

Digital twins for a floating photovoltaic system with experimental data mining and artificial intelligence modelling

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ABSTRACT

Floating photovoltaic (FPV) systems face complex multi-physics interactions from wave-induced hydrodynamics and solar variability, yet there is a lack of a digital framework to balance the large amount of data, modelling accuracy, and real-time adaptability. This study addresses this gap by developing an AI-driven digital twin framework that integrates physical experimentation, data integration, and neural network-based modelling. A novel FPV system was experimentally tested under 150 + scenarios in different solar irradiance and water wave conditions, capturing hydrodynamic, thermal, and power performances. A two-tier artificial neural network architecture was implemented, providing a high-fidelity model for detailed analysis and a reduced-order model for real-time applications. The virtual twin can predict key outputs, including heave, surge, pitch, mooring forces, PV temperature, and power output, which potentially reduces the need for sensors on the physical twin and provides more comprehensive information. In summary, the proposed digital twin framework enables remote monitoring, prediction, and intelligent management of FPV systems. Moreover, it holds the potential to support wave-adaptive panel control energy system management, and predictive maintenance. These functions position the digital twin as a core enabler for efficient, reliable, and scalable offshore solar energy deployment.

1. Introduction

Floating photovoltaic (FPV) systems have emerged as an innovative solution to address the growing global demand for sustainable energy, while simultaneously enabling the efficient utilisation of water surfaces [1]. These systems offer several notable advantages, including enhanced cooling of photovoltaic modules due to the thermal buffering effect of water [2,3], reduced dependency on land resources [4,5], and the potential for integration with existing hydrological infrastructure [6]. Prototypes of offshore FPV systems have already been developed and tested by companies such as Ocean Sun and HelioRec [7,8], and numerous countries have begun constructing and deploying FPV installations at various scales [1].

According to the 'Floating Solar Landscape 2024' report by Wood Mackenzie, the global installed capacity of FPV systems is projected to reach 77 GW (GW) by 2033 [9]. Despite their promising benefits and increasing adoption, the deployment of FPV systems introduces considerable complexity. This complexity arises from the inherently

dynamic nature of aquatic environments, where structural motions induced by the liquid surface of water, causing fluctuations in solar irradiance, and integrated fatigue in mechanical connections and mooring systems [10,11]. Such multi-physics interactions pose significant challenges for accurate modelling, stability analysis, and performance prediction of FPV systems in real-world conditions.

One of the most extensively studied topics in the field of FPV systems is the impact of wave-induced motion on system performance, particularly in sea-based environments [12]. Previous research has primarily employed two methodological approaches: experimental studies and simulations. In experimental investigations, researchers have examined the interaction between water waves and FPV systems by testing various structural configurations [13–16] and wave conditions [8,17,18]. These studies provide valuable insight into the dynamic response of FPV platforms under controlled settings. On the other hand, numerical studies typically model both the motion of the FPV arrays and the surrounding fluid dynamics using computational techniques to analyse wave-structure interactions [19–21]. While numerical modelling offers

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flexibility and cost-efficiency, it often fails to fully capture the complex interplay among multiple environmental and structural factors—such as FPV geometry, platform motion, hydrodynamic loads, solar irradiance, and ambient temperature.

Although experiments and simulations have greatly enhanced our understanding of FPV system dynamics and energy output, they remain predominantly offline tools with limited practical applicability. These conventional methods, while effective under controlled conditions, do not support real-time monitoring, predictive maintenance, or autonomous control—capabilities essential for reliable FPV operation in variable and often harsh aquatic environments [22–24]. The lack of continuous integration of real-world data hinders dynamic adaptation to environmental or mechanical changes, complicating long-term performance optimisation. Consequently, there is an urgent need for a deployable engineering solution that integrates sensor data, advanced modelling algorithms, and user-centric interfaces to enable adaptive, real-time decision-making and control.

Recently, digital twin technology has increasingly attracted attention as a novel engineering tool. A digital twin is defined as a virtual replica of a physical entity, process, or system that is continuously synchronised with its real-world counterpart through sensors, data acquisition, and modelling techniques. This virtual representation enables real-time prediction, simulation, monitoring, and optimisation of system behaviour. Conceptually, a digital twin can be regarded as a “virtual counterpart” that perceives the current condition of a physical asset, forecasts its future performance, and even anticipates potential faults before they occur. Many major industrial enterprises have adopted digital twin technology to detect issues and improve operational efficiency. For example, the National Aeronautics and Space Administration (NASA) uses digital replicas to monitor spacecraft status, while energy companies such as General Electric (GE) and Chevron utilise digital twins to track the operational performance of wind turbines [25,26]. However, most conventional digital twin models remain grounded in numerical simulations based on physical system principles [26], which may constrain their adaptability in highly dynamic or data-intensive environments.

In the context of floating solar farms, the role of a digital twin extends far beyond system modelling [27,28]. By continuously ingesting data from embedded sensors—such as those monitoring motion, stress, temperature, and power output—a digital twin enables informed decisions that directly impact system reliability and economic performance. For instance, maintenance activities can be scheduled based on predicted wear and degradation rather than fixed intervals, significantly reducing downtime and extending asset lifespan. Similarly, real-time simulation and forecasting of power generation under evolving wave and irradiance conditions support smarter grid integration and energy dispatch strategies. These capabilities not only improve safety and operational efficiency, but also contribute to reducing the Levelized Cost of Energy (LCOE), making offshore renewables more competitive [29]. The digital twin therefore serves as a critical layer in the transition toward autonomous, adaptive, and cost-effective floating solar infrastructure.

In contrast to conventional digital twin frameworks that primarily depend on physics-based numerical models, this approach introduces artificial intelligence as an innovative enhancement to improve adaptability and predictive performance. By integrating artificial intelligence (AI) into the digital twin architecture, complex system behaviours can be learned from data.

At this stage, AI algorithms have been considered due to their inherent intelligence and adaptability. AI techniques can simulate real-world systems and environments based on data, enabling effective modelling and prediction of complex, nonlinear problems. In contrast to traditional physics-based modelling approaches, AI does not require complete mathematical formulations or fully defined system parameters; instead, it can learn system behaviour directly from data and generate accurate outputs. In the context of energy systems, AI

algorithms have been widely applied for improving energy efficiency and optimizing energy utilisation, demonstrating substantial potential across various applications [30].

Several studies have employed various artificial neural network (ANN) models to forecast the performance of FPV systems [31–33]. However, most of these studies have not explored the integration of such models within a digital twin framework for FPV applications. This gap presents a valuable opportunity, as the demonstrated predictive capabilities of AI, particularly ANN-based approaches, underscore its potential to serve as the core computational engine in the development of intelligent, real-time digital twins for floating photovoltaic systems.

In this study, a digital twin framework for floating photovoltaic FPV systems is developed, combining physical sensing infrastructure, cloud-based data processing, and artificial intelligence AI modelling (Fig. 1). The physical twin comprises a sensor-equipped FPV platform deployed on a water surface, continuously monitoring key variables such as irradiance, platform motion, wave conditions, temperature, structural stress, and power output. These sensor data are first transmitted to a cloud-based data platform, enabling centralized storage and high-speed computational processing. The digital twin operates in the cloud environment, where AI models are employed to simulate system behaviour and forecast performance under varying environmental conditions. Crucially, the system does not merely react to anomalies after they occur. Instead, it enables predictive warning capabilities, identifying potential risks in advance based on trend analysis and learned patterns. For example, early signs of excessive motion, abnormal thermal rise, or power degradation can be detected before reaching critical thresholds. Upon generating such warnings, the system automatically alerts human operators or engineers, who can then take informed corrective actions on the physical system. This cloud-enabled closed-loop interaction, from sensing to forecasting to decision support, enhances the system's operational resilience, enabling smarter maintenance strategies and real-time risk mitigation. As a result, the framework demonstrates significant potential as a deployable, intelligent control solution for offshore renewable energy platforms.

This study proposes a comprehensive digital twin framework for FPV systems that integrates high-resolution experimental measurements with data-driven AI modelling techniques. An FPV system was developed in a novel experimental facility, where a solar simulator, a floating solar unit, and a wave tank are integrated. The system is then subjected to a series of 155 controlled experiments, simulating a wide range of wave and irradiance conditions. Using the collected time-series data, a two-tier ANN architecture was developed, consisting of a high-fidelity (strong) model capable of learning complex system dynamics and a reduced-order (light) model designed for rapid inference in user-facing applications. The resulting AI-enabled digital twin not only provides accurate predictions of mechanical, thermal, and electrical responses across varying environmental conditions but also enables real-time performance visualization through a straightforward interface, such as a browser. This framework paves the way for future integration with sensor feedback loops and autonomous operational strategies, establishing a foundation for smart, adaptive control in next-generation floating solar energy systems. Ultimately, the integration of digital twin technology represents a paradigm shift—from passive monitoring to intelligent control—driving the future of modular, ocean-based renewable energy systems.

The main contributions of this study are summarised as follows:

- 1) The study introduces, for the first time, the concept of a digital twin tool for FPV systems, integrating experimental and data-driven components within a unified framework.
- 2) It overcomes the limitations of conventional experiments and numerical simulations in terms of scalability, flexibility, and real-time capability, providing a practical alternative for dynamic FPV analysis.

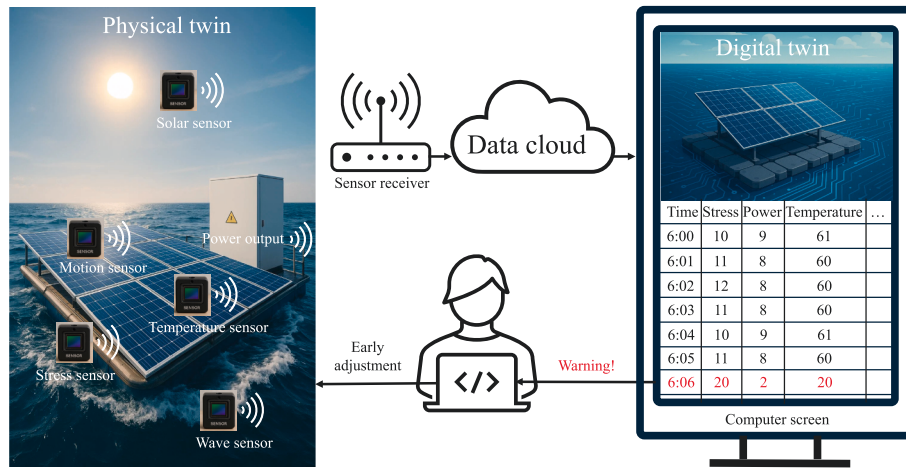


Fig. 1. Digital twin framework for floating photovoltaic (FPV) systems.

- 3) A hybrid methodology combining large-scale data mining and artificial intelligence algorithms is developed to extract, learn, and model the nonlinear interactions within FPV systems.
- 4) An adaptive digital twin platform is established, capable of unified analysis and prediction of FPV performance across hydrodynamic, thermal, and electrical domains.

The remainder of this paper is organised as follows. Section 2 outlines the methodological framework, which is divided into three primary components: the experimental design of the FPV system; the procedures for data collection and processing; and the development of AI models for

digital twin. Section 3 presents a comprehensive multi-physics analysis of the FPV system, encompassing hydrodynamic, mechanical, thermal, and electrical behaviours based on the experimental dataset. Section 4 details the construction of the digital twin using ANN models, comprising three successive elements: a high-fidelity (strong) model, a reduced-order (light) model, and a user-oriented application for real-time deployment. Finally, Section 5 provides a summary of the key findings and conclusions of the study. The code developed in this study is shared with readers via Appendix A. The comprehensive experimental facility and tested parameters are detailed in Appendix B and Appendix C.

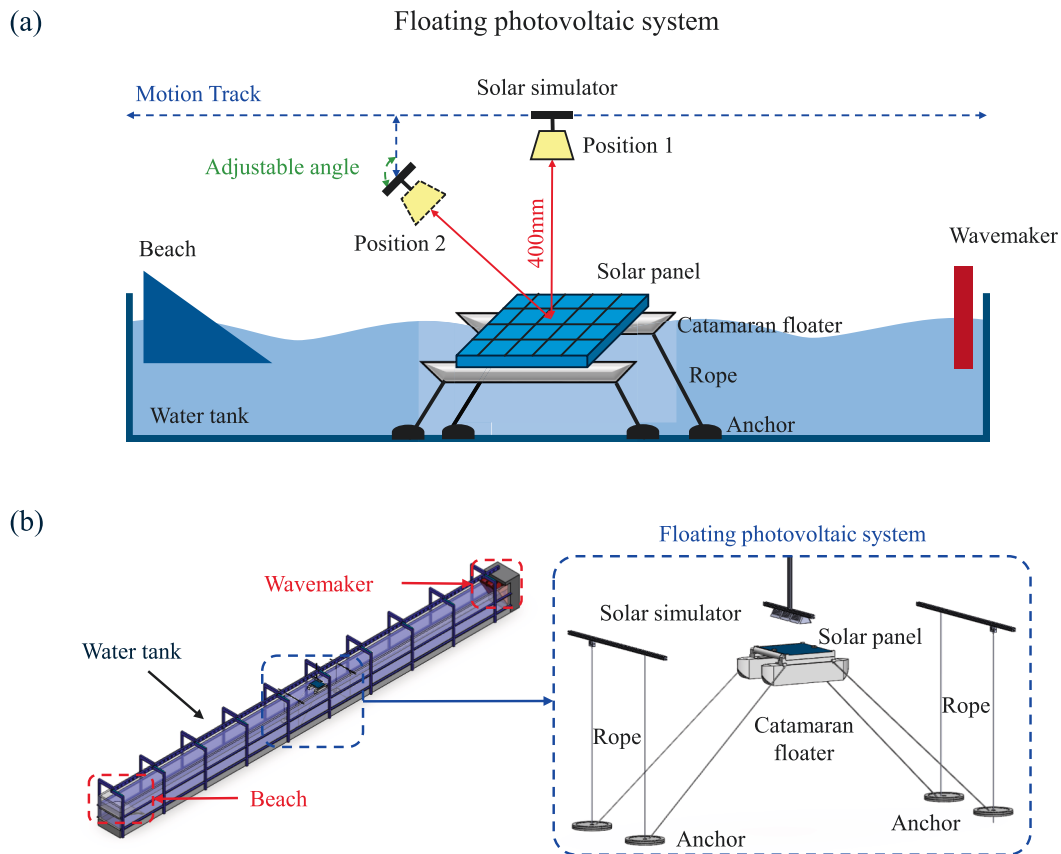


Fig. 2. Schematic and three-dimensional view of the experimental setup for a floating photovoltaic (FPV) system. (a) Side-view schematic showing a PV panel mounted on a catamaran-type floater, tethered to anchors at the tank bottom, with a solar simulator positioned 400 mm above the panel. (b) Three-dimensional overview of the wave tank setup, including the wave generator, wave absorber, and the centrally located FPV system.

2. Methodology

2.1. Experiment design

To enable the development of a digital twin for an FPV system, it is imperative to first establish a physical experimental platform capable of capturing high-fidelity, representative data to support accurate numerical modelling and simulation. The experimental platform was intentionally designed as a controlled and repeatable environment to capture representative hydrodynamic, thermal, and electrical responses under simplified conditions. It does not aim to replicate the full complexity of real marine environments, but rather to provide high-quality, structured data for AI model training and validation.

Fig. 2 presents the experimental setup constructed within a controlled laboratory environment. Fig. 2 (a) depicts a side-view schematic of the configuration. A PV module is installed atop a catamaran-type floating structure, centrally located within a hydrodynamic test tank. The platform is secured via mooring lines affixed to all four corners and anchored to the bottom of the tank, thereby maintaining spatial stability in the presence of wave-induced forces. A solar simulator, positioned 400 mm above the PV surface and equipped with adjustable inclination, delivers consistent and controllable irradiance. A motion tracking rail is mounted above the setup to capture the dynamic response of the floating system under varying wave conditions. Fig. 2 (b) provides a three-dimensional rendering of the full-scale experimental assembly. A wave generator positioned at one end of the tank is used to produce periodic wave patterns of tuneable amplitude and frequency, while a wave-absorbing structure at the opposite end mitigates reflection to emulate open-sea conditions. The FPV system is situated at the tank's midpoint and is further detailed in an inset schematic showing the PV module, floating platform, mooring system, and solar simulator. This experimental infrastructure is designed to facilitate a comprehensive investigation of the hydrodynamic responses, energy harvesting performance, and overall stability of FPV systems operating in dynamic aquatic environments.

2.1.1. Main equipment

The wave tank facility at Cranfield University is a controlled experimental environment designed to study hydrodynamic interactions. Measuring 30 m in length and 1.5 m in width, the tank is filled with fresh water to a depth of 1.5 m. It is specifically designed to generate regular waves with frequencies ranging from 0.1 Hz to 1.1 Hz and a maximum wave height of 28 cm. To produce controlled wave conditions, a three-paddle wavemaker, developed by Edinburgh Designs, is installed at one end of the tank. On the opposite side, a full-width parabolic beach functions as an energy dissipation mechanism, preventing wave reflection and ensuring that the middle section of the tank mimics an open-sea environment. For the experiments, a floating solar unit was deployed near the tank's centre. The device was carefully positioned to maintain a 42 cm clearance from both sidewalls, minimising the influence of lateral wave reflections on the hydrodynamic behaviour of the structure. This setup ensures that the experimental conditions remain as representative as possible of real-world floating solar installations.

The floating solar unit comprises a PV panel and a catamaran-style floater. The PV panel is a commercial monocrystalline silicon module, model T050M365, manufactured by TDG Holding Co., Ltd, with a maximum power output of 50 W. For experimental purposes, the solar simulator was calibrated to ensure that the PV panel generates 30 W of power under still water conditions, serving as a baseline for FPV power measurements under wave conditions. The floater features a catamaran configuration, newly designed in this study as an alternative to conventional cuboid floaters to optimise material usage. Its hydrodynamically efficient design reduces wave and current loads, resulting in lower structural motion and diminished loads transferred to the mooring system. This makes it a promising candidate for ocean-based FPV applications. While contemporary FPV floaters are typically made of

hollow composite materials, which constitute a significant portion of system costs, the proposed catamaran floater employs extruded polystyrene (XPS), an innovative and cost-effective material. XPS offers a favourable combination of strength and buoyancy, with a density of $38.44 \text{ kg}\cdot\text{m}^{-3}$ and a compressive strength of 64.6 psi.

A solar simulator was positioned above a wave tank to provide controlled illumination. This system emits high-intensity light beams capable of activating the solar panel positioned below, enabling it to generate electricity. The solar simulator consists of three Eterna Lighting CTH500SL 500 W halogen floodlights, arranged in a 3×1 matrix to ensure uniform coverage of the solar panel's location. The complete setup, including the solar simulator and wave tank, where detailed schematics and dimensions of the experimental facility are provided in Appendix B.

During the experiment, the floating solar unit was secured to the bottom of the wave tank using four mooring lines, each consisting of a high-tension fishing line and a spring. The springs had an initial static length of 18.3 cm and a stiffness of 454.5 N/m, while the total length of each mooring line measured 220 cm. To ensure structural stability, the mooring lines were arranged symmetrically, connecting the four corners of the solar unit to the bottom of the tank. Additionally, the longitudinal distance (along the tank's length) between the mooring points on the structure and the bottom of the tank was precisely set at 150 cm to prevent roll, yaw, and sway motions caused by asymmetric forces. After positioning the mooring lines, fine adjustments were made to the attachment points at the tank bottom to ensure uniform pretension across all lines. The force sensors installed on each mooring line measured the preload forces, which were recorded as 16.864 N for the flat plate device and 18.720 N for the catamaran device. The minor discrepancy in preload values resulted from differences in draft levels between the two structures. Nevertheless, final adjustments ensured that all springs maintained identical initial tension, keeping the mooring lines in a stretched state and thereby stabilizing the motion of the floating solar unit.

2.1.2. Sensors

To support the development of a digital twin for the FPV system, a diverse set of sensors and instruments was strategically deployed to collect high-resolution, real-time data across mechanical, environmental, and electrical domains. The collected dataset provides the foundation for training AI models, which are subsequently used to construct a digital twin capable of accurately simulating and predicting the operational behaviour of the FPV system under various environmental conditions.

To comprehensively monitor the system's performance and dynamic responses, several key parameters were measured, as summarised in Table 1. Upstream and downstream hydrodynamic forces acting on the floating platform were recorded using Vernier Go Direct Force and Acceleration sensors, operating at a sampling frequency of 10 Hz with Vernier Graphical Analysis software. These sensors were coupled with RS PRO steel extension springs ($44.6 \text{ mm} \times 9 \text{ mm}$) to improve force transmission fidelity.

Kinematic motion responses—including heave, surge, and pitch—were captured using Witmotion accelerometer-inclinometers, also sampling at 10 Hz. Two units were mounted on the PV panel, positioned at the upstream and downstream edges, to provide spatially distributed motion data. Ambient, water, and PV surface centre temperatures were monitored via thermocouples integrated with PicoLog software, ensuring continuous thermal profiling during experiments.

Surface elevation and wave-induced displacement were measured using two PEPPERL + FUCHS ultrasonic distance sensors placed at both ends of the floater and interfaced with LabView for synchronised data acquisition. Electrical performance was quantified using an EL 9000B Electronic DC Load, controlled via EA Power Control software and operated under a triangular waveform protocol ($U(A) = 22.83 \text{ V}$, $t_1 = 0.05 \text{ ms}$, $t_2 = 0.05 \text{ ms}$, $I_{\text{limit}} = 2.94 \text{ A}$, $P_{\text{limit}} = 50 \text{ W}$). Lastly, solar

Table 1
Specifications of all sensors utilized for data acquisition.

Data	Sensor/ Equipment	Accordant Software	Data Output Frequency	Additional Notes
Upstream Force	Vernier – Go Direct Force and Acceleration	Vernier Graphical Analysis	10 Hz	RS PRO Steel Extension Spring, 44.6 mm x 9 mm attached
Downstream Force	Vernier – Go Direct Force and Acceleration	Vernier Graphical Analysis	10 Hz	RS PRO Steel Extension Spring, 44.6 mm x 9 mm attached
Motion (Heave, Surge and Pitch)	Witmotion – Accelerometer- Inclinometer	Witmotion	10 Hz	Two placed on PV panel (Upstream and Downstream on PV surface)
Temperature (Ambient, Water and PV Centre)	Thermocouple	Picolog	10 Hz	Thermocouple on the PV surface positioned using heat-resistant tape
Ultrasonic Distance	PEPPERL FUCHS – 60947-5-2	LabView	10 Hz	Two sensors: Upstream and Downstream
Power Output	EL 9000B Electronic DC Load	EA Power Control	10 Hz	Triangle Configuration: U (A) = 22.83 V, t1 = 0.05 ms, t2 = 0.05 ms. U (Start/End) = 22.83 V, I (Limit) = 2.94A, P(Limit) = 50 W
Irradiance	RS PRO Solar Power Meter ISM410	N/A	One-off reading	Readings taken at upstream, centre and downstream of PV surface to calculate average

irradiance was measured with an RS PRO Solar Power Meter (ISM410), using point measurements taken at three locations on the panel—upstream, centre, and downstream—to compute an average effective irradiance input.

2.1.3. Experimental case settings

To generate a sufficiently diverse and comprehensive dataset for training AI models—ultimately enabling the development of a digital twin of the FPV system—a total of 155 experimental and control cases were designed, as summarised in Table 2. The test matrix includes systematic variations in key parameters such as light incidence angle, wave amplitude, and wave length, ensuring the dataset reflects a wide range of operating conditions relevant to marine environments.

In the experimental group, five light incidence angles (90°, 75°, 60°, 45°, and 30°, as shown in Fig. 3) were combined with two wave

amplitudes (0.025 m and 0.0375 m) and fifteen wave lengths ranging from 1.5 m to 5.0 m in 0.25 m increments. This resulted in a multidimensional dataset capturing the coupled effects of optical and hydrodynamic conditions on system behaviour.

The control group employed the same set of light incidence angles but under quiescent water conditions, with wave amplitude and wave length both set to zero. These cases serve as baselines to isolate the influence of wave-induced motion.

This experimental design was specifically tailored to supply high-quality, structured data suitable for data-driven modelling approaches, thereby enhancing the robustness and predictive accuracy of AI-based digital twin frameworks for FPV systems. More details can be found in Appendix C.

2.1.4. Wave conditions

The generated waves were periodic sine waves, mathematically described by the Stokes wave theory [34]:

$$\eta = h + \frac{H}{2} \cos(kx - \omega t) \quad (1)$$

$$u = \frac{[GSLPI]H}{T} \frac{\cosh k(z + h)}{\sinh kh} \cos(kx - \omega t) \quad (2)$$

$$w = \frac{[GSLPI]H}{T} \frac{\sinh k(z + h)}{\sinh kh} \sin(kx - \omega t) \quad (3)$$

where, η represents the free surface elevation of the water waves, u and w denote the velocity components along the x-axis and z-axis, respectively, H is the wave height, defined as twice the wave amplitude a , T is the wave period, k is the wave number, characterizing the spatial properties of the wave, $\omega = 2\pi f$ is the angular frequency, where the wave frequency is given by $f = 1/T$.

For the physical wave generator, the wave height H and period T were predefined, while the wavelength λ was determined using the following dispersion relation:

$$k \tanh kH = \omega^2/g \quad (4)$$

This equation describes the relationship between wave number k , wave height H , and angular frequency ω . The gravitational acceleration g is taken as 9.81 m·s⁻².

2.2. Data collection and processing

The data collection procedure followed a structured and repeatable protocol to ensure consistency across all experimental cases. As illustrated in Fig. 4, the process comprised three key steps. First, all sensors were activated and synchronised to UK local time to ensure temporal alignment across diverse data streams, including motion, force, temperature, irradiance, and electrical output. Next, the wavemaker was initialized with the predefined amplitude and frequency corresponding to the test case configuration. Once the wave conditions stabilised, data acquisition commenced. The system was run under steady-state conditions for two minutes, during which all sensor data were recorded

Table 2
Experimental and control case settings with parameter configurations.

Parameters	Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Experimental group:																
Lights angles / °	5	90	75	60	45	30										
Amplitude / m	2	0.025	0.0375													
Wave length / m	15	1.5	1.75	2	2.25	2.5	2.75	3	3.25	3.5	3.75	4	4.25	4.5	4.75	5
Control group:																
Lights angles / °	5	90	75	60	45	30										
Amplitude / m	0	0														
Wavelength / m	0	0														
Sum of cases	155															

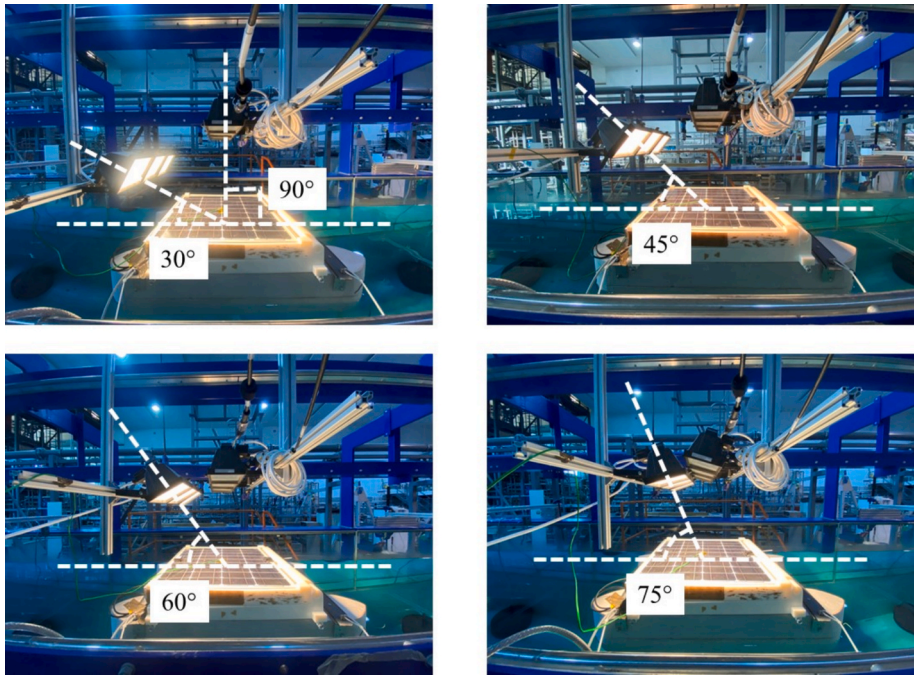


Fig. 3. Experimental setup showing five different solar simulator incidence angles (30°, 45°, 60°, 75°, and 90°) directed onto the floating photovoltaic (FPV) module surface. The variation in irradiance angle is controlled to investigate the effect of incident light direction on power output and system dynamics.

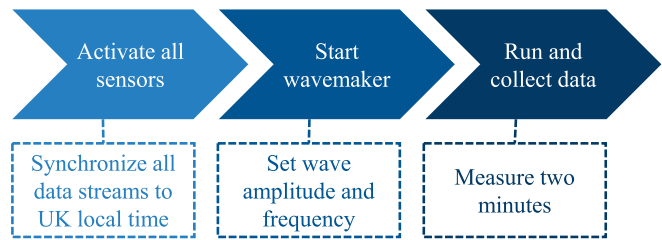


Fig. 4. Standardized procedure for experimental data acquisition, including sensor activation and synchronization, wave condition setup, and two-minute continuous data recording.

continuously at a sampling rate of 10 Hz. This standardised process enabled the generation of high-resolution time series datasets suitable for AI model training and subsequent digital twin development.

The data processing workflow was systematically structured to

prepare all experimental measurements for use in AI-based digital twin development. As shown in Fig. 5, data from various sources—including temperatures, motions, power outputs, mooring forces, solar irradiance, wave conditions, and light angles—were first converted into.xlsx format to ensure consistency. For each experimental case, the individual data streams were then assembled into a single Excel file. These files were synchronized to UK local time, and a clean segment of 1 min and 30 s of valid data was extracted. During this step, any remaining or erroneous entries were removed. Motion data were further processed to derive heave and surge displacements, providing additional physical insight into the system’s dynamic behaviour. Finally, all processed parameters were merged into a unified dataset, which was formatted for direct implementation into AI models. This comprehensive and standardized procedure ensured the generation of clean, consistent, and time-aligned datasets essential for accurate machine learning and digital twin modelling.

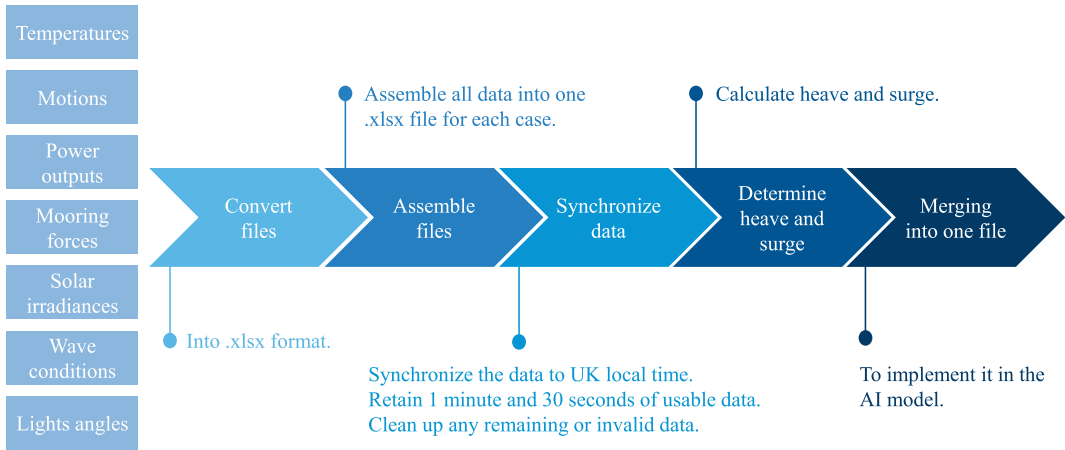


Fig. 5. Data processing workflow for AI model development, including file conversion, synchronization, motion analysis, and merging of all parameters into a unified dataset.

2.3. Ai-based digital twin modelling

Traditional physics-based modelling of floating photovoltaic systems typically requires solving coupled hydrodynamic, thermal, and electrical equations using methods such as potential flow theory, computational fluid dynamics (CFD), finite-element thermal analysis, or equivalent electrical circuit models. While these approaches provide explicit physical interpretation, they rely on simplifying assumptions and are computationally intensive, making real-time prediction and control challenging.

To overcome these limitations, AI models are introduced as the core engine of digital twin development. By training on high-quality experimental data, the AI-based digital twin can capture the nonlinear coupling among wave dynamics, structural motion, temperature, and power output without relying on explicit governing equations. This data-driven approach enables accurate replication of system behaviour, prediction under unseen conditions, and near real-time monitoring and control.

2.3.1. Feedforward neural network

A feedforward neural network (FNN), widely used for pattern recognition, function approximation, and classification, is employed in this study as a foundational model for data-driven analysis [35,36]. The term “feedforward” means that information flows in one direction only—from the input layer to the output layer—without any loops or backward connections as shown in Fig. 6.

A typical FNN consists of three main types of layers: Input layer receives raw data, such as images, numbers, or text. Each “neuron” in this layer represents a feature of the input data. Hidden layers process the input by applying mathematical transformations. More hidden layers make the network more powerful in learning complex relationships. Output layer produces the final result, which could be a numerical value (for regression problems) or a category label (for classification problems).

Each neuron in one layer is connected to neurons in the next layer through weights, which are adjustable parameters that the network learns during training. The neuron applies a mathematical function (activation function) to determine whether it should pass information to the next layer.

In this study, a classical FNN was selected instead of deep learning architectures such as recurrent or convolutional networks. This choice was motivated by the relatively limited dataset size and the real-time performance requirements of the digital twin framework. The FNN offers sufficient predictive capability while maintaining low computational cost, which is essential for rapid simulation and online deployment.

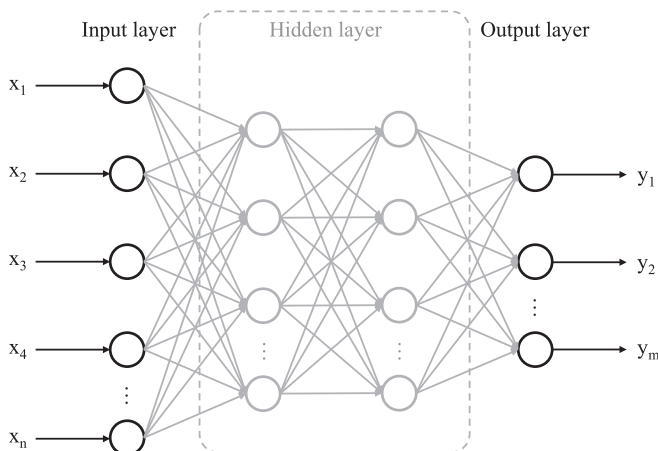


Fig. 6. Illustration of the feedforward neural network (FNN).

2.3.2. Input–output structure and feature design in AI-based digital twins

In this study, AI is employed as a central tool to develop a digital twin of the FPV system. The primary objective is to construct a data-driven predictive model capable of simulating key system behaviours—including platform motion, surface temperature, mooring force, and electrical output—based on a limited set of input parameters. As summarised in Table 3, this approach significantly reduces the need for extensive physical experiments, while improving modelling efficiency.

Table 3 highlights the structural differences in inputs and outputs between the experimental process and the digital twin framework. During physical experiments, a large number of variables are required as inputs, including time, light incidence angle, wave amplitude and frequency, solar irradiance, water temperature, and structural dimensions of the FPV system. Corresponding outputs include measured responses such as heave, surge, and pitch, mooring line forces, PV panel temperature, voltage, current, and power output.

In contrast, the digital twin model is implemented as a supervised multi-output regression network, trained on experimental data. Once trained, the model requires only a subset of essential input features—such as wave characteristics, light angle, and solar irradiance—to accurately predict the full range of system responses. This input–output compression is a key advantage of digital twin technology: enabling rapid, cost-effective simulations without the need for continuous sensor monitoring or repeated testing, thereby enhancing system scalability and deployment efficiency.

It is important to note that the AI model’s input parameters—referred to as features—are critical to its predictive accuracy and generalisation capability. Careful selection and preprocessing of these features, including normalisation and dimensionality reduction, are

Table 3

Overview of data inputs and outputs across experiment and digital twin workflow.

Data Series	For experiment – Inputs	For experiment – Outputs	For digital twin – Inputs	For digital twin – Outputs
Time	✓		✓	
Length of FPV	✓		✓	
Height of FPV	✓		✓	
Width of FPV	✓		✓	
Draft of FPV	✓		✓	
Length between mooring lines	✓		✓	
Length of water tank	✓		✓	
Height of water tank	✓		✓	
Width of water tank	✓		✓	
Light angle	✓		✓	
Wave amplitude	✓		✓	
Wave frequency	✓		✓	
Solar irradiance	✓		✓	
Heave	✓			✓
Pitch	✓			✓
Surge	✓			✓
Temp of PV panel	✓			✓
Ambient temperature	✓		✓	
Water temperature	✓		✓	
Mooring force – upstream	✓			✓
Mooring force – downstream	✓			✓
Voltage		✓		✓
Current		✓		✓
Power output		✓		✓

essential for capturing the nonlinear relationships embedded in the experimental data (e.g., between irradiance and power output, or wave amplitude and platform motion).

In summary, comprehensive experimental data collection provides the foundation for AI training, while the digital twin, once constructed, offers a powerful and efficient surrogate for simulating system behaviour, enabling performance evaluation, real-time forecasting, and intelligent control of floating solar systems.

2.3.3. Architectural framework of an AI-driven digital twin model

The digital twin system developed in this study is constructed based on AI algorithms, with its overall architecture illustrated in Fig. 7. The model comprises three interconnected components: a high-fidelity AI model, a reduced-order model, and a user-oriented digital twin application. These components are linked through a unidirectional data flow that spans from experimental data acquisition and AI training to model compression and deployment for real-time inference.

In the initial stage, a high-fidelity (strong) neural network model is trained using experimental data as input. This model captures the complex physical behaviour of the FPV system by learning from a wide range of variables, including light incidence angle, wave amplitude and frequency, solar irradiance, structural characteristics of the FPV platform, and environmental conditions such as water and ambient temperatures. The output of this model includes key physical responses such as power output, upstream and downstream mooring forces, and motion parameters including heave, surge, and pitch. These outputs, denoted as “1” in the figure, represent high-accuracy predictions directly learned from experimental observations.

To address the computational demands of the high-fidelity model, a reduced-order (light) model is developed in the second stage. This model is trained on a curated dataset composed of selected outputs from the high-fidelity model, along with supplemental experimental data, enabling it to replicate core system behaviours with significantly lower computational overhead. The reduced-order model retains sufficient accuracy while enhancing execution speed, making it suitable for real-time deployment. The corresponding outputs from this model are marked as “2”.

In the final stage, the trained reduced-order model is integrated into a user-facing digital twin application. Unlike the experimental or high-

fidelity modelling processes, users of this application are only required to input a small subset of essential environmental features—such as wave amplitude, wave frequency, solar irradiance, and light angle—to obtain real-time predictions of system behaviour. The outputs include power generation, platform motions, mooring forces, and PV surface temperature, as represented by the “3” series variables. This stage enables rapid simulation and virtual monitoring without relying on real-time physical measurements.

From a data flow perspective, the process moves sequentially from left to right: experimental data feeds into the high-fidelity model; its outputs, along with part of the experimental data, are used to train the reduced-order model; finally, user-defined inputs are passed into the reduced model to produce the desired system responses. This hierarchical structure allows the digital twin to transition from a data-rich training phase to an efficient, low-input predictive tool.

Both the strong and light models were constructed using the same feedforward neural network (Fitnet) architecture but designed for different operational purposes. The strong model was trained on the full experimental dataset to learn complex nonlinear relationships among environmental and structural variables. However, the large data volume and network depth made the model computationally intensive, causing significant latency when invoked repeatedly. Such delays are incompatible with the real-time prediction required for a functional digital twin.

To overcome this limitation, a secondary light model was developed. Its inputs mainly comprise the simulated results from the strong model—such as power, mooring forces, and motion responses—with additional experimental parameters like light angle and irradiance as supplementary inputs. This structure allows the light model to reproduce the strong model’s behaviour within an acceptable error margin while operating with substantially reduced computational demand. When integrated into the digital-twin application, the light model can generate output predictions in less than one second for real-time inputs, ensuring responsiveness and practicality for real-world deployment.

Through this layered design, the AI-enabled digital twin system balances physical fidelity, computational efficiency, and real-world applicability, providing a robust framework for performance assessment, virtual experimentation, and intelligent control of floating photovoltaic systems.

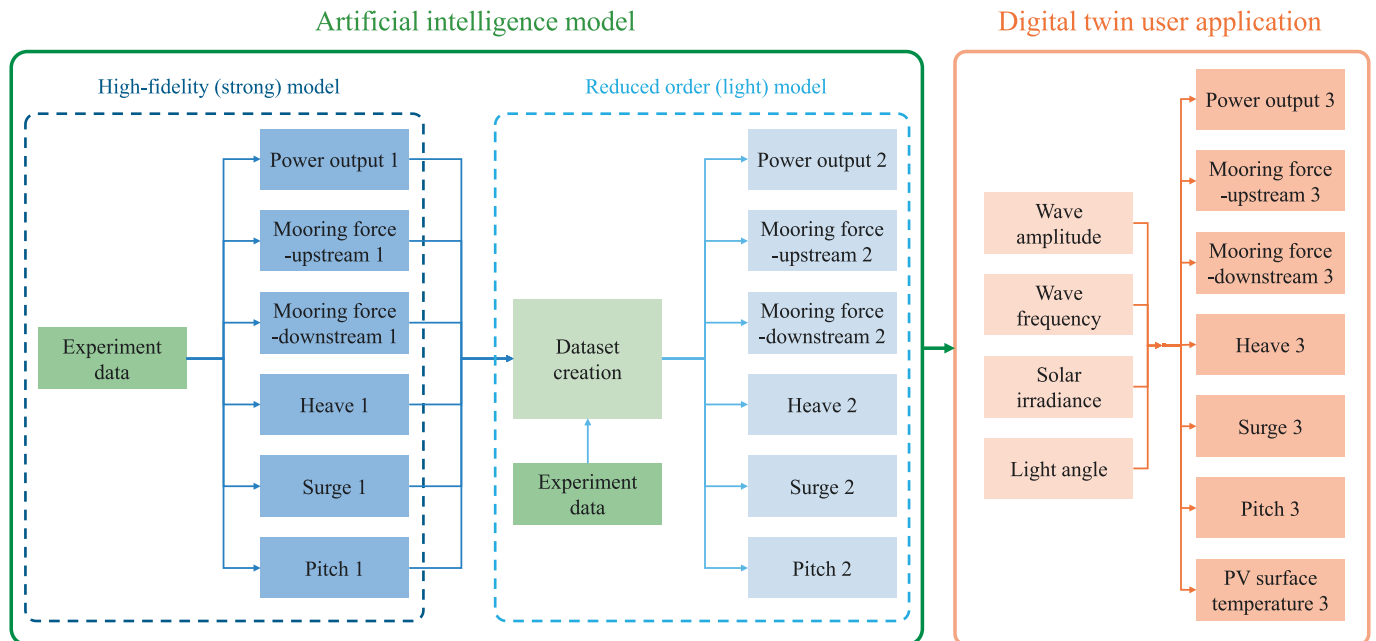


Fig. 7. Architecture of the AI-based digital twin system, consisting of a high-fidelity model, a reduced-order model, and a user-facing application layer. Data flows sequentially from experimental input to predictive output through layered AI model processing.

2.3.4. Neural network development and architecture optimisation

The development of the neural network models was implemented in MATLAB using the *fitnet* function. Both the strong and light models employed feedforward neural networks trained through supervised learning, but with different configurations and input datasets.

For the strong model, the full experimental dataset was used, containing environmental and structural variables such as wave parameters, irradiance, temperature, and mooring forces. The input and output data were first normalised to the $[0, 1]$ range using the *mapminmax* function to remove scale bias. The performance was evaluated in terms of the root mean square error (RMSE), and coefficient of determination (R^2).

The light model was constructed with the same network type but simplified architecture and different inputs. Instead of using all raw experimental data, its inputs were primarily derived from the strong model's simulated results (e.g., power, motion, and mooring responses), complemented by a limited number of experimental parameters such as light angle, wave frequency, amplitude, and mean irradiance. This hybrid input structure enabled the light model to achieve near-real-time computation while maintaining acceptable prediction accuracy. The model was trained using conjugate gradient backpropagation and evaluated with the same statistical metrics.

The architecture of the ANN used in the digital twin system was specifically tailored for each output variable to optimise predictive performance and computational efficiency. As summarised in Table 4, both the high-fidelity model (SM: strong model) and the reduced-order model (LM: light model) adopt feedforward neural network structures with two hidden layers. The number of neurons in each hidden layer was selected based on output complexity and sensitivity to input features.

For outputs such as power output and mooring forces (upstream and downstream), the networks used relatively simple architectures with 10 neurons in each of the two hidden layers for the strong model, and similar or slightly reduced configurations in the lightweight model, as no logarithmic transformation was required. In contrast, for motion-related outputs—heave, surge, and pitch—logarithmic transformation was applied to both input and output data to improve numerical stability and regression performance. These outputs also required more complex network structures in the lightweight model, with up to 30 and 15 neurons in the first and second hidden layers, respectively, reflecting their nonlinear and dynamic nature.

For PV surface temperature, a moderately complex architecture was adopted, without transformation, using 10–20 neurons across both models, depending on the complexity required. This customised configuration for each output ensures that the ANN structure is both functionally efficient and well-suited to capturing the diverse physical relationships present in the experimental dataset.

3. Experimental results for the floating solar energy system

Based on the experimental measurements, key operational parameters of the FPV system were quantified under varying environmental and structural conditions. These include the platform's hydrodynamic responses—heave, surge, and pitch—as well as the mooring forces at the

upstream and downstream anchors, the surface temperature of the PV panel, and the corresponding electrical power output. These parameters provide a comprehensive characterisation of the FPV system's behaviour and serve as critical output variables for both performance evaluation and AI-based digital twin modelling.

3.1. Hydrodynamic behaviour

Fig. 8 illustrates the time-domain dynamic responses of the FPV system, including heave, surge, and pitch motions, under three distinct combinations of light angle, wave amplitude, and wave length. Each case is color-coded in the plot: the red curve corresponds to a light angle of 60° , wave amplitude of 0.0375 m, and wave length of 3 m; the blue curve represents a light angle of 30° , wave amplitude of 0.025 m, and wave length of 5 m; and the green curve reflects a light angle of 90° , wave amplitude of 0.0375 m, and wave length of 1.5 m.

In the heave response in Fig. 8(a), the red curve exhibits the largest vertical displacement, reaching approximately ± 4 cm. This indicates a possible near-resonant condition, where the intermediate wave length and high amplitude lead to significant vertical excitation. The blue curve, associated with a longer wave length and smaller amplitude, shows moderate heave displacement with a smoother waveform. The green curve, despite having the same amplitude as the red case, results in a smaller heave response, likely due to inefficient energy transfer from the high-frequency, short wave condition.

The surge motion (Fig. 8(b)) displays a similar trend. The red curve again shows the largest horizontal displacement (around ± 2 cm), suggesting strong longitudinal excitation. The blue curve follows with a moderate response, while the green curve remains nearly flat, indicating minimal surge displacement and enhanced longitudinal stability under short-wave conditions.

In contrast, the pitch response (Fig. 8(c)) reveals that the green curve produces the highest angular oscillation, with angles reaching up to $\pm 4^\circ$. This suggests that short wave lengths with higher frequencies are more effective at exciting rotational modes of the platform. The red and blue curves exhibit smaller and more stable pitch oscillations, consistent with their longer wave lengths and lower-frequency excitation.

Overall, the results demonstrate that the FPV system's motion responses are highly sensitive to variations in wave and irradiance conditions. Intermediate wave lengths with high amplitudes (red case) effectively excite both vertical and horizontal motions. Short wave conditions (green case), though less effective in translational responses, induce stronger pitch due to higher-frequency forcing. The long wave–low amplitude condition (blue case) produces the mildest overall response. These insights provide valuable guidance for future design optimisation, mooring strategy development, and digital twin modelling of FPV systems.

3.2. Mechanical behaviour

Fig. 9 presents the time-domain responses of the mooring forces at the upstream (a) and downstream (b) ends of the FPV platform under

Table 4
Structural parameters of the artificial neural network for each output.

Outputs	Neurons SM hidden layer 1	Neurons SM hidden layer 2	Logarithmic transformation	Neurons LM hidden layer 1	Neurons LM hidden layer 2	Logarithmic transformation
Power output	10	10	No	10	5	No
Mooring force – upstream	10	10	No	20	15	No
Mooring force – downstream	10	10	No	10	10	No
Heave	10	10	Yes	30	15	Yes
Surge	10	10	Yes	30	15	Yes
Pitch	10	10	Yes	30	15	Yes
PV surface temperature	10	10	No	20	10	No

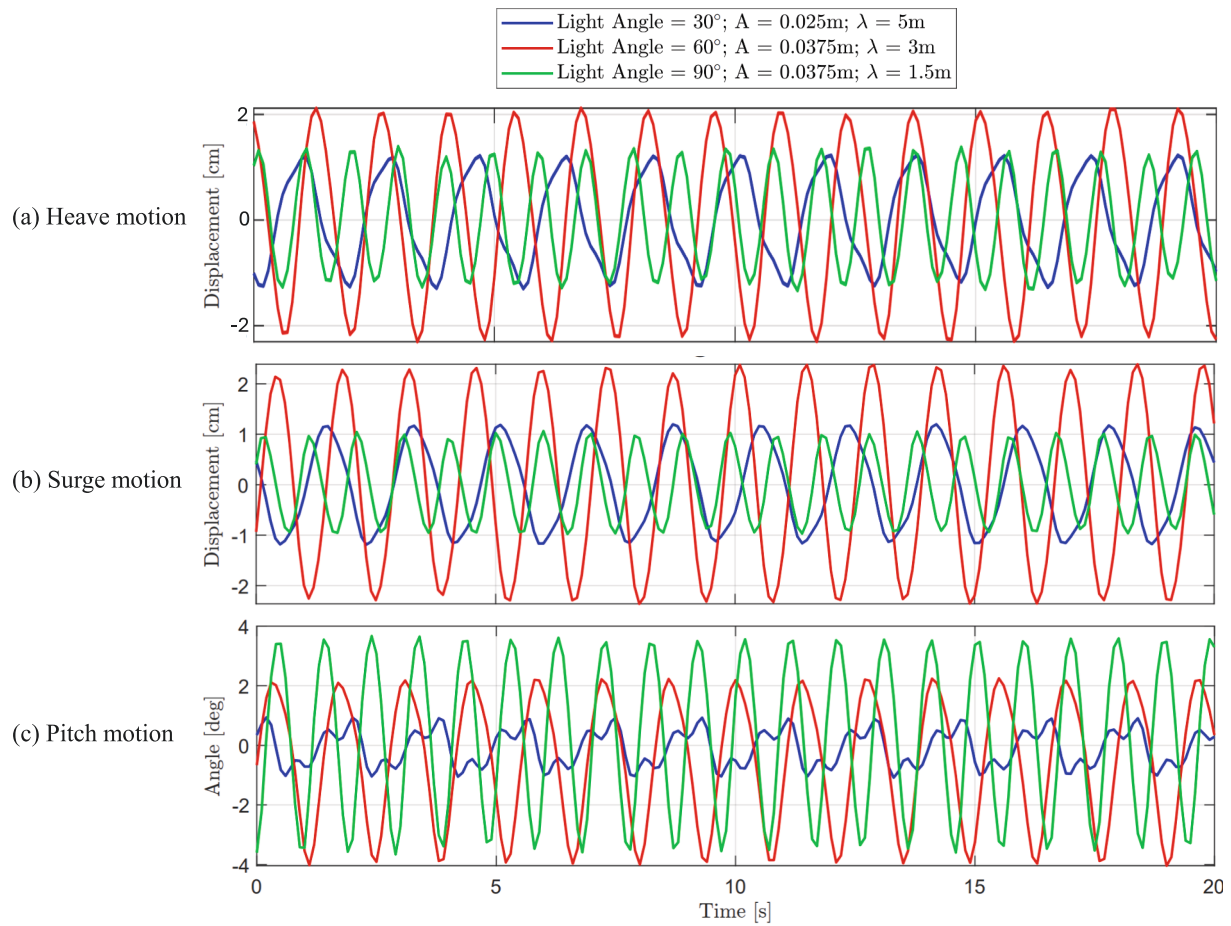


Fig. 8. Time-domain motion responses of the floating photovoltaic (FPV) system under three environmental conditions with varying light angles, wave amplitudes, and wave lengths: red (60° , 0.0375 m, 3 m), blue (30° , 0.025 m, 5 m), and green (90° , 0.0375 m, 1.5 m). (a) Heave motion; (b) Surge motion; (c) Pitch motion. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

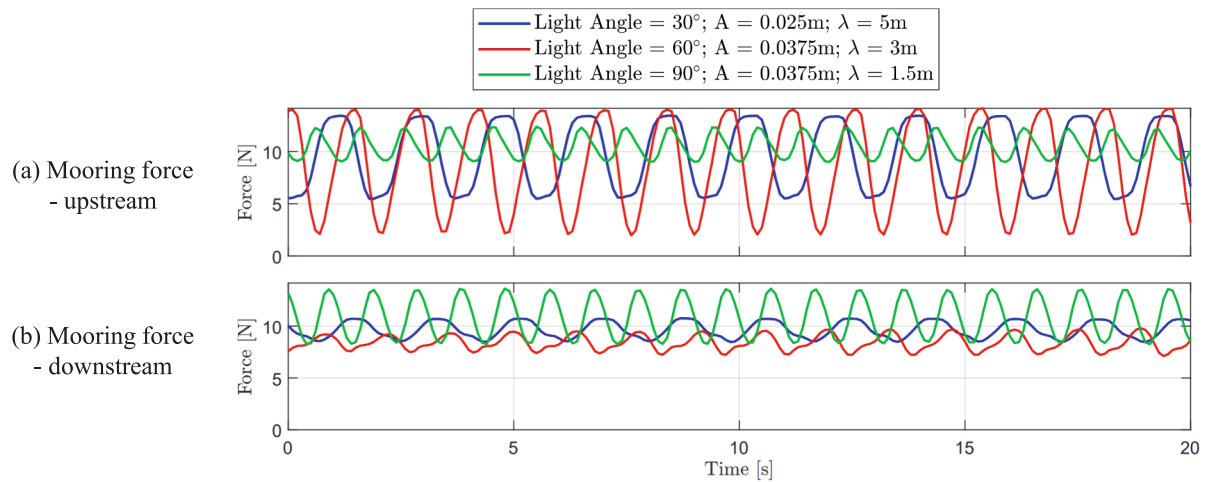


Fig. 9. Time-domain mooring force responses of the floating photovoltaic (FPV) system under three environmental conditions with varying light angles, wave amplitudes, and wave lengths: red (60° , 0.0375 m, 3 m), blue (30° , 0.025 m, 5 m), and green (90° , 0.0375 m, 1.5 m). (a) Upstream mooring force; (b) Downstream mooring force. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

three representative environmental conditions. The specific combinations of light angle, wave amplitude, and wave length for each case have been detailed in the previous section.

In Fig. 9 (a), the red curve exhibits the most pronounced fluctuations in the upstream mooring force, with peak values exceeding 12 N. This

suggests that the corresponding wave condition strongly excites the platform's longitudinal motion, leading to substantial tension in the mooring line. The blue curve shows a moderate response with a smoother waveform, while the green curve—associated with higher wave frequency—demonstrates more frequent but lower-magnitude

oscillations, indicating weaker energy transfer despite increased excitation frequency.

In Fig. 9 (b), the differences in downstream mooring force amplitudes are less pronounced. However, the green curve shows the highest average force level and displays more regular periodicity, suggesting that short-period waves impose more consistent and sustained loads on the downstream anchor point. The red and blue curves are similar in magnitude, though the red case reveals slightly larger cyclic variations due to stronger wave-platform interaction.

Overall, the upstream mooring line is more sensitive to dynamic wave excitations, exhibiting greater variability and peak forces, whereas the downstream line primarily reflects average loading characteristics influenced by wave frequency. These findings are critical for informing mooring system design, fatigue assessment, and structural safety analysis in floating solar applications.

It should be noted that the variation in the light incidence angle has a negligible effect on the hydrodynamic and mechanical behaviour of the FPV platform. The platform motions and mooring forces are primarily governed by wave characteristics such as amplitude, frequency, and wavelength. The inclusion of different light angles in the experimental design was mainly to investigate their influence on the thermal–electrical performance, rather than to modify the hydrodynamic excitation conditions.

3.3. Thermal behaviour

Fig. 10 presents the time-dependent surface temperature of the PV module under three different light incidence angles. Although wave amplitude and wavelength vary across the test conditions, the figure primarily highlights the influence of light angle on temperature behaviour. The blue, red, and green curves correspond to light angles of 30° , 60° , and 90° , respectively.

The results show that the PV surface temperature remains stable throughout the 20-second observation period in all cases, indicating that thermal equilibrium was achieved within this timeframe. However, the absolute temperature levels differ significantly among the three conditions: the highest temperature, approximately 63°C , occurs under the 90° light angle (green curve); the 60° condition (red curve) results in a moderate temperature of around 57°C ; and the lowest temperature, approximately 42°C , is observed at the 30° angle (blue curve).

This trend aligns with the physical principles governing solar irradiance absorption on tilted PV surfaces. When the light is incident at 90° , it strikes the PV panel perpendicularly, maximising irradiance absorption and surface heating. As the angle decreases, the incidence becomes more oblique, reducing the effective irradiated area and increasing reflection losses, which leads to reduced thermal gain and lower surface temperature. In addition, panel temperature reflects irradiance absorption and is closely linked to power output, which is presented in the next

section.

Furthermore, the flat profile of each temperature curve indicates that wave-induced motion has a negligible impact on the thermal response under these experimental conditions. Therefore, the light incidence angle is identified as the dominant factor influencing PV surface temperature, while hydrodynamic effects appear to play a minimal role in short-duration heating behaviour.

3.4. Electrical behaviour

Fig. 11 shows the time-domain variation of the power output from the FPV system under three environmental conditions with different light incidence angles. The blue, red, and green curves represent light angles of 30° , 60° , and 90° , respectively, while wave parameters also differ slightly across the cases, as detailed previously.

The results clearly demonstrate that the power output is directly affected by the light incidence angle. The green curve (90°) shows the highest and most stable power output, consistently near 5 W. The red curve (60°) yields a moderately lower output, fluctuating around 4 W, while the blue curve (30°) has the lowest output, averaging around 2.5 W. This trend is consistent with the irradiance geometry: as the light angle becomes more oblique, the effective irradiated area on the PV surface decreases, reducing the amount of absorbed solar energy and thus electrical generation.

These observations are further supported by the PV surface temperature results in Fig. 10, where the same ranking of $90^\circ > 60^\circ > 30^\circ$ was observed in terms of surface heating. The thermal response is a proxy for irradiance absorption, confirming that more perpendicular light not only increases surface temperature but also enhances electrical output.

To further understand the impact of platform motion on photovoltaic performance, the motion responses shown in Fig. 8 are compared with the power output data in Fig. 11. Across the three representative cases, variations in heave and pitch are clearly reflected in the fluctuations of power generation. In the red case (60° light angle, wave amplitude 0.0375 m, wave length 3 m), the platform exhibits the largest heave (± 4 cm) and moderate pitch ($\pm 2.5^\circ$), corresponding to an average power output of around 4 W with significant oscillations. This indicates that strong vertical and angular motions can cause dynamic misalignment with the light source, leading to unstable energy output. In contrast, the blue case (30° light angle) has milder motion (heave ± 2.5 cm, pitch $\pm 1.5^\circ$), yet shows the lowest power output (~ 2.5 W) with moderate fluctuations, suggesting that an unfavourable irradiance angle can dominate even when mechanical disturbances are limited. Interestingly, in the green case (90° light angle), despite the largest pitch oscillation ($\pm 4^\circ$), the power output is highest (~ 5 W) and most stable. This highlights that vertical incidence is geometrically tolerant to pitch motion, allowing the panel to maintain optimal alignment and stable

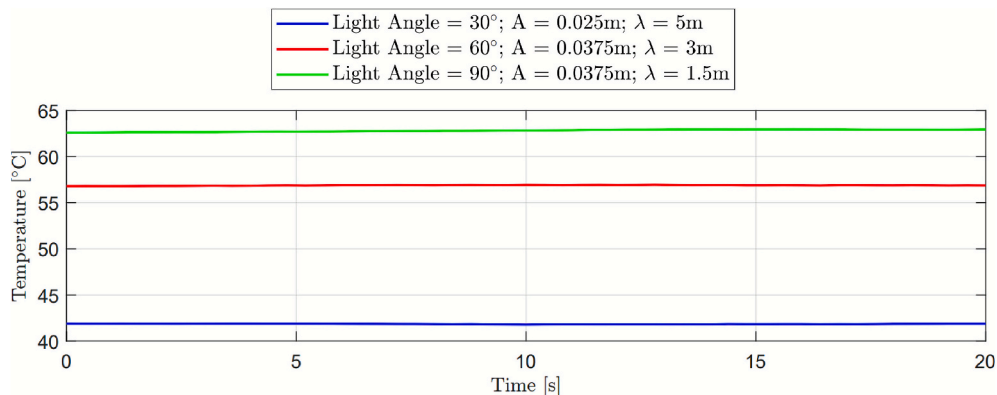


Fig. 10. Surface temperature response of the photovoltaic (PV) panel under three different light incidence angles (30° , 60° , and 90°), showing stable values over time and highlighting the influence of irradiance angle on thermal behaviour.

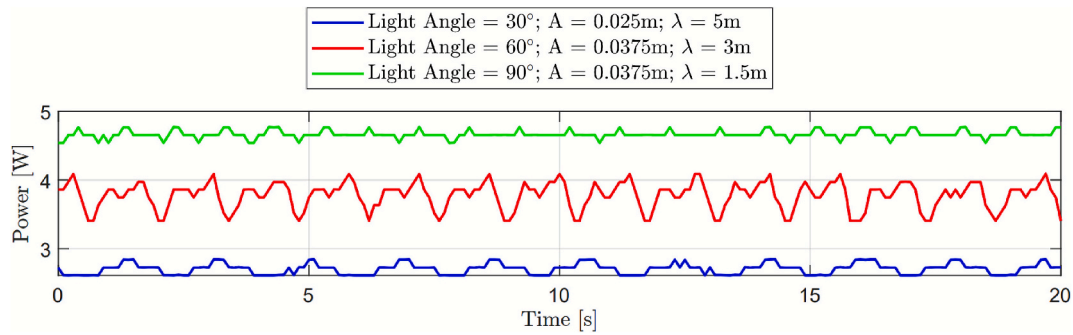


Fig. 11. Time-domain power output response of the floating photovoltaic (FPV) system under three light incidence angles (30°, 60°, and 90°), showing the combined effects of irradiance geometry and platform motion on energy generation.

energy conversion. Overall, these comparisons demonstrate that both heave and pitch influence power variability—particularly through pitch-induced angular deviation—but an optimal light angle (e.g., 90°) can mitigate such motion-induced disturbances.

To further interpret the observed trends in power output under different light incidence angles, a comparison was made against the theoretical cosine dependence of irradiance. In an ideal scenario, the effective irradiance on a photovoltaic surface is proportional to the cosine of the angle between the incident light and the panel normal. In this experiment, a 90° light angle corresponds to perpendicular incidence ($\theta = 0^\circ$), while 60° and 30° angles represent $\theta = 30^\circ$ and $\theta = 60^\circ$, respectively. According to the cosine law, the relative irradiance should follow $\cos(0^\circ) = 1.00$, $\cos(30^\circ) \approx 0.866$, $\cos(60^\circ) \approx 0.50$.

The experimental results closely match these theoretical values. The average power at 90° light incidence is approximately 5 W, which reduces to around 4 W at 60° and 2.5 W at 30°, consistent with the cosine relationship. This confirms that the power output is primarily governed by geometric irradiance alignment and supports the physical validity of the experimental setup. Minor deviations from the ideal cosine values may arise from platform motion and other environmental influences, but overall the trend demonstrates strong agreement with theoretical expectations.

In summary, the power output of the FPV system is governed by a combination of light incidence geometry and dynamic platform behaviour. Maximising solar absorption through optimal panel orientation and minimising wave-induced motion are both critical to achieving consistent and high-efficiency power generation in floating PV applications.

4. Digital twin based on the artificial intelligence

To develop the digital twin of the floating solar system, experimental data were used to train artificial neural network (ANN) models. To balance modelling accuracy and computational efficiency, a two-tier architecture was implemented, comprising a high-fidelity (strong) ANN model and a reduced-order (light) ANN model. The strong model captures detailed system dynamics, while the light model enables faster real-time prediction with reduced complexity. All trained models and associated data were ultimately integrated into a user-facing application, resulting in a functional and deployable floating solar digital twin platform.

4.1. High-fidelity (strong) model based on the original experiment data

Fig. 12 presents the performance of the high-fidelity (or strong) artificial neural ANN model trained directly on the original experimental dataset. The plots compare the real experimental measurements (blue solid lines) with the ANN-predicted outputs (red dashed lines) across seven critical system response variables: heave, surge, pitch, upstream mooring force, downstream mooring force, power output, and

PV surface temperature. The horizontal axis in each subplot represents the sample number (i.e., time sequence), and the vertical axis corresponds to the magnitude of each response.

The model demonstrates excellent agreement with the experimental data across all variables, capturing both steady-state trends and high-frequency dynamics. In the heave and surge plots (Figs. 12(a) and (b)), the ANN successfully learns the oscillatory patterns driven by wave excitation, including amplitude modulation and frequency characteristics. Despite the nonlinearity and noise inherent in experimental data, the predicted signals closely follow the real responses over time.

In the pitch response Fig. 12(c), which includes sharp transitions due to dynamic platform rotation, the ANN remains robust, accurately replicating both gradual changes and sudden drops in angular displacement. Similarly, for mooring forces (Figs. 12(d) and (e)), the model captures both the peak loading and relaxation phases in the upstream and downstream directions, maintaining fidelity even under complex dynamic loading conditions.

The ANN's ability to model power output Fig. 12(f) is particularly notable. Power output is governed by both optical input (irradiance angle) and mechanical motion, making it a compound variable. Nevertheless, the predicted power curve aligns well with the measured data, reflecting the model's capability to learn cross-domain couplings.

Finally, in the PV surface temperature response Fig. 12 (g), the model achieves near-perfect tracking. Since temperature evolves more slowly and smoothly compared to other variables, it provides an excellent check for long-term trend consistency. It is noted that the thin, irregular spikes occasionally visible are not physical temperature changes but measurement artefacts from the thermocouple logging system. The PV surface temperature was recorded using a PicoLog multi-channel logger at 10 Hz, and momentary contact resistance or scan-channel switching sometimes caused single-sample outliers that appear as vertical jumps. Within each experimental case, the temperature remained quasi-steady, with peak-to-peak variations $\leq 0.1^\circ\text{C}$. These artefacts were not removed from the dataset prior to model training; however, their presence does not degrade model performance. The ANN shows strong robustness against such noise, maintaining high predictive accuracy ($R^2 > 0.9$) for the temperature response.

In summary, the high-fidelity ANN model trained on experimental data provides a highly accurate mapping from environmental and structural input features to key output variables of the floating solar system. It demonstrates excellent time-series prediction performance, high adaptability to nonlinearity, and strong robustness against measurement noise. This model serves as the backbone for training the subsequent reduced-order model and for validating the digital twin system's accuracy under realistic dynamic conditions.

Table 5 summarises the prediction performance of the high-fidelity (strong) ANN model across seven key output variables using two standard metrics: root mean square error (RMSE) and coefficient of determination (R^2). The model demonstrates robust predictive capabilities, particularly for variables with smoother temporal trends.

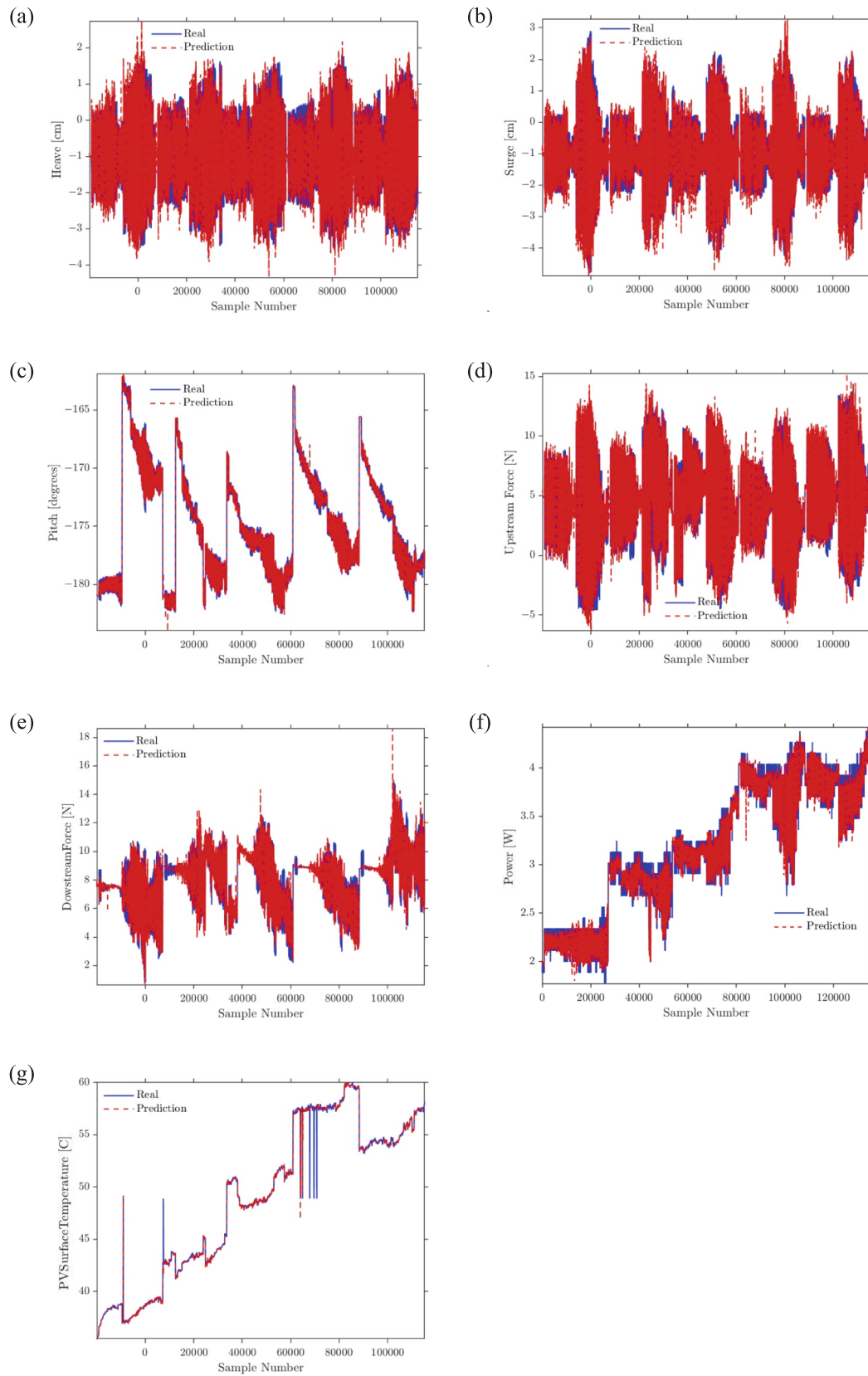


Fig. 12. Prediction performance of the high-fidelity (strong) artificial neural network (ANN) model trained on experimental data. Real values (blue) and ANN predictions (red dashed) are compared for the following outputs: (a) heave, (b) surge, (c) pitch, (d) upstream mooring force, (e) downstream mooring force, (f) power output, and (g) PV surface temperature. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5

Performance metrics (RMSE, R^2) of the strong model for each output variable. Note: RMSE = Root mean square error; R^2 = Coefficient of determination.

Strong model	RMSE	R^2
Power	1.0636	0.9189
Upstream force	1.1424	0.9080
Downstream force	0.7095	0.8533
Heave	0.4546	0.8401
Surge	0.4054	0.8853
Pitch	0.2643	0.9968
Temperature	0.1526	0.9996

Among all outputs, the PV surface temperature is predicted with the highest accuracy, achieving an R^2 of 0.9996 and a remarkably low RMSE of 0.1526, indicating an almost perfect match between predicted and actual values. Power output and mooring forces also show strong performance, with R^2 values above 0.85, which is commendable given their dynamic and nonlinear characteristics.

For motion responses, the model captures pitch with high precision ($R^2 = 0.9968$), reflecting its effectiveness in modelling rotational behaviour. While the heave and surge components also maintain acceptable RMSE and R^2 values (both above 0.84), their evaluation is complicated by the oscillatory nature and low mean values of these signals, which can pose challenges in error quantification. Nonetheless, the strong correlations demonstrated by R^2 across all outputs confirm the model's validity for time-series prediction tasks.

Overall, the strong ANN model exhibits reliable and consistent performance across a wide array of physical variables, providing a solid foundation for further applications within a digital twin framework.

4.2. Reduced-order (light) model for performance prediction

Fig. 13 illustrates the prediction performance of the reduced-order (light) ANN model across seven key output variables: heave, surge, pitch, upstream mooring force, downstream mooring force, power output, and PV surface temperature. In each plot, the Strong curves (blue solid lines) represent the results of the high-fidelity strong model, while the Light curves (red dashed lines) correspond to the outputs of the reduced-order light model. This comparison therefore reflects the approximation capability of the light model relative to the strong model rather than direct experimental measurements.

Unlike the strong model, which was trained directly on the full experimental dataset, the light model was trained on a curated and compressed dataset generated by the strong model. Its primary objective is to reduce computational cost while preserving sufficient accuracy for real-time or embedded applications such as mobile or cloud-based digital twin deployments.

The results show that the light model maintains reasonably good predictive consistency with the strong model across all output dimensions. For the motion responses—heave, surge, and pitch (Fig. 13 (a–c))—the light model reproduces the overall dynamic patterns, including the amplitude variations and transition behaviours, as represented by the strong model. Although the light model sacrifices a small degree of accuracy for real-time performance—resulting in minor discrepancies from the strong model at certain points—it accurately predicts the majority of cases. In particular, the heave and surge responses achieve coefficients of determination (R^2) above 0.83 and 0.87, respectively, indicating reliable predictive capability across the tested conditions.

For the mooring forces (Fig. 13(d and e)), the model tracks both the mean loading trends and high-frequency fluctuations with fair precision. While certain local mismatches and underfitting zones are visible, especially during rapid transitions, the model remains reliable for practical prediction tasks involving anchoring force estimation.

In the case of power output (Fig. 13(f)), the light model performs well in reproducing the stepwise increases and nonlinear growth trends

seen. Some intermittent gaps and overshoots occur, primarily due to the reduced network complexity and temporal resolution in the training data. However, the general power profile is captured effectively.

The PV surface temperature prediction (Fig. 13(g)) demonstrates excellent agreement between the strong model and the light model. Given the temperature's slow-varying nature, the light model handles long-term thermal trends with high reliability, confirming its suitability for predictive monitoring and energy management applications.

In summary, the reduced-order ANN model achieves a good trade-off between computational efficiency and prediction accuracy. Although some fine-scale variations are smoothed out due to model simplification, the core system behaviours are well preserved. This makes the light model well-suited for integration into real-time digital twin platforms, especially where inference speed and hardware limitations are critical factors.

Table 6 presents the performance metrics of the reduced-order (light) ANN model for seven key output variables, using root mean square error (RMSE) and coefficient of determination (R^2) as evaluation criteria. Compared to the high-fidelity model, the light model offers a well-balanced compromise between predictive accuracy and computational efficiency, making it suitable for real-time digital twin applications.

The model demonstrates particularly strong predictive capability for power output, downstream mooring force, and temperature. Power prediction achieves an R^2 of 0.9073 and a low RMSE of 0.1986, indicating accurate tracking of the system's dynamic electrical response. Downstream mooring force and temperature are also predicted with high accuracy, with R^2 values of 0.8537 and 0.9660, respectively, underscoring the model's robustness in capturing mechanical loads and thermal conditions.

For motion-related outputs such as heave and surge, the light model maintains reasonable accuracy, with R^2 values above 0.83. These results are promising given the oscillatory and nonlinear nature of wave-induced motions, which pose significant modelling challenges in simplified networks. The prediction of upstream mooring force yields a moderate R^2 of 0.7204, suggesting effective capture of average force trends despite some limitations in resolving finer dynamic variations.

The pitch response remains the most difficult to model, with the lowest R^2 of 0.5988. This may reflect the inherent complexity of rotational dynamics on floating platforms, which are more sensitive to subtle hydrodynamic interactions that may not be fully represented in a reduced-order model.

Overall, despite some constraints in modelling certain motion variables, the light ANN model shows strong generalization across key outputs relevant to system monitoring and energy forecasting. Its reduced complexity and faster inference capabilities make it an attractive candidate for integration into real-time digital twin frameworks.

4.3. Three-dimensional (3D) performance prediction considering the influence of input conditions

Fig. 14 presents the three-dimensional surface predictions of key performance variables of the FPV system using the trained neural network model. Each subplot shows how two input parameters jointly influence one output variable, revealing nonlinear sensitivities and interaction effects. These 3D plots are critical for understanding system behaviour under varying oceanic and irradiance conditions, and for enabling informed design and control decisions within the digital twin framework.

The surface in Fig. 14(a) demonstrates that heave displacement is highly nonlinear with respect to both wave length and amplitude. A peak heave response occurs when the wave length is around 2.5 m–3.5 m with higher amplitudes (~ 0.035 m), indicating near-resonant conditions. In contrast, for short or long wave lengths, the heave response diminishes even with increasing amplitude, confirming the selective sensitivity of vertical motion to specific wave characteristics. In Fig. 14(b), the surge response shows a smoother dependence on input

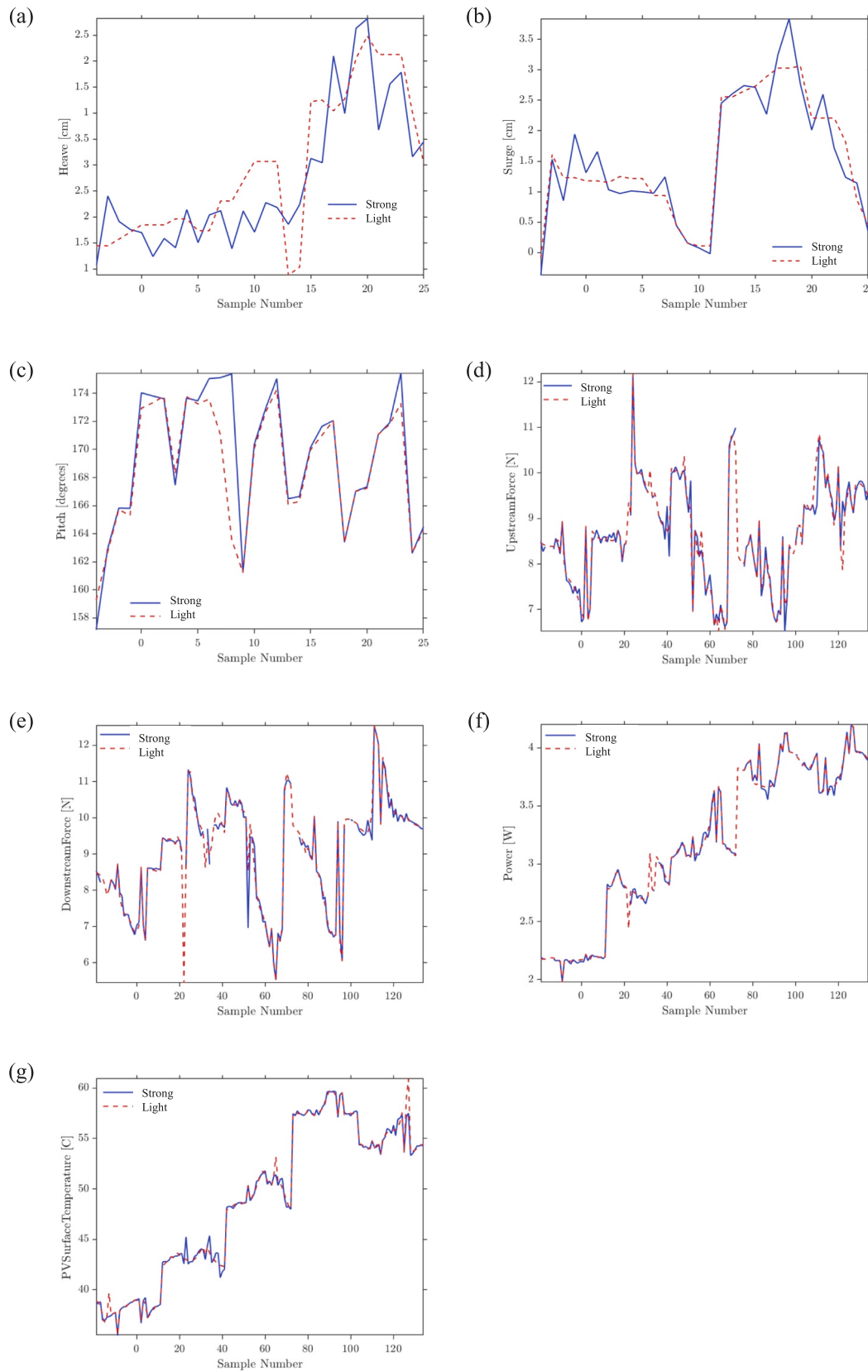


Fig. 13. Prediction performance of the reduced-order (light) artificial neural network (ANN) model across seven output variables. The Strong curves (blue solid lines) represent the outputs of the high-fidelity strong model, while the Light curves (red dashed lines) correspond to the reduced-order light model results. The comparison therefore reflects the approximation accuracy of the light model relative to the strong model rather than direct experimental measurements. Results are shown for: (a) heave, (b) surge, (c) pitch, (d) upstream mooring force, (e) downstream mooring force, (f) power output, and (g) PV surface temperature. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6

Performance metrics (RMSE, R^2) of the strong model for each output variable. Note: RMSE = Root mean square error; R^2 = Coefficient of determination.

Light model	RMSE	R^2
Power	0.1986	0.9073
Upstream force	0.5474	0.7204
Downstream force	0.3176	0.8537
Heave	0.2877	0.8354
Surge	0.3423	0.8740
Pitch	0.0895	0.5988
Temperature	1.3300	0.9660

parameters compared to heave. The peak surge occurs at moderate wave lengths (~ 2.5 m) and higher amplitudes. However, the response plateau suggests that surge is less sensitive to long waves, and more governed by horizontal energy transfer at intermediate scales. Fig. 14(c) reveals a complex and irregular surface, with sharp gradients indicating strong sensitivity of pitch to small changes in wave conditions. The pitch reaches its peak at wave lengths around 2–3 m and amplitude near 0.03 m. Multiple local maxima suggest that rotational behaviour is particularly sensitive to wave spectrum interactions.

For the mooring forces, Fig. 14(d) shows a curved surface where upstream mooring force increases with frequency and amplitude up to a point, then decreases. This reflects dynamic coupling between mooring tension and wave-induced oscillations. At frequencies around 0.6–0.8 Hz and amplitude ~ 0.03 m, peak forces are observed, beyond which force levels decline, possibly due to phase mismatches or damped responses. Fig. 14(e) illustrates a clearer, more monotonic trend. The downstream force increases steadily with amplitude, but shows a downward slope with increasing frequency. This suggests that downstream mooring loads are more influenced by steady drag and less by dynamic oscillation, in contrast to upstream behaviour.

Power output is influenced by multiple interacting parameters. Fig. 14(f) shows the power surface as a function of irradiance and light angle. As expected, the highest power output occurs when irradiance is high and light angle is near 90° , meaning perpendicular incidence. A strong gradient is visible along the light angle axis, confirming the dominant role of geometric orientation in energy capture. Power decreases sharply as the incidence becomes oblique ($<60^\circ$). Fig. 14(g) presents a 3D surface showing the variation in power output with respect to wave length and amplitude. Unlike the irradiance-based power surface in subplot (f), this plot highlights the indirect influence of hydrodynamic motion on power generation. The surface reveals that higher wave amplitudes generally enhance power output, especially when combined with longer wave lengths ($\lambda > 4$ m). This trend suggests that moderate platform motion—induced by specific wave conditions—can positively affect photovoltaic efficiency, potentially by dynamically optimizing panel orientation or cooling the module surface. However, at low amplitudes and short wave lengths, the power output plateaus or declines, indicating suboptimal energy capture under calm or mismatched wave states.

PV surface temperature increases steadily with irradiance and is moderately influenced by light angle, as shown in Fig. 14(h). At high irradiance levels, the temperature can exceed 75°C , especially when light angle is optimal. However, the surface flattens at low irradiance, showing that the temperature sensitivity is primarily irradiance-driven.

These 3D prediction surfaces provide a comprehensive view of how wave and solar conditions affect FPV performance across structural, mechanical, and energy domains. They clearly reveal that hydrodynamic responses (heave, surge, pitch) exhibit nontrivial dependencies on wave spectra. Mooring forces respond asymmetrically upstream vs. downstream, governed by a mix of dynamic and static loads. Besides, power and temperature outputs are highly correlated with irradiance and light incidence, affirming the importance of optimal orientation.

The trained ANN model effectively captures these multi-dimensional relationships, making it a valuable component of the floating solar

digital twin for performance forecasting, design optimisation, and control strategy development.

4.4. Digital twin for user-specific applications

To facilitate real-time performance prediction and scenario exploration by end users, a user-oriented digital twin interface was developed using MATLAB App Designer. The application integrates the trained reduced-order ANN model and provides an intuitive platform for users to input environmental parameters and instantly visualize corresponding system responses. As shown in Fig. 15, the interface allows users to specify four key input variables: wave amplitude, wave frequency, solar irradiance, and light incidence angle.

Upon clicking the “Predict” button, the app uses the embedded ANN model to calculate and display predicted outputs in one second including upstream and downstream mooring forces, power output, PV surface temperature, and maximum values for heave, surge, and pitch. This functionality enables quick evaluation of system performance under custom conditions without the need for physical testing or complex simulations.

To enhance safety and prediction reliability, a real-time input validation mechanism is implemented. The system checks whether user-defined inputs fall within the range of training data. If any value exceeds the predefined bounds—Amplitude: 0.025–0.0375 m, Frequency: 0.4–1 Hz, Irradiance: 237–348 W/m^2 , and Light Angle: 30° – 90° —a warning window is triggered (Fig. 15(b)), alerting users with the message: “Be Careful! Input Data out of the range.” In such cases, the output values are masked to prevent misinterpretation or misuse of extrapolated results.

The current application interface demonstrates the foundational structure of a deployable digital twin tool. Once integrated with real-time sensor inputs from an operational FPV system, the interface can provide dynamic data in real time, supporting continuous prediction and control. The virtual twin can predict key outputs, including heave, surge, pitch, mooring forces, PV temperature, and power output, which potentially reduces the need for sensors on the physical twin and provides more comprehensive predictions.

The application of digital twin technology in FPV systems extends beyond performance prediction to a range of high-value functions. For example, it can be integrated with platform attitude control to enable wave-adaptive panel adjustment for optimal solar capture. In multi-unit FPV farms, it can support power coordination and load balancing between modules. When combined with weather forecasting, the digital twin can enable predictive energy dispatch. It can also track system conditions over time for degradation assessment and lifecycle management, and support virtual commissioning before large-scale deployment. These applications highlight the potential of digital twins as the “intelligent brain” of future offshore solar systems.

Beyond performance prediction, the developed digital twin can also evolve towards real offshore deployment. When the complete setup—including sensors, data acquisition units, and AI computational models—is installed on an operational FPV platform at sea, it can continuously collect large volumes of real-time data under varying marine conditions. These real-world datasets can then be used to retrain and update the AI models, creating a refined, site-specific digital twin that mirrors the true behaviour of the offshore system. This adaptive process bridges laboratory experiments and real applications, enabling continuous improvement of system design, predictive maintenance, and autonomous operation in practical ocean environments.

Additionally, in real offshore operations, extreme weather conditions such as strong winds, large waves, or sudden changes in irradiance may lead to abnormal system behaviour or unexpected sensor signals. Similar incidents were also observed during laboratory testing, where the mooring rope occasionally broke due to wear, resulting in abrupt and irregular readings from the tension sensors. The digital twin framework is capable of recognising such anomalies: when abnormal sensor inputs

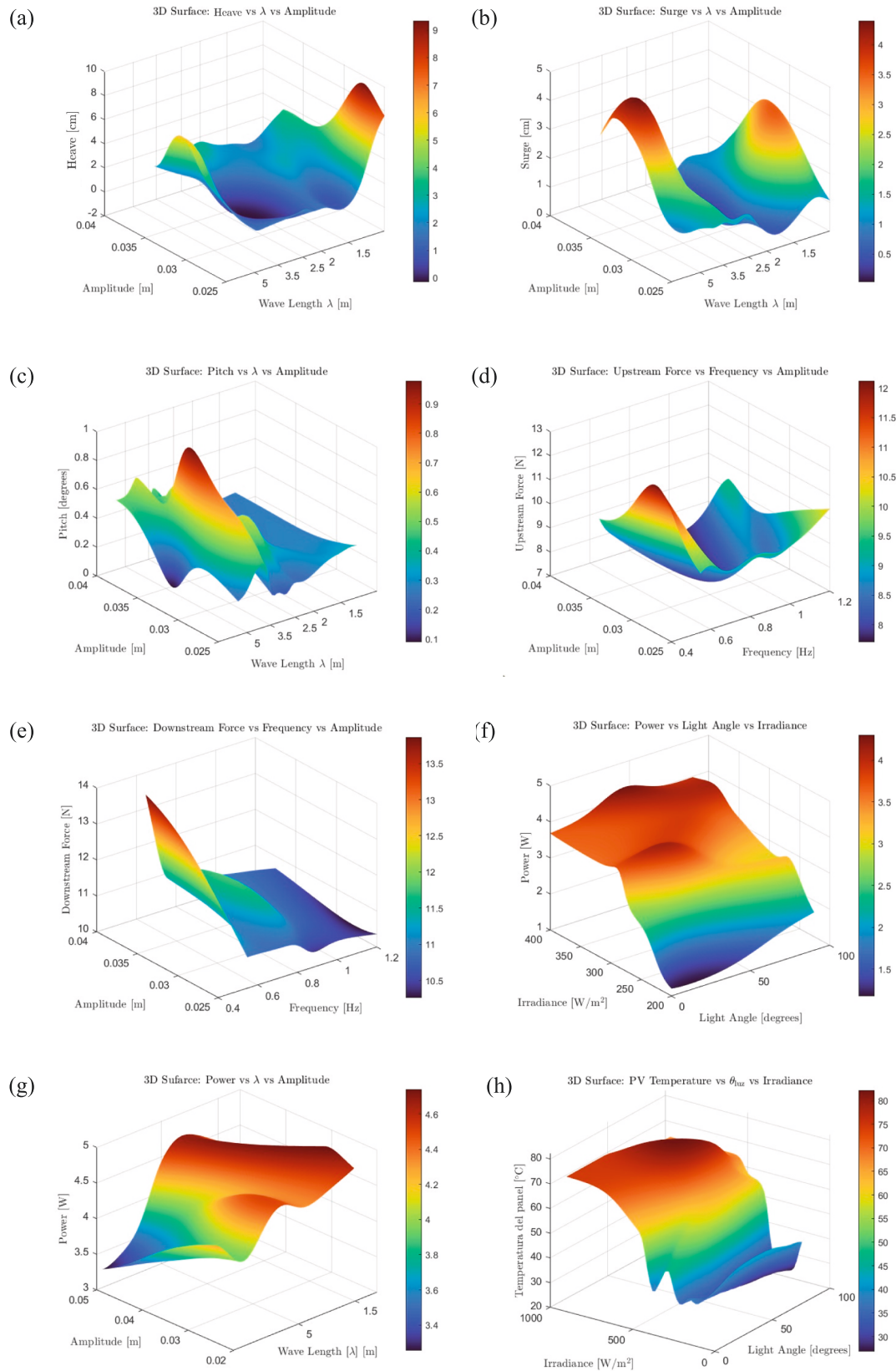


Fig. 14. 3D surface predictions of hydrodynamic and mooring responses of the floating photovoltaic (FPV) system under varying wave conditions. (a) Heave vs. wave length and amplitude; (b) Surge vs. wave length and amplitude; (c) Pitch vs. wave length and amplitude; (d) Upstream mooring force vs. frequency and amplitude; (e) Downstream mooring force vs. frequency and amplitude; (f) Power output vs. irradiance and light angle; (g) Power output vs. wave length and amplitude; (h) PV surface temperature vs. irradiance and light angle.

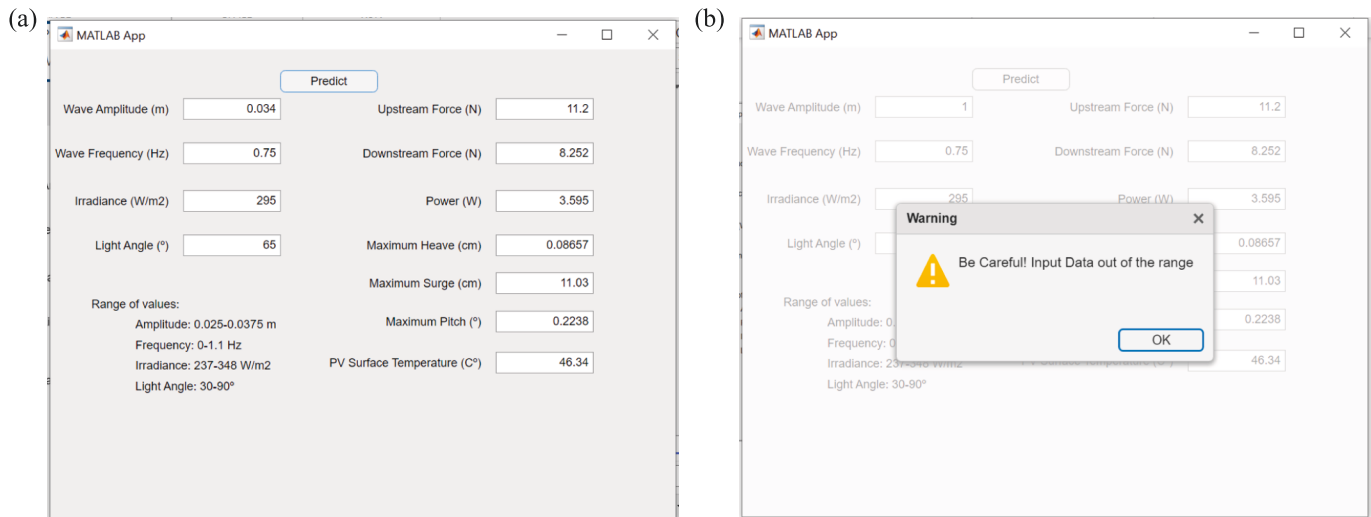


Fig. 15. User interface of the digital twin application developed in MATLAB. (a) The prediction panel shows inputs and model-predicted outputs based on user-defined wave and solar conditions. (b) An automatic warning is triggered when any input exceeds the trained model range, ensuring prediction safety.

cause computational inconsistencies or prediction errors, the system can promptly identify that an unexpected or fault condition has occurred. This mechanism enables early fault detection and rapid maintenance response, thereby enhancing the reliability and safety of the floating photovoltaic system under harsh or unforeseen marine environments.

4.5. Discussions about the model limitations

The present AI models were trained on a laboratory dataset that included five levels of light intensity, two wave heights, and fifteen wavelengths. Although this dataset was sufficient to demonstrate the feasibility of the digital twin concept, its limited size and operating range may lead to potential risks of overfitting. The models might have learned specific patterns within these experimental conditions, which could reduce generalisation when applied to broader scenarios. To address this limitation, future work will focus on expanding the range of laboratory experiments and, more importantly, conducting additional tests under real marine conditions to improve data diversity and minimise overfitting.

Due to the relatively narrow range of training conditions, model accuracy may also decline when encountering unseen combinations of environmental parameters beyond the tested range. This limitation highlights the importance of extending the dataset to cover more representative sea states and solar conditions. The next stage of research will therefore involve long-term offshore experiments, where the digital twin can be retrained and adapted with field data collected under diverse and dynamic marine conditions. Such efforts will substantially enhance model robustness, reliability, and applicability to real-world FPV systems.

Additionally, experimental sensor data inevitably contain noise. The motion sensors are particularly sensitive, as noise in acceleration signals tends to be amplified when integrated into displacement. To mitigate these effects, the raw signals were pre-processed using high- and low-pass filtering together with outlier removal to minimise noise and maintain data consistency. Nevertheless, residual noise may still affect prediction accuracy. Future experiments will therefore employ higher-precision, low-noise sensors to further improve measurement quality and model reliability.

4.6. Offshore-to-cloud data communication for FPV digital twins

For a digital twin framework to perform real-time prediction and condition monitoring, robust offshore-to-cloud data transmission is

essential. Sea-based systems such as FPV platforms require resilient communication pathways that can operate under dynamic environmental conditions and over extended distances [37]. This study recognises the importance of integrating sensor nodes with smart communication modules that can transmit high-resolution data from offshore locations to centralised cloud platforms.

To enable real-time monitoring based on digital twin, sensing and data transmission have also been key challenges at sea. FPV platforms and other sea-based systems must operate under dynamic and often harsh marine conditions, making it feasible to only use few sensors, supporting the necessity of a digital twin. Existing commercial sensors may be impractical to attach to sea systems due to bulky geometries, cumbersome operations, or being vulnerable to the sea environment, let alone being well serviced [38–40]. The existing functional units, e.g. sensing system, have been assembled with components by bonding, soldering or rivet joining where additional processing is required, with more wastes created (including electronics wastes), but also it may be a risky factor for potential failures, such as debonding from cyclic loads or residual thermal stress. Moreover, due to the bulky and inflexible design of existing sensing devices, it brings added difficulty in assembly with complicated geometrical design of offshore components, nor being well serviced in sea environments.

Instead, embedded in composite materials, such novel nano-electronics developed and synthesized for different monitoring purposes, can be corporate within various components (e.g. floating structures, solar systems, mooring systems, and dynamic cables). The integration with embedding the nanocomposite sensors and encapsulation will be developed for their sea operation and improved environmental and mechanical resistance and therefore an extended service life for in-situ monitoring. The sensors will enable us to monitor key parameters during operation, such as wave conditions, structural responses (e.g., stresses, motions), temperature, and solar irradiance. These data streams are processed at edge-level microcontrollers, equipped with initial filtering and compression algorithms to reduce bandwidth load. The data packets are then transmitted via wireless marine communication protocols such as LTE, LoRaWAN [41], or satellite uplinks [42], depending on site remoteness and bandwidth requirements.

Once received by the cloud infrastructure, the data is decoded, time-synchronised, and ingested into the digital twin model. The cloud-hosted twin then executes prediction routines using pre-trained AI models, such as the two-tier ANN framework described in this study, to present a virtual twin of the FPV system. The results, including predicted

mechanical stresses, power fluctuations, or potential anomalies, are visualised via a remote dashboard and can trigger energy management systems or maintenance workflows. Results are visualised on a secure remote dashboard, allowing for intuitive real-time insights, and can be used to trigger automated alerts, energy balancing actions, or predictive maintenance workflows. Importantly, the offshore-to-cloud system supports bidirectional communication, enabling dynamic update loops where revised control strategies, firmware upgrades, or retrained AI model weights can be securely transmitted back to offshore modules. This closed-loop, intelligent communication framework ensures that the digital twin remains contextually aware and operationally actionable. It forms a foundational component of future-proof, autonomous control architectures for ocean-based modular renewable energy systems, supporting scalability, resilience, and long-term cost-efficiency.

5. Conclusions

A digital twin framework for floating photovoltaic (FPV) systems was developed by integrating physical wave tank experiments, multi-sensor data collection and processing, and artificial neural network (ANN) modelling. The key conclusions drawn from this study are summarised as follows:

- A total of 155 controlled test cases were conducted using a custom-built wave tank facility, simulating a wide range of wave lengths (1.5 m to 5.0 m), wave amplitudes (0.025 m and 0.0375 m), and solar incidence angles (30° to 90°). These experiments captured time-series data of hydrodynamic motion (heave, surge, pitch), mooring line forces, PV surface temperature, and power output. The resulting dataset, sampled at 10 Hz and spanning mechanical, thermal, and electrical domains, served as the empirical foundation for training and validating the digital twin models.
- A two-tier ANN architecture was developed to balance accuracy and computational efficiency. The high-fidelity (strong) model directly trained on experimental data achieved excellent predictive performance, with R^2 values reaching 0.9996 for PV surface temperature and 0.9189 for power output. A reduced-order (light) model was derived for real-time applications, retaining strong performance with minimal compromise—achieving R^2 values of 0.9073 for power and 0.9660 for temperature. This architecture supports both accurate analysis and lightweight deployment in user-facing tools.
- The ANN models effectively predicted a wide range of system responses. For example, the high-fidelity model accurately captured oscillatory behaviours in surge and pitch motions, despite nonlinearity and environmental noise. It also reproduced rapid variations in mooring forces and transient power fluctuations, with root mean square errors (RMSEs) as low as 0.1986 W for power and 0.1526 °C for PV temperature. The reduced model, though simplified, maintained adequate precision for engineering use, especially in smooth and slow-varying outputs like thermal response and average power trends.
- Three-dimensional performance maps generated by the trained models revealed strong nonlinear interactions between environmental inputs and system behaviour. For instance, heave motion peaked under wave lengths of 2.5–3.5 m and higher amplitudes (~0.0375 m), indicating resonant conditions. Power output was maximized when solar irradiance exceeded 340 W/m² with a 90° incidence angle, and PV temperature surpassed 75 °C under the same conditions. These insights enable predictive optimisation and enhance understanding of FPV performance under variable sea states.
- To support deployment and interaction, a user interface was developed. Users can input four environmental variables—wave amplitude, frequency, irradiance, and light angle—and obtain predicted outputs including platform motions, mooring forces, PV temperature, and power output. The application includes a real-time

validation system that alerts users when inputs exceed trained boundaries (e.g., irradiance beyond 348 W/m²), ensuring prediction reliability and model safety in practical use.

- Finally, the digital twin system shows significant promise for real-world engineering deployment, particularly in remote or offshore environments. With sensor data relayed via marine communication networks (e.g., LoRaWAN or satellite), the digital twin can provide near-instant forecasting, anomaly detection, and condition-based maintenance alerts. Operators on land could access cloud-based platforms to visualize FPV performance and make informed decisions—moving from passive monitoring to AI-enhanced autonomous energy management.

Although the experimental and modelling framework demonstrated promising results, it should be noted that the laboratory-scale setup does not fully replicate the complex and dynamic conditions of real marine environments. Several limitations therefore remain. The current models were trained on a limited dataset obtained under controlled laboratory conditions, which may not fully capture the complexity of real ocean environments. Long-term effects such as PV degradation, fouling, and corrosion were not considered, nor were additional environmental factors like wind, rain, and currents. The system also lacks real-time sensor integration and closed-loop control capabilities. Furthermore, the neural networks used do not provide uncertainty quantification or interpretability. Future work will focus on expanding the training dataset with in-situ measurements, incorporating degradation and multi-environment modelling, exploring lightweight architectures for real-time edge deployment, and integrating explainable AI and uncertainty analysis to enhance reliability and practical applicability. Additionally, once larger and long-term datasets become available from field deployments, deep learning architectures such as recurrent or hybrid neural networks will be explored to enhance temporal feature extraction and long-sequence prediction within the digital twin framework.

This study proposes a practical and scalable digital twin framework for FPV systems, integrating artificial intelligence to accurately predict performance under dynamic marine conditions. It enhances power forecasting and supports predictive maintenance, offering a cost-effective and efficient solution for the intelligent management of offshore solar platforms. The framework contributes to the digitalisation and resilience of future ocean-based renewable energy systems.

CRedit authorship contribution statement

Danlei Yang: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Wenxuan Shi:** Writing – original draft, Methodology, Investigation, Conceptualization. **Javier Aliseda:** Writing – original draft, Formal analysis, Data curation. **Noé Gervais:** Writing – original draft, Formal analysis, Data curation. **Saseeban Rathakrishnan:** Writing – original draft, Formal analysis, Data curation. **Khalifa Ibrahim:** Validation, Resources, Methodology, Investigation, Data curation. **Xiangcheng Lyu:** Methodology, Investigation, Data curation. **Chenhao Mi:** Validation, Methodology, Data curation. **Luofeng Huang:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data underlying the results are available as part of the article and no additional source data are required.

Appendix A:. MATLAB codes

The codes for the high fidelity (strong) model, reduced-order (light) model, and dataset generation are available at: <https://github.com/DanleiY/Digital-twin-for-floating-solar-energy-system>.

Appendix B:. Floating PV system and wave tank

The geometry of the floating PV structure, along with the wave tank facility, including the floating PV system and mooring system, is shown in the Appendix Fig. B1 and Appendix Fig. B2.

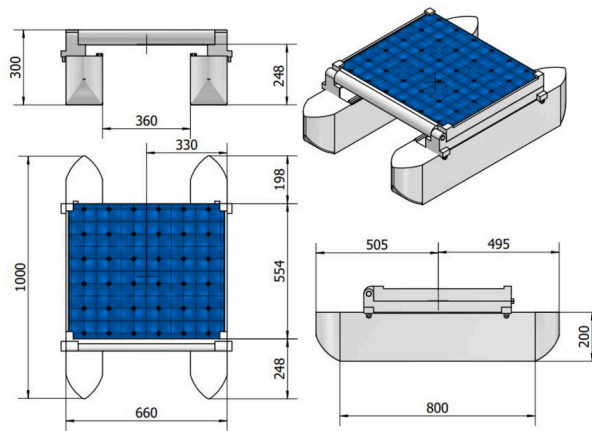


Fig. B1. Geometry of the floating PV structure.

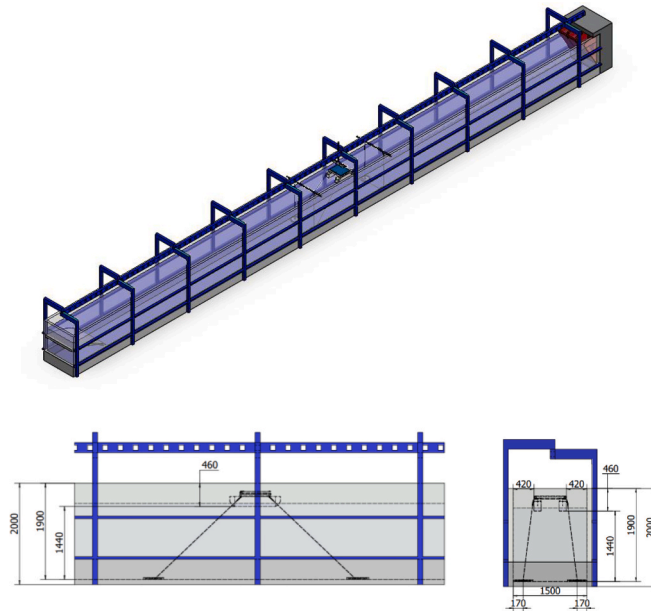


Fig. B2. The wave tank facility plus the floating PV system and mooring system.

Appendix C. 3: Experiment case settings and parameter details

The Appendix Table. C1 displays all 31 test cases corresponding to the 30° light angle. In total, 155 cases were investigated, covering five different light angles, each with an identical set of 31 cases. For the other four angles, only the light angle was varied, while all other parameters remained constant.

Table C1
Wave conditions and geometric setup for light angle 30°.

Case No.	Light angle (°)	Wave amplitude (m)	Catamaran length (m)	Wave length (m)	Wave frequency (Hz)
30-1	30	0	1	0	0
30-2	30	0.025	1	5	0.546066482
30-3	30	0.025	1	4.75	0.562582785
30-4	30	0.025	1	4.5	0.580165497
30-5	30	0.025	1	4.25	0.598966109
30-6	30	0.025	1	4	0.619174519
30-7	30	0.025	1	3.75	0.641031404
30-8	30	0.025	1	3.5	0.664845191
30-9	30	0.025	1	3.25	0.691015605
30-10	30	0.025	1	3	0.720067022
30-11	30	0.025	1	2.75	0.752696886
30-12	30	0.025	1	2.5	0.789848397
30-13	30	0.025	1	2.25	0.832824394
30-14	30	0.025	1	2	0.883475528
30-15	30	0.025	1	1.75	0.944531458
30-16	30	0.025	1	1.5	1.020228439
30-17	30	0.0375	1	5	0.546066482
30-18	30	0.0375	1	4.75	0.562582785
30-19	30	0.0375	1	4.5	0.580165497
30-20	30	0.0375	1	4.25	0.598966109
30-21	30	0.0375	1	4	0.619174519
30-22	30	0.0375	1	3.75	0.641031404
30-23	30	0.0375	1	3.5	0.664845191
30-24	30	0.0375	1	3.25	0.691015605
30-25	30	0.0375	1	3	0.720067022
30-26	30	0.0375	1	2.75	0.752696886
30-27	30	0.0375	1	2.5	0.789848397
30-28	30	0.0375	1	2.25	0.832824394
30-29	30	0.0375	1	2	0.883475528
30-30	30	0.0375	1	1.75	0.944531458
30-31	30	0.0375	1	1.5	1.020228439

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