HYBRID DIGITAL TWIN: LEVERAGING 3D MODELING AND STRUCTURED DATA FOR PHOTOVOLTAIC SYSTEM AUTONOMY

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Abstract

This work highlights the significant aspects of developing a digital twin (DT) for photovoltaic (PV) systems, with a focus on digital models that enable the safe and efficient use of autonomous platforms. Autonomous systems in this context refer to unmanned air systems (UAS) and ground robots. The integration of autonomous systems introduces the need for a different approach to modeling principles to enhance navigation coordination and real-time image transfer. As part of ongoing research, this study investigates aspects of 3D modeling and database implementation. We present findings from the terrestrial laser scanner (TLS), structure-from-motion (SfM) 3D models, and interaction with the database structure for an experimental PV farm. As part of the project outcomes, we clarify the distinguishing factors between a digital twin for PV systems and advanced robotics systems. The potentials, research gaps, and critical lessons learned are also highlighted for in-depth understanding. This report aims to provide foundational documentation for future research or industrial implementation with a similar focus. It is envisaged that current and future solar photovoltaics research in this area will build on these insights, highlighting the realities and benefits of DT technology while enhancing in-depth penetration, management, and control of renewable energy systems.

1 Introduction

An increase in complexity, number of modular installations, and size of energy systems, coupled with unique demand profiles, has resulted in an unprecedented need for more advanced digitalization platforms [1], [2], [3]. The digital twins' concept describes an advanced digitalization mode, where virtual replicas of physical energy systems are created to enhance bidirectional control and real-time monitoring, optimization, and predictive maintenance [4], [5] DTs are configured to integrate real-time data from sensors, keep historical records, and process the data using various machine learning (ML) or artificial intelligence (AI) algorithms to produce dynamic models that replicate the structure and characteristics of their physical counterparts or physical twin (PT) [6]. DTs can be implemented for individual components, sub-systems [7], or whole systems [8], making it possible to develop highly scalable energy systems as they become increasingly complex and interconnected. This offers unprecedented opportunities for improving the efficiency, reliability, and sustainability of very large energy systems such as local microgrids or utility scales. Note that the complexity of a DT itself is dependent on the use necessitating its development.

DTs have been implemented mostly using simulations for several energy systems, such as wind [9], bioenergy [10], micro-grid [11], and PV systems [12]. This work focuses on the development of DTs for PV systems based on the need to integrate UAVs and UGVs for installed PV systems maintenance. We focus on the use of 3D models and data storage to enable real-time interaction and control of the UAV/UGV, providing valuable insights into the challenges and potential for future development.

2 DT for PV Systems

2.1 Conventional Approach

Several references indicate the implementation of DT for PV systems. While most of them are at the component or sub-module level [13], [14]; others do not reflect the true nature of a DT, which is bi-directional and real-time interaction and control [15], [16]. DTs can largely be classified into model-driven (MD-DT), data-driven (DD-DT), or hybrid models (H-DT) [6] depending on the purpose of the DT. Model-driven DTs rely on mathematical or physical models of the physical twin to determine a relevant output, while data-driven DTs are reliant on historical or real-time data, which are processed and applied for feedback. Hybrid models combine both for a more detailed evaluation. System integration in model-driven DTs can sometimes be extended to the use of computer-aided-design (CAD) models for immersive and real-time applications. This creates a wholesome and rigorous process that ensures verifiable and trustworthy systems. This work aims to implement a hybrid-model DT using CAD models to ensure safe autonomy in large systems maintenance and monitoring.

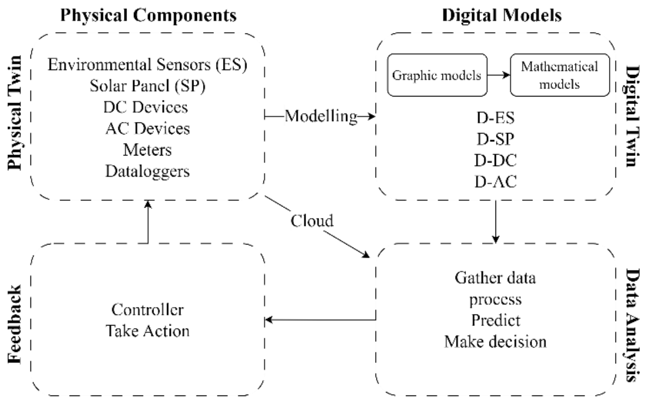


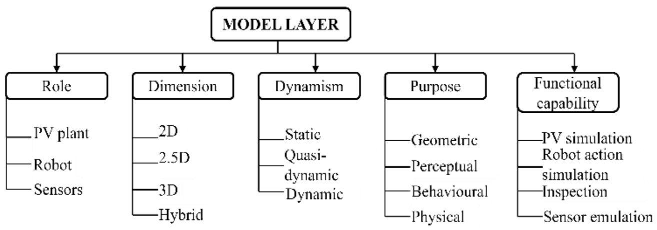
Fig. 1: Simplified overview of conventional PV DT

PV systems have been conventionally monitored using different digitized platforms that do not have to utilize real-time data, such as those described in [17], [18]. The platforms are also not capable of implementing real-time control, thus limiting the system's reliability and ease of management. [19] implemented advanced monitoring DT with real-time bidirectional data flow and system control. In Fig. 1, we present a simplified overview of the PV DT showing the interaction between the PT and DT. Note that for the conventional PV-DT, the models are often mathematical models only or implemented in parallel with 2D graphic models. This is simply because there is no need to use a 3D model except for aesthetic purposes. However, with the increasing need to alleviate the rigor associated with PV plant maintenance and the existence of autonomous platforms capable of remote maintenance activities, there is a new gap for developing models that simplify such activities while ensuring the safety of assets and involved humans.

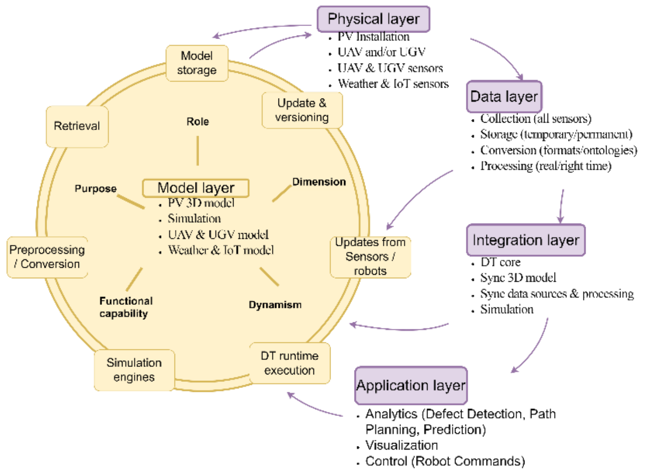
2.2 PV-DT models

Autonomous platforms drastically reduce inspection time and enable frequent monitoring activities for remote and large-scale systems. However, there exists limited literature detailing the physical implementation of a DT for solar PV, and not only simulation, such as in [20]. Determining a suitable model in this use case depends on a variety of parameters, and core to this is the need to safely navigate the platforms around the PV infrastructure, little animals that roam the site, and humans involved in the overall monitoring and maintenance procedures.

In Fig. 2a, we highlight different functions and perspectives of a PV-DT model, while the DT layer-level architecture and model integration are depicted in Fig.2b.



a



b

Fig. 2 PV-DT (a) Model layer taxonomy, (b) Model-layer integration.

As shown in PV-DT taxonomy of Fig. 2a, the digital model layer can be developed based on the various context and use envisaged. For integration with autonomous platforms as implemented in this work, the 3D model is applied to aid physical observation of the navigation and inspection of the robots, while retaining the capability to depict spatio-temporal changes in the PV system output. This implies that the integration of the model layer in the overall DT architecture (Fig. 2b) must be designed to ease bi-directional data transfer between the 3D-model-database-physical layer, where the autonomous platforms operate in real-time.
As described in Section 2.1, the model developed in this work is defined as a hybrid model because it combines the functionality and dimensionality of a model-driven DT and a data-driven DT. While the model aspect is used for PV simulation and autonomous platform control, the data-driven aspect incorporates data from sensors and the PV system to define required actions and recommendations.

In the following sections of this work, we provide progress for the ongoing implementation of a PV DT designed to enable bidirectional control of autonomous platforms and highlight important considerations.

3 3D-Model Development for a PV Installation

In this section, we describe the development of 3D models for our experimental solar installation using two methods: (i) a terrestrial laser scanner, and (ii) UAS SfM. We explore the challenges, benefits, and limitations of each model. Note that the models were developed to enable navigation and ease of control for autonomous platforms, which are to be integrated for routine or targeted maintenance operations on the site.

3.1 Terrestrial Laser Scanning (TLS) Model

Data acquisition has been done with the use of a terrestrial laser scanner (TLS). A TLS is a land surveying instrument that allows the creation of a discrete 3D model of the surface of the object or terrain. The working principle is based on sending a laser beam and recording the time-of-return, phase, and angle of the reflected beam. Continuous scanning creates a set of data points or outputs referred to as a point cloud. The coordinates of each point are calculated as follows:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = d \begin{bmatrix} \sin(V)\cos(Hz) \\ \sin(V)\sin(Hz) \\ \cos(V) \end{bmatrix} \quad (1)$$

$$d = \frac{\Delta\Phi c}{4\pi f n} \quad (2)$$

where, $c, c_{atmos}, n, t, d, Hz, V, \Delta\Phi, f, X, Y, Z$ are the speed of light traveling through a vacuum, $3 \times 10^8 m/s$, speed of light in standard atmosphere, light refractive index, in standard atmosphere $(20^0 C) \approx 1.0003$, laser beam total time-of-flight, distance from the object, horizontal bearing, vertical angle, phase difference between sand and return signal, frequency of the laser signal, and coordinates of each surface point.

The laser scanner used for this project was Leica RTC360, a 3D laser scanner with an integrated HDR spherical imaging system and a Visual Inertial System (VIS) for real-time registration. It is a white light phase scanner with a type 1 laser class system (following IEC 60825-1:2014). The range of this scanner is 0,5 – 130 m and the field of view is 360^0 horizontally and 300° vertically. The angular accuracy is 18'', range accuracy of 1mm+10 ppm. 3D point accuracy is described as follows 1.9 mm @ 10 m, 2.9 mm @ 20 m, 5.3 mm @ 40 m. Range noise up to 0,5 mm at 20 m. The average full coverage scan takes 2 minutes.

The survey was planned such that it would capture the geometry of the solar farm panels, supports, wiring, and mounting structure. This meant that there have been stations on each side of each panel and stations in front and in the back of each panel. In cases where it was necessary, the height of the setup was changed to create a better line of sight for elements close to the ground and high above.

The registration (alignment) of the setups was done in two steps. Initial registration was done in Leica Cyclone REGISTER 360 PLUS office software that was installed on the tablet, which was also used to control the scanner. Registration showed some problems due to the highly repeatable look of the object, the number of reflections, and the change of height in the setups. Due to this, the Leica registration was treated as pre-registration, the point clouds were exported to .e57 format, and then imported to AutoCAD ReCap for checking and refinement. A 3-point semi-automatic registration was then performed in this software.

Fig. 3 TLS 3D-model

Further cleaning of the point cloud was done in Autodesk Recap. The cleaning consisted of removing the surrounding buildings, grass, and other kinds of vegetation and artefacts. In this case, since it was a scan of a metal object within a metal fence, a large number of reflected objects, presenting as 'snow' in the sky, have been observed. They were relatively easy to identify and clean. The developed 3D TLS model from this work is shown in Fig. 3. An immediately interesting result of this survey was the number and localisation of artefacts. TLS, mostly those that use invisible light, are prone to reflections from highly reflective objects, such as glass or polished metal. Also, dark or black objects occasionally disappear from the resulting point clouds since the reflective index I is so low that the internal software can't read them, or they are dismissed as noise. Both of those cases depend to some extent on the angle the laser beam hits the object, since longer travel of the beam within the glass/black object introduces more disturbance. A solar farm consists of different types of solar panels. The difference between them is not immediately obvious to the naked eye; however, the TLS generated significantly different point clouds for each of the types.

3.2 Structure for Motion (SfM) Model

Structure-from-Motion (SfM) combines computer vision and photogrammetry. SfM has become one of the most popular means of obtaining 2D/3D data, including ortho-mosaics, point clouds, and mesh models, during the last decade. SfM algorithms work based on estimating a 3D scene (sparse point cloud), camera intrinsic parameters (focal length, centre of projection, etc.), and camera extrinsic parameters (3D pose, translation, rotation) from a set of overlapping images. The first step is to extract a set of distinctive local features; the second is robustly matching them between images, the third is optimising their 3D positions, the fourth is determining the camera parameters, and then iteratively adding more images to the reconstruction.

The outputs of this process are the above-mentioned camera parameters and a sparse point cloud with 3D points resulting from matched 2D features. The sparse point cloud can then be processed into final products. Since the camera parameters are fixed, a dense point cloud can be estimated in a process called Multi-View Stereo (MVS). This process is frequently based on performing dense binocular stereo matching between pairs of images with large overlap and then combining multiple depth maps created in this way. A dense point cloud can be transformed into a triangle mesh called 'reality mesh' if it is covered with textures processed from original images. A resulting point cloud or mesh may be scaled and georeferenced using Ground Control Points (GCPs); however, scaling and georeferencing can be done earlier during the scene reconstruction stage or sparse point cloud stage. SfM offers the potential of filling the gap between expensive but accurate laser scanning and cheap but limited traditional survey. In addition, SfM requires only a simple camera, which is more portable and offers faster data acquisition than TLS. In most cases, postprocessing of data is automated. In general, SfM offers a less accurate point cloud; however, the visual representation is usually better, more realistic (due to a blend of multiple images).

In this work, we describe the steps required to acquire a detailed and near-accurate 3D model using SfM (Fig. 4). The equipment used is the DJI Mavic 3 Thermal Drone with RTK module and Emlid Reach RS2+ as a base for RTK. The Emlid Reach M2 was used to create the GCP, and the data was processed in DJI Terra. The Actual flight plan using DJI Pilot 2 in oblique was implemented. The parameters of the flight plan are stated in Table I.

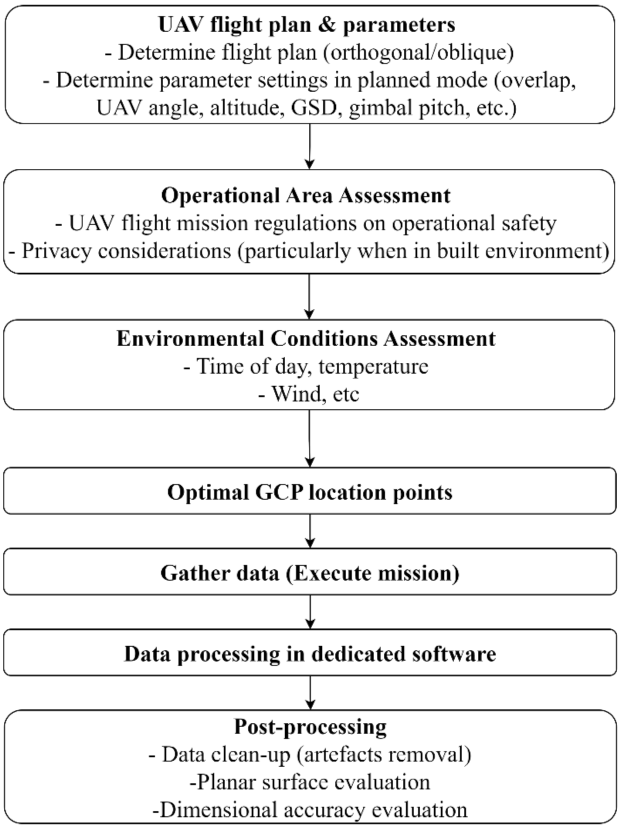


Fig. 4 SfM process flow

Table 1 Flight parameters

Parameter	Value
Flight altitude	15m (relative to take-off)
Ground Separation Distance (GSD)	2.28cm/pixel
Gimbal pitch	60^{0} (nearby buildings constraint)
Speed	2.5m/s
Pitch	243^{0}
Side-overlap ratio	60%
Front-overlap ratio	70%
Photo-mode	Time interval shot

The operation area must be assessed to ensure compliance with UAV regulations, privacy, overcast daytime periods, minimal shadows, reflections, and other environmental conditions that could cause unwanted artefacts in the reconstruction process. The outcome of the 3D SfM model developed in this work is shown in Fig. 5.

Fig. 5 SfM 3D model

4 Structured Data Flow and Analytics

In this section, we describe the implemented data collection process and integration with the 3D models. Since the goal of this work is to enhance PV system monitoring using autonomous platforms, we first consider the essential functions and data to be collected.

4.1 HDT process flow

Fig. 6 describes the proposed HDT platform. It also provides a detailed process flow between the implemented 3D models and the autonomous platforms.

In a PV farm, the autonomous platforms are mostly applied for imaging applications. The imaging process could be a general inspection or a targeted inspection. It could also be any type of camera (infra-red, electroluminescence, RGB, and more). Additionally, the data collected may be required for real-time analytics or stored for right-time analytics. Regardless of the mode and specification, this implies that image data collection is essential. Aside from the image data collected, there are other data collected by the autonomous platform; however, they are for its navigation and situational awareness.

For an HDT as implemented in this work, the 3D model is primarily used to assist precise and real-time tracking of the autonomous platform. Consider a ground robot assigned to a targeted inspection mission. It requires at least a LiDAR, an RGB camera, and a real-time kinematics RTK-GPS module for navigation to the target point. The waypoints or target coordinates are delivered to the robot using the high-fidelity 3D model previously created. The robot then plans its paths around the PV arrays, mounting structures, and other obstacles to reach the desired location. Accurate tracking in this case depends on the 3D model being a true replica of the physical counterpart. To perform the actual inspection, the robot can be remotely controlled or autonomously designed to capture all images at the target location and direction. The robot can only do this once it arrives at the target location. The captured image files are converted to robotic operating system files (ROS), compressed, and encoded before being converted to formats that can be archived or processed in other external storage. At this point, the image files can be saved in a local directory or transferred to the HDT for further processing, reconstruction, or analysis.

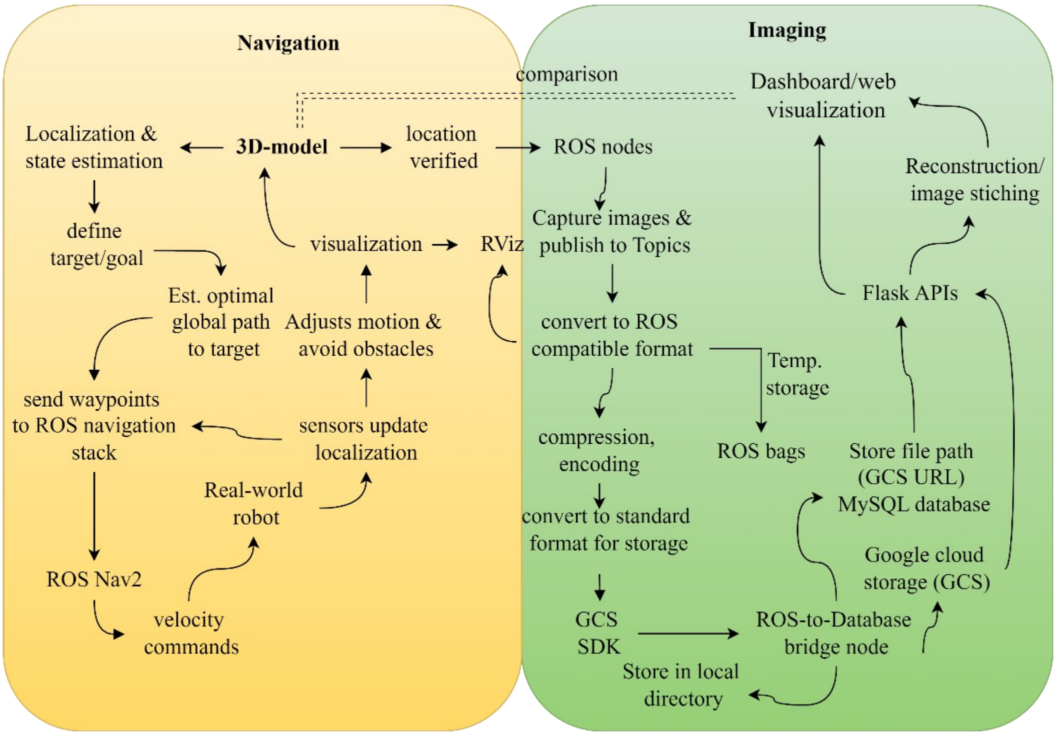


Fig. 6 HDT process flow

Note that the ROS is applied for the robot navigation and initial image processing. It is envisaged that in the near future, there may be physics engines that can simultaneously perform both functions as well as capture the multiphysics simulations and analysis required for the PV panels themselves. This will provide a higher synchronization level and real-time data analytics.

The process developed for this work is to patch the images through a ROS-to-Database bridge node and store the files in Google Cloud Storage, while the URLs are stored in a SQL database for easy retrieval. This is applicable to the framework described in [21].

4.2 Structured Database Development

The process of data collection required for the various parts of the HDT is shown in Fig. 7. The database structure provides a closed-loop oversight on the interaction of the PV system and the autonomous platform. Since this work is aimed at the development of DT for PV systems, the data collection and transfer from the PV system to the autonomous platform distinguishes it from any other ROS simulation designed for autonomous platform navigation.

The process described in Fig. 7 details the current implementation for the experimental 200 kWp PV system at the Institute for Safe Autonomy, University of York, United Kingdom. The system has about 500 PV modules and 4 inverters. The data collected are from the inverters and three sets of weather dataloggers installed at different sections of the plant, other IoTs, and the UAV/UGV images and sensor data. The data is collected via both manufacturer-provided APIs and self-implemented APIs as part of the data collection pipeline. More detail is captured in the image.

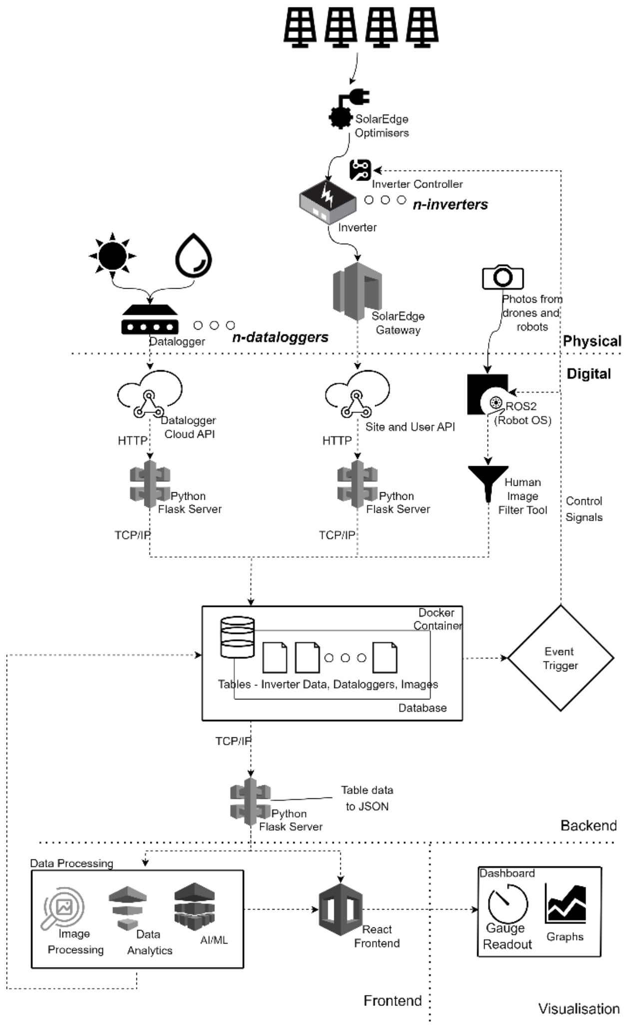


Fig. 7 Structured database

It is worth noting that the overall data flow in a commercial system will be more complex, as there will be a need to incorporate data security and ethical practices to avoid leakage or litigation. The current structure highlights the basic flow that can be implemented for essential data collection and synchronization via respective open-source APIs and tools.

5 Model Verification

As previously mentioned in Section 3.2, the SfM model, which appears as the most realistic and easiest to develop, does not provide an accurate point cloud and must be rescaled to ensure high accuracy in digital model dimensions compared to the physical model. The verification method employed in this work is executed using Marvelmind robotics (R) 018-210002 Super-Beacons. The beacons were applied using the non-inverse architecture (NIA) and are capable of achieving $\pm 2cm$ accuracy. This is important due to the nature of targeted inspection that may be required in robot inspection of a PV module within a large array.

Fig. 8 Real-time model verification

The beacons were integrated into Rviz2 on ROS 2 – Humble (Fig. 8). Stationary beacons were attached to the edges of the PV array, and the mobile beacon was moved around as required to obtain actual site dimensions. This measurement was initially implemented at a very low wind speed $< 0.5m/s$, however, final verifications were made in a large indoor facility to ensure accuracy. This is because the beacons are more suited for indoor measurements. Other outdoor real-time kinematics devices can be explored as well.

The 3D accuracy results are represented in Table II. The result shows an average difference of about 10cm and 5cm in the length and width of the arrays. This may be sufficient for some simulations, but could also be applied to rescale the 3D model.

The model created in this work was created as 4 separate blocks, making it easier to rescale per section. The rescaled model can now be applied for accurate real-time navigation.

Table 2 Dimension verification

Parameter	Length (Meas./Act.) m	Width (Meas./Act.) m	Height (Meas./Act.) m
Array1	13.70/14.11	5.67/5.74	2.42/2.63
Array 2	12.72/12.77	5.27/5.34	2.74/2.98
Array 3	3.07/3.16	3.40/3.47	2.73/3.03
Array 4	12.74/12.77	5.30/5.34	2.80/2.78
Array 5	16.63/16.68	5.03/5.04	3.02/2.72
Est. Ave. Error	**0.13**	**0.05**	**0.09**

6 Limitations and Challenges

In this Section, we highlight specific challenges to the hybrid DT model approach being developed for autonomous PV maintenance as discussed previously. Notable challenges are listed below.

6.1 Multiphysics Simulation Engine

One of the most significant challenges in hybrid PV_DT development is the multiphysics engine capable of co-simulating both the PV system and robot operation. While robo operating systems are simulated with a focus on the mechanics, the PV systems are simulated with a focus on the opto-electrical properties. As such, the PV-DT is operated on a separate platform, interpreting data from the different physics engines. It is envisaged that research into interoperable systems will provide suitable solutions for similar implementations.

6.2 Robot navigation constraints due to mesh artefacts

This limitation is based on reconstruction artefacts in the 3D models. A clear example of this is when the TLS model is compared to the SfM model. Since the SfM model was constructed from images collected by flying a UAV over the site, the reconstructed model is significantly bugged with meshes that are non-existent under the PV modules. In contrast to this, the TLS model is collected at the PV module level and therefore provides a clear description of the PV mounting structure and regions beneath the PV modules. This implies that the navigation and inspection with ground robots will be better under the TLS model compared to the more visually realistic SfM model.

6.3 Computational requirement versus cost

From Sections *III-A* and *VI-B*, the TLS model appears to provide the required fidelity. This is true, but it is at the expense of enormous computational requirements for processing and the final utility of the point-cloud data. While the data-gathering process is quite laborious, it may become impractical for the several hectares of land covered by utility-scale PV systems, which are now in several GigaWatts of peak power. This is mainly because the implementation cost may outweigh the overall financial benefits when compared to the SfM model.

6.4 Integration with existing PV simulation platforms

Existing PV simulation platforms are not designed to provide models suitable for PV-DT 3D models. This is mainly because of their limitation in capturing post-construction changes, such as terrain modifications, layout dimension accuracy when translated from design to physical installation by construction workers, landscaping issues, real-time API integration from design software, 3D model file types, and more. This limits the readiness of DT integration with existing PV simulation platforms. It is envisaged that, as the commercial implementation of PV-DTs increases, probable solutions will be integrated into the existing platforms.

6.5 Component-level fidelity

The accuracy of component-level modelling in terms of location and dimensions for all equipment on a PV site remains a major challenge. While it may be extremely challenging to model sub-ground level components, such as cabling and base structures, modelling small components, especially electrical components such as optimizers, and cable connectors, with the required accuracy. Capturing such components with required accuracy becomes challenging when making measurements at a large scale (system level).

6.6 Dynamic component modelling

This limitation affects the navigation of the robots the most. It could be because of components that change position due to high winds, recent human activity, small animals, or seasonal variation. An example of this is grass, which is modelled as hard meshes in the 3D model, meanwhile they are flexible in real-time. While it is possible to identify and modify the component texture for smaller systems, it becomes a tedious task for large installations. Going a step further is the fact that they dry out in some seasons and no longer exist. In other seasons, they grow to the height of lower-level modules and require targeted maintenance activity to trim them. This dynamic component remains a challenge, and more research effort will be required to resolve this issueAs previously mentioned in Section 3.2, the SfM model, which appears as the most realistic and easiest to develop, does not provide an accurate point cloud and must be rescaled to ensure high accuracy in digital model dimensions compared to the physical model.

7 Conclusion

This work has successfully implemented 3D models for integration and full-scale development of a PV-DT using a real-time system at the University of York, United Kingdom. The system-level integration with the database has been described to highlight practical considerations for the development of such systems. This fills a gap in the literature where simulations are frequently used due to the cost and technical capability limitations. We present the results obtained, challenges observed, and the numerous research gaps required for full-scale systems. It is observed that compared to several information available in literature, the implementation of a DT for PV systems for autonomous systems is severely limited. In addition, the research gaps realized are not only specific to PV systems, but several interoperable systems within and outside the context of energy system monitoring and maintenance. It is envisaged that this and similar research works will provide more context and solutions to delivering safe autonomy leveraging precision and hyper-realistic 3D models developed at scale and economically viable.

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