initially anticipated. This led to delays in milestone completion, especially related to machine learning model training and image analysis. Despite these challenges, the project stayed on course and ultimately met its goals through careful adaptation and prioritization.

Five main risks were identified during the planning phase:

1. Position tagging technology might not function reliably in offshore conditions, especially due to movement and lack of GPS signals.

2. Corrosion detection using IR and hyperspectral imaging might not deliver mature, usable data offshore, where light and surface conditions differ significantly from lab settings.

3. 3D scanning could fail offshore due to wave reflections and suboptimal lighting, reducing the accuracy of spatial mapping.

4. The combined data processing requirements for tagging, detection, and 3D positioning might exceed available computing power, especially for real-time or near-real-time analysis.

5. The software platform needed to integrate with existing ERP systems and function in offline mode due to limited or no connectivity offshore.

Not entirely. While the overall project goals and structure remained intact, several milestones took longer than expected. This was primarily due to underestimated computing power needs for training and executing machine learning models. Procuring sufficient computational resources on a project budget proved challenging, and upscaling these resources would have made the project considerably more expensive. Additionally, delays in hardware delivery due to global supply chain disruptions impacted the timeline. However, the project team adapted the work plan accordingly and completed all key deliverables.

The project faced two unexpected problems:

1. Global hardware supply chain disruptions: Triggered by the COVID-19 pandemic, these delays and price increases were unforeseen and affected delivery of essential IT components.

2. Lack of annotated image data: Acquiring generalizable and diverse datasets for corrosion detection proved much more difficult than anticipated. Furthermore, the manual annotation process was highly time-consuming and costly, posing additional resource constraints.

These issues did not derail the project but required flexibility in planning and extended timeframes for certain technical components, especially related to model training and data preparation.

# 5. Project results

This section outlines the technical foundation of the PACMAN system, developed to digitalize and automate corrosion inspection workflows for offshore and industrial assets. By integrating advanced technologies such as 3D scanning, LiDAR-based localization, deep learning-based image analysis, and spatial visualization, the system delivers a structured, repeatable, and efficient inspection process. The following subsections detail each component of the workflow from data acquisition to visualization and integration and highlight how they collectively enable predictive maintenance and improved decision-making.

## 5.1 System Overview

The system is designed to streamline and digitalize corrosion inspection through a structured and repeatable workflow. The process integrates 3D scanning, sensor fusion, deep learning, and intuitive visualization. It consists of the following steps:

1. **3D Scanning the Asset**
   The user captures a high-resolution 3D scan of the asset using a laser scanner. This scan produces a dense, coloured point cloud that serves as a reference map for all future inspections. This step is typically performed once per asset.
2. **Image Acquisition**
   The user walks through the asset with a mobile data recorder - a custom-built device combining a camera and LiDAR sensor. The system is calibrated so the spatial relationship between the camera and LiDAR is known. As images are captured, the LiDAR data is used to localize each image within the reference 3D scan.
3. **Image Detection**
   Deep learning algorithms automatically analyse the images to detect and segment both corrosion and structural objects. These two outputs are overlaid to determine the context of each defect - for example, identifying corrosion on a specific pipe.
4. **Mapping**
   Because each image is localized in the 3D scan, the findings can be projected into the 3D model. Each corrosion instance is assigned a unique ID and stored in a structured database. The system also supports metric measurements of instance size using the 3D scan's spatial data.
5. **Visualization**
   All findings, images, and the 3D scan are presented in a browser-based user interface. This allows users to intuitively explore the asset, inspect and filter corrosion findings, and understand their spatial context.
6. **Data Export and Integration**
   The system supports exporting all data in standard formats, enabling integration with existing asset management or maintenance planning systems.

Steps 2-5 can be repeated as needed - for example, to perform follow-up inspections or quality assurance after repairs - while the initial 3D scan (Step 1) typically only needs to be performed once.

## 5.2 Imaging Technology Assessment for Enhanced Corrosion Detection

As part of the project's efforts to automate corrosion detection, a key activity involved evaluating and selecting suitable imaging technologies for capturing corrosion-related features on offshore infrastructure. The primary objective was to assess whether alternative imaging modalities could offer improvements over conventional RGB imaging, particularly in terms of detection reliability and classification accuracy. The initial scope included a broad survey of imaging technologies, ranging from standard digital photography to more advanced methods such as hyperspectral imaging. These alternatives were assessed based on their technical feasibility, maturity (TRL), cost, and practical applicability in offshore environments.

Hyperspectral imaging was identified as a promising technology due to its ability to capture detailed spectral information beyond the visible range. This capability allows for the detection of subtle material differences and corrosion-related changes that may not be visible in RGB images. Demonstration tests using VNIR and SWIR hyperspectral systems confirmed the potential of this approach, showing that corrosion could be classified based on spectral signatures rather than visual features alone.

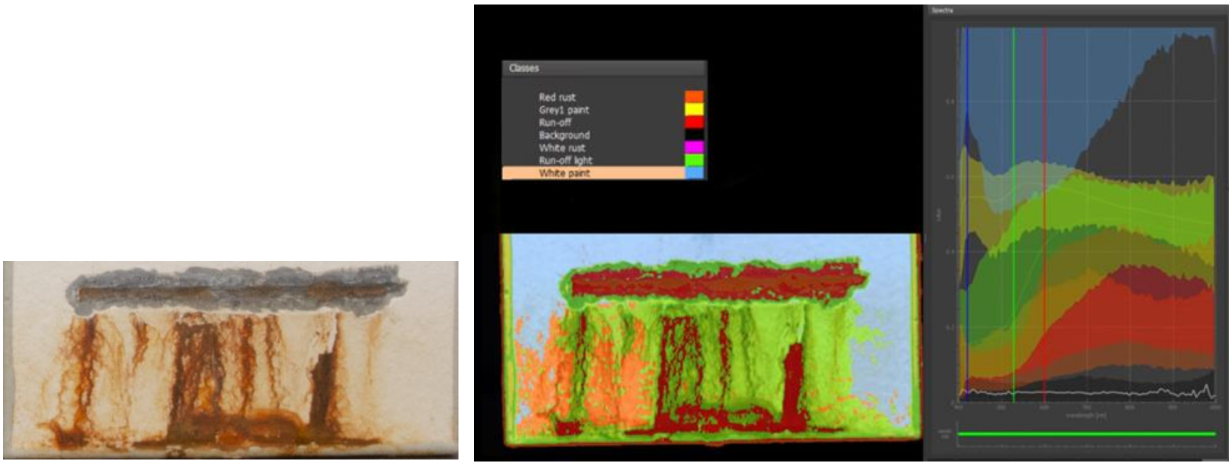



Figure 1 - Example of corrosion classification using hyperspectral data (right). The classifier was trained on a different sample with a distinct paint system and then applied to the current image. For comparison, an RGB image of the same sample is shown on the left.

However, several practical limitations were identified. Hyperspectral systems typically require controlled lighting conditions, which are difficult to ensure in offshore environments where lighting varies significantly due to weather and structural shading. Additionally, the systems tested required either mechanical movement (e.g., rotation stages) or extended acquisition times, which complicates deployment in the field. SWIR systems, while offering deeper penetration into coatings, were found to be cost-prohibitive and more complex to operate compared to VNIR systems.

Given these considerations, it was concluded that conventional RGB imaging remains the most practical and scalable solution for corrosion detection in the current context. RGB cameras offer sufficient resolution, ease of use, and compatibility with existing data processing pipelines. In addition, RGB-based computer vision models are more mature and benefit from a broader ecosystem of tools and pretrained models, even though domain-specific annotated datasets - such as offshore corrosion - are still limited.

In summary, while alternative imaging technologies demonstrated technical potential, their limitations in terms of cost, complexity, and sensitivity to environmental conditions led to the decision to proceed with RGB imaging as the primary approach for corrosion detection. The evaluation process also provided a useful foundation for future exploration of advanced imaging methods, particularly if challenges related to lighting control and system integration can be addressed in subsequent development efforts.

## 5.3 Automated Corrosion and Object Identification

A central component of the PACMAN project was the development of automated methods for identifying corrosion and critical structural elements in offshore infrastructure. This capability is foundational to predictive corrosion management, which aims to assess the severity of corrosion in context and prioritize maintenance accordingly. The overarching goal was to reduce the reliance on manual inspection, improve detection accuracy, and enable scalable, cost-effective monitoring of offshore assets.

The project addressed two main tasks: detecting corrosion in images and identifying the objects on which corrosion occurs - such as pipes, beams, and other structural components. These tasks were approached using semantic segmentation techniques based on deep learning, allowing for pixel-level classification of corrosion and object boundaries.

One of the main challenges encountered was the limited availability of annotated data specific to offshore corrosion. Although a large dataset of RGB images was available, only a subset had been manually labelled for corrosion and object segmentation. To address this, two complementary strategies for synthetic data generation were developed. The first used generative adversarial networks (GANs), to add realistic corrosion to real images. The second used NVIDIA Isaac Sim to generate fully synthetic 3D scenes with labelled corrosion and objects. These synthetic datasets were used to supplement training data and improve model generalization.

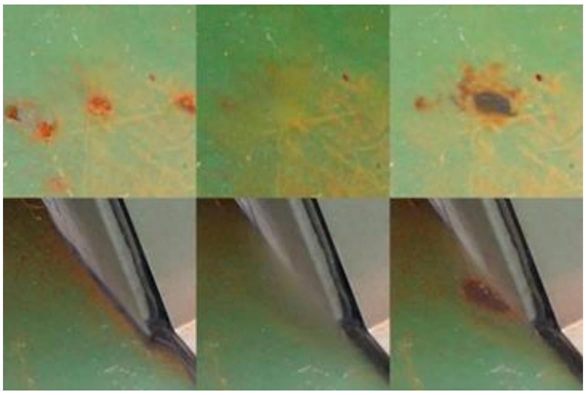


Figure 2 - Image crops from corrosion generation. Original (left), removed corrosion using inpainting (middle), generated corrosion (right).

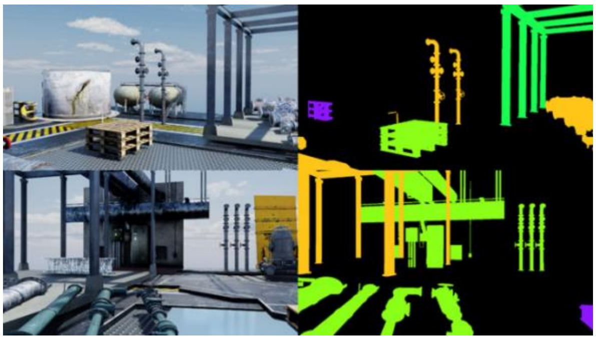


Figure 3 - Examples of images generated with Issac Sim (left) with associated object segmentation masks (right).

For object segmentation, initial efforts using DeepLabv3+ were constrained by the limited size and variability of the available dataset. To improve performance, a pretrained segmentation model - Segment Anything Model (SAM) - was adapted and fine-tuned to segment critical objects without requiring manual prompts. By modifying only the decoder component, the model was tailored to the task with relatively modest computational resources and training data.

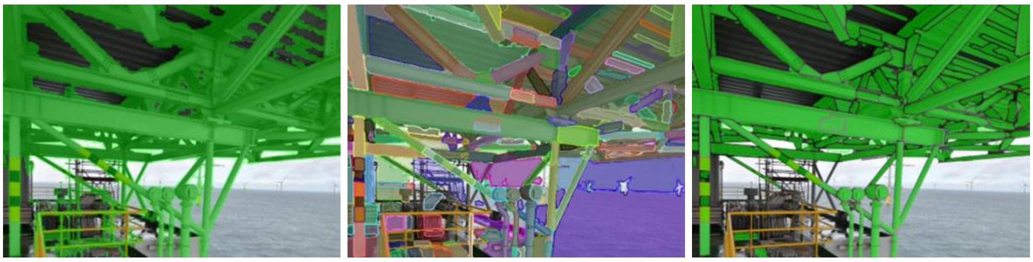


Figure 4 – Example of object segmentation. Segmentation mask produced by the tuned model (left), output from the SAM model (middle), and final segmentation mask with refined edges using the SAM output (right).

Corrosion detection was also explored through an alternative approach using a generative adversarial network (GAN) trained to transform images by removing visible corrosion. By comparing the original image with its cleaned counterpart, a corrosion mask could be derived from the differences between the two. This method showed potential, particularly for isolating corrosion regions, though it proved more effective at removal than at generating realistic corrosion patterns. Its performance was also influenced by factors such as image resolution and content complexity.

Figure 5 - Example of corrosion segmentation. Original image with corrosion (left), image with removed corrosion using GAN (middle), corrosion segmentation mask obtained from difference between the first two images (right).

Overall, the project achieved its core objectives, though some adjustments were necessary along the way. The integration of synthetic data, the adaptation of SAM for object segmentation, and the use of multiple detection strategies contributed to a flexible and modular solution. While the performance of the models varied depending on the task and data quality, the results demonstrated that automated corrosion and object segmentation is feasible and can support further development of predictive maintenance tools.

The work also highlighted areas for future improvement. These include expanding the dataset with more diverse examples and refining severity classification methods. Continued collaboration with industry partners will be important for validating the models in operational settings and ensuring that the tools developed are aligned with practical needs.

In summary, the work on corrosion and object segmentation provided a solid foundation for predictive corrosion management. It demonstrated the potential of combining deep learning, synthetic data, and advanced segmentation models in a real-world industrial context, while also identifying clear directions for further development and refinement.

## 5.4 3D Scanning of Assets

To support automated corrosion detection and contextual analysis, a key component of the project involved establishing a reliable method for 3D scanning of offshore infrastructure. The purpose of this work was to generate a spatial representation of the asset that could serve as a reference for mapping corrosion findings, supporting severity classification, and enabling virtual inspection workflows.

A set of functional requirements was first defined to guide the selection of suitable scanning equipment. These included portability, ease of use, sufficient accuracy and resolution, and the ability to operate in offshore environments. The scanner needed to be lightweight and operable by a single person, with minimal setup time and no reliance on external hardware. It also had to deliver coloured point clouds and panoramic images, with a scanning range suitable for both confined and open areas on the platform.

Following a market survey of available technologies, a tripod-mounted laser scanner - specifically the Faro Focus S150 - was selected. This choice was based on a combination of technical specifications, scan quality, and cost. While several competing alternatives were considered, the selected model offered a good balance between performance and affordability at the time of selection. However, as the project progressed, handheld scanning technologies evolved rapidly. These newer systems offer greater flexibility and faster operation while still delivering sufficient scan quality and precision for the intended use. If the selection were made today, a handheld scanner might be preferred due to its operational efficiency and ease of use in complex environments.

To ensure consistent and high-quality data acquisition, a detailed scanning procedure was developed. This included recommended scanner settings, scanning strategies, and post-processing workflows. Key aspects of the procedure included:

- Ensuring sufficient overlap between consecutive scans to support accurate registration.
- Managing lighting conditions and minimizing the presence of moving objects during scanning.
- Using post-processing software to align and merge scans into a unified 3D model, apply filters to reduce noise, and prepare the data for further analysis.

The resulting 3D scans serve multiple purposes. They provide a global map of the asset, which supports positioning and navigation. They also enable corrosion findings from 2D images to be projected into 3D space using camera calibration and pose data. A dedicated data interface for managing this integration has been developed and will be described in a later section.

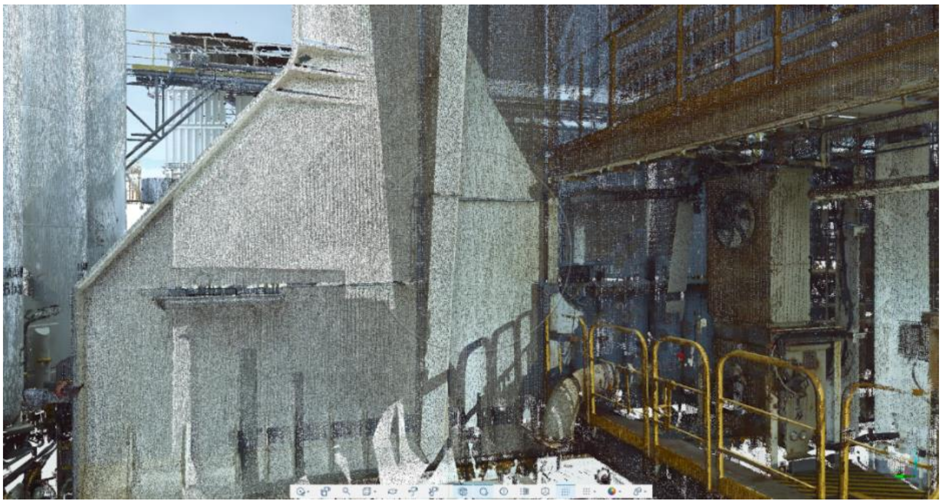


Figure 6 - Example of a 3D scan of the asset represented as a coloured point cloud.

In summary, the 3D scanning component of the project established a practical and effective method for capturing detailed spatial representations of offshore assets. This capability is essential for contextualizing corrosion findings, supporting severity assessment, and enabling future developments in digital asset management and predictive maintenance.

## 5.5 Image Localization and Corrosion Mapping

To enable accurate mapping of corrosion findings within a 3D spatial context, a custom image acquisition and localization system was developed. The system is designed to capture high-resolution images of offshore infrastructure while simultaneously determining the precise position and orientation of each image relative to a pre-scanned 3D reference model of the asset.

The core of the system is a LiDAR-based localization approach. A LiDAR sensor is used to estimate the position of the device within the 3D scan of the asset, providing an initial pose estimate. The localization is based on the extraction of point features in both the global map of the asset and the local point cloud from the LiDAR. The features are then matched to find the best possible correspondences. The positioning of the matched local map to the global map derives the transformation between the two, and thereby the position of the LiDAR in the asset map at the given time. This position estimate is then refined using an Iterative Closest Point algorithm, which improves alignment by minimizing the distance between the current LiDAR scan and the reference point cloud. This refinement step is essential to ensure that each captured image can be accurately projected into the 3D model.

The localization system is paired with a calibrated camera. Calibration ensures that the spatial relationship between the LiDAR and the camera is well-defined, allowing transformations between the two sensor coordinate systems. This typically involves capturing a series of images and LiDAR scans of a known calibration target, from which the relative pose between the sensors can be estimated. Once calibrated, the system can compute the transformation from each image to the global 3D reference frame.

The hardware platform, referred to as the Mobile Data Recorder, was developed through several design iterations. Each version focused on reducing the size and improving the usability of the device. The final prototype is a compact, handheld, battery-powered unit equipped with a user interface screen and a capture button. It allows operators to view captured images in real time and control the acquisition process directly. While still a proof of concept, the device functions as intended and demonstrates the feasibility of the approach, though further refinement is possible to improve ergonomics, robustness, and integration.

Throughout development, the system was tested with a range of sensors. For LiDAR, the Velodyne VLP-16 was used to provide 3D spatial data. For image capture, three different cameras were evaluated: the Intel RealSense D435i depth camera, the JAI GO-5000C industrial vision camera, and the Nikon Z6 II DSLR camera. All sensors are controlled by a single board computer, which also handles data storage during acquisition. These sensors were assessed for their performance, integration feasibility, and image quality.

Figure 7 - Front and back views of the Mobile Data Recorder. The device integrates a LiDAR sensor, camera, and single board computer into a handheld unit. It features a built-in touchscreen interface with an integrated capture button, allowing users to preview and record images during inspection.

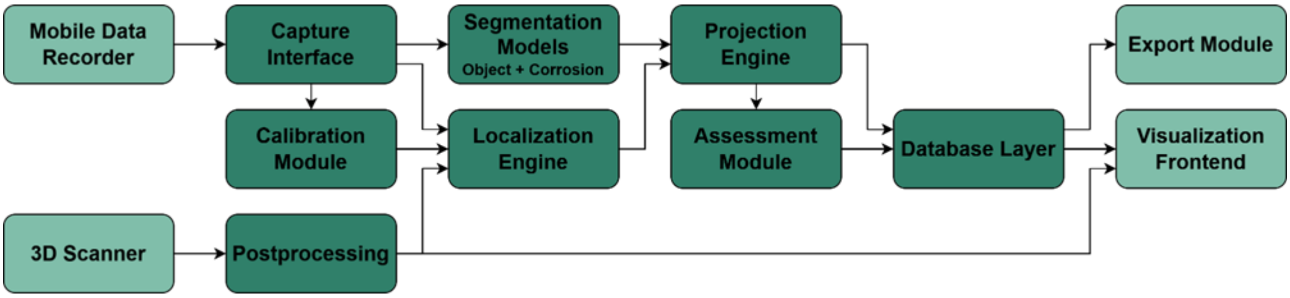
The combined localization and image acquisition system makes it possible to determine the exact position where each image was captured and provides all necessary transformations to project each image into the 3D model, enabling precise spatial mapping of corrosion findings.

This spatial mapping is critical for assigning unique identifiers to corrosion instances, measuring their size and shape, and associating them with specific structural elements. While the system performs well in most scenarios, it can be challenged in environments where the reference map or LiDAR data is sparse or lacks distinctive geometric features. Examples include large flat surfaces, repetitive structures, or areas with limited scan coverage. In such cases, localization accuracy may degrade, and additional refinement or manual intervention may be required.

In summary, the image acquisition and localization system provides a functional and flexible platform for capturing corrosion data in a spatially aware manner. It forms a key part of the overall corrosion management workflow by enabling the integration of image-based findings into a unified 3D representation of the asset.

## 5.6 Software Implementation and Visualization

A modular software system was developed to support the full corrosion detection workflow, integrating all major components of the project into a unified processing pipeline. This includes data acquisition, localization, image analysis, and projection of findings into the 3D reference model. The system architecture defines how data flows through each stage, ensuring consistency, scalability, and traceability across the entire process.




| Component | Description |
|---|---|
| Capture Interface | Interfaces with the mobile data recorder to capture raw data. |
| Calibration Module | Maintains and applies the camera-LiDAR transformation. |
| Localization Engine | Determines the position and orientation of each image within the reference map. |
| Segmentation Models | Deep learning models for object and corrosion detection. |
| Projection Engine | Projects 2D segmentations into 3D space. |

| | |
|---|---|
| Assessment Module | Evaluates, measures and compares detected corrosion. |
| Database Layer | Stores all findings, metadata, and spatial relationships. |
| Visualization Frontend | Web-based UI for exploring 3D scan, images, and findings. |
| Export Module | Converts data into formats compatible with external systems (e.g., CSV). |

Figure 8 - System Architecture and software components

A proof-of-concept visualization frontend was also developed. This interface allows users to explore the 3D model of the asset, view the captured images and their spatial positions, and inspect a list of detected corrosion findings. Each finding is linked to its location in the 3D model and includes relevant metadata such as size and associated images. While still in prototype form, the visualization tool demonstrates the potential for intuitive inspection and review of corrosion data in a spatial context.

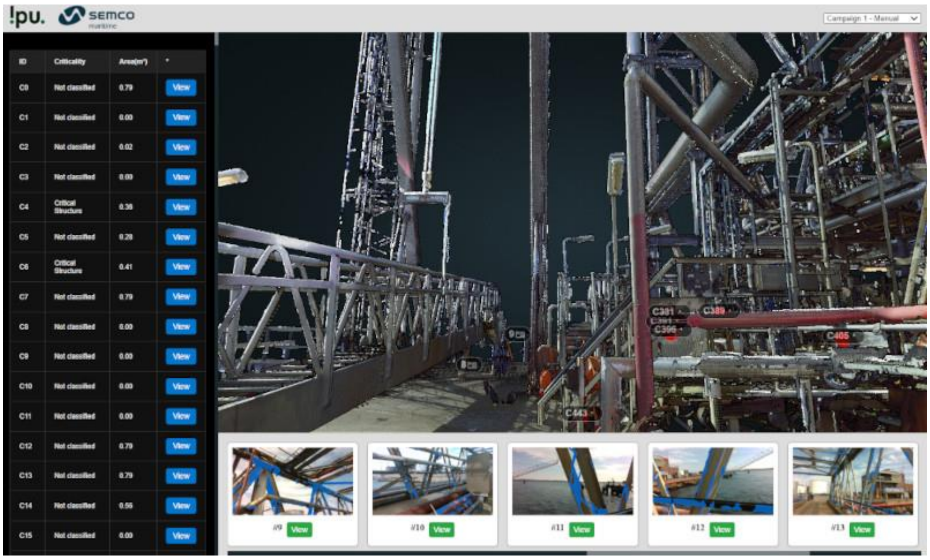
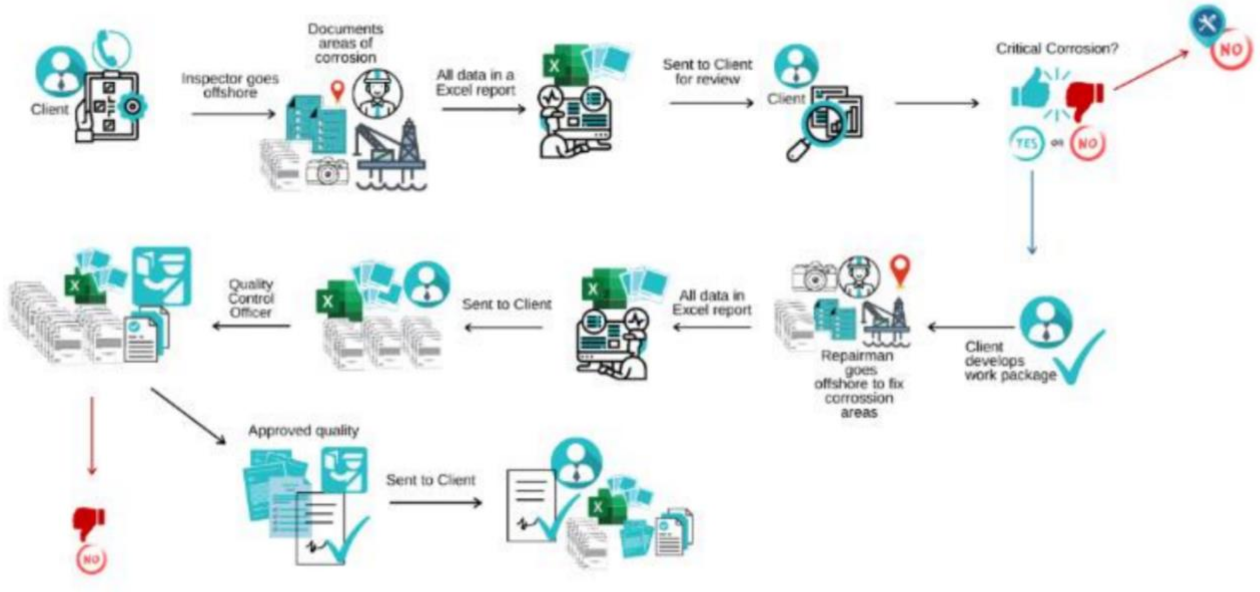


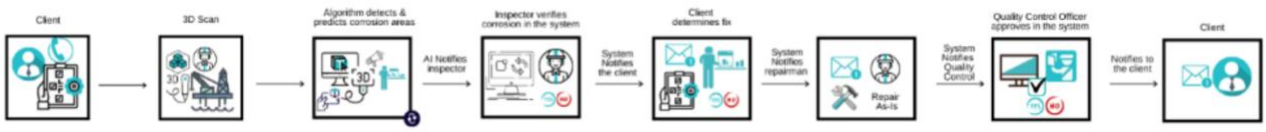
Figure 9 - Screenshot of the visualization frontend showing the 3D model, spatially positioned images, and a list of corrosion findings.

## 5.7 Operational Strategy for Sustainable Corrosion Management

The current (AS-IS) operational strategy for offshore corrosion management, revealing a highly manual, reactive, and inefficient process. It relies heavily on physical documentation, multiple offshore trips, and subjective assessments by service providers, often resulting in high costs, long lead times, and significant environmental impact.




The PACMAN project introduced a future (TO-BE) strategy focused on digitalization, automation, and predictive corrosion detection. By integrating AI-based image analysis, 3D scanning, and a unified digital platform, the new process reduces offshore visits by up to 67%, eliminates printed documentation, and cuts end-to-end process time by 85%.



Key results include a strategic shift from reactive, partner-driven workflows to proactive, AI-assisted planning, enabling better decision-making, enhanced regulatory compliance, and greater sustainability. The PACMAN solution transforms corrosion management into a streamlined, standardized, and cost-effective practice — reducing both environmental footprint and operational complexity for offshore asset owners.

# 6. Utilisation of project results

The technological results developed in the PACMAN project will be utilized by both service providers and asset owners in the energy and infrastructure sectors, particularly within offshore and onshore environments where corrosion management is critical.

Service providers will use the PACMAN system to enhance their corrosion inspection and maintenance offerings, enabling more efficient data collection, improved documentation quality, and predictive planning capabilities. The technology will streamline their workflows, reduce offshore trips, and improve reporting accuracy.

Additionally, asset owners themselves will have the option to perform data collection independently using the PACMAN platform. This allows for greater operational flexibility and supports the growing trend of digital in-house asset management. Owners can leverage the platform to gain early insight into corrosion progression, prioritize maintenance efforts, and improve long-term planning ultimately supporting safer, more cost-effective, and sustainable operations.

The commercial results of the PACMAN project will be further developed and commercialised jointly by IPU and Semco Maritime. Building on the technological foundation established during the project, the partners aim to create a market-ready product that can be offered to infrastructure and energy asset owners particularly those operating offshore or in corrosion-critical environments.

The commercial solution will be designed to support asset owners in managing corrosion more proactively and efficiently through a digital platform that combines automated inspection, advanced image analysis, and predictive maintenance planning. IPU will contribute with continued technological development and refinement of the core algorithms and software platform, while Semco Maritime will act as a commercialization partner, leveraging its strong market position and network in the offshore industry to bring the solution to clients.

This commercialisation strategy ensures that the value created in the project will be translated into a practical, scalable solution capable of meeting real-world industry needs.

The PACMAN project directly supports national and international energy policy objectives by contributing to a more sustainable, cost-efficient, and secure operation of energy infrastructure particularly in the offshore sector.

By enabling predictive and digitally supported corrosion management, the project reduces the need for resource-intensive and carbon-heavy offshore inspections. This aligns with **climate and sustainability goals** by significantly lowering the number of transport operations, reducing emissions, and minimizing the environmental footprint of maintenance activities.

Furthermore, PACMAN enhances the **reliability and longevity of energy assets**, supporting infrastructure resilience — a key objective in ensuring stable and secure energy supply from renewable sources such as offshore wind. By protecting critical infrastructure more efficiently, the project reduces unplanned downtime and maintenance costs, ultimately supporting the **economic viability of green energy investments**.

Lastly, by promoting **digitalisation and innovation** in a traditionally manual and fragmented domain, the project contributes to the broader transition toward a smarter, data-driven energy sector a core ambition of many national and EU-level energy strategies.

The students involved in the PACMAN project have contributed to development activities, particularly in areas related to machine learning, computer vision, and digital corrosion detection.

The insights and findings from the project are being integrated into academic curricula and teaching activities at the involved institutions, particularly in graduate-level courses related to predictive maintenance, applied AI, and offshore infrastructure management.

In addition, the project results have been disseminated through conference presentations, technical workshops, and peer-reviewed publications, helping to share knowledge with both academic and industrial audiences.

In addition, the project results have been disseminated through conference presentations, technical workshops, and peer-reviewed publications, helping to share knowledge with both academic and industrial audiences. The PACMAN project has served as a valuable case study for illustrating real-world application of AI and digitalisation in the energy sector, and has thereby strengthened the link between research, education, and industry innovation.

# 7. Project conclusion and perspective

The PACMAN project successfully developed and demonstrated a fully digital and predictive corrosion management system tailored for offshore and energy infrastructure. The main conclusions include:

- **Efficiency and Accuracy**: The system significantly reduced the need for manual inspection hours and improved the accuracy of corrosion detection through machine learning and automated imaging.
- **Technological Integration**: A modular, scalable platform was created, combining 3D scanning, spatial tagging, deep learning models for corrosion and object detection, and a browser-based visualization interface.
- **Operational Shift**: The project introduced a shift from reactive, manual inspection practices to proactive, data-driven maintenance strategies.
- **Feasibility and Usability**: Field demonstrations confirmed that the system is practical for both onshore and offshore environments, with a full-scale test conducted on a processing facility.
- **Environmental Impact**: The solution supports significant sustainability benefits, reducing offshore trips and documentation needs, thereby lowering $CO_2$ emissions and operational costs.

These results confirm that predictive corrosion management is not only feasible but also advantageous from both technical and economic perspectives

The PACMAN system is poised for further development and commercial rollout. The next steps include:

- **Commercialization**: IPU and Semco Maritime will jointly develop a market-ready product. Semco will lead commercialization efforts, leveraging its position in the offshore market.
- **Product Refinement**: Continued work will focus on refining the algorithms, enhancing hardware integration (e.g., exploring handheld scanners), and improving the user interface.
- **Operational Deployment**: Service providers can integrate PACMAN into their corrosion inspection offerings. Asset owners may also deploy the system for in-house inspections, increasing autonomy and reducing reliance on external consultants.
- **Broader Application**: The technology is adaptable to various corrosion-critical infrastructures such as offshore wind farms, transformer stations, and oil & gas platforms.
- **Education and Research**: The results will be used in academic programs and shared through conferences and publications to promote wider adoption and stimulate further research in predictive maintenance.

The PACMAN project's outcomes have strong implications for the future of digital infrastructure management:

- **Industry Transformation**: The system provides a blueprint for modernizing maintenance workflows, moving from fragmented, manual processes to streamlined, AI-assisted operations.
- **Sustainability and Climate Goals**: By reducing offshore transport and extending asset lifetimes, PACMAN supports national and international energy policy goals related to sustainability and carbon reduction.
- **Economic Efficiency**: The reduction in inspection costs and downtime can contribute to the economic viability of renewable and conventional energy infrastructure.
- **Scalability**: The modular nature of the system allows adaptation to other industrial sectors facing similar corrosion challenges, increasing the potential for cross-industry impact.

- **Innovation in Education**: Education and knowledge dissemination: The PACMAN project contributes to educating the next generation of engineers through collaboration with universities and using project results in teaching and professional knowledge sharing.

# 8. Appendices

- Maskinmesteren – January 2025
  https://ipaper.ipapercms.dk/MaskinmestrenesForening/Maskinmesteren/2025-mm1/
  8-pages article and frontpage cover
- LinkedIn Posts about the project
  https://www.linkedin.com/posts/energyclusterdenmark_pacman-rust-bek%C3%A6mpes-med-innovativ-3d-platform-activity-7285658916623945728-ig2C/?originalSubdomain=dk

  https://www.linkedin.com/posts/ipu_hsi-corrosiondetection-disruptivetech-activity-7081643996992696320-NP8B/

- Pacman Project video
  https://www.youtube.com/watch?v=Sg8xoUROP74