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Towards a holistic digital twin solution for real-time monitoring of aquaculture net cage systems

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A R T I C L E I N F O

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A B S T R A C T

Digital twins and relevant concepts are being applied in a wide variety of ways, and they are of most use when an actual real-world physical system or process (a physical twin) is changing over time and when measurement data correlated with this change can be captured. In this work, a digital twin model was implemented for real-time monitoring of aquaculture net cage systems, which is notoriously challenging because of several difficult-to-measure properties, such as forces on and deformation of the flexible netting structures, waves and flow field alterations around the cage and complex stiffness behaviour of the mooring elements made by fibre ropes. These properties were set to be adaptable according to the resultant outputs, such as cage responses and mooring loads that were continuously compared with the measurement data obtained from remote monitoring sensors. In this way, real-time sensor data were assimilated into the numerical simulation model for representing the actual net cage system. No dedicated sensors were used for fish monitoring, but the fish behavioural responses to current, wave and cage deformation were modelled according to relevant field observational data. A wireless sensor network has also been tested for the digital twin implementation, which was found to be suitable for practical uses in fish farms.

1. Introduction

Since the first mention of the word “digital twin” (by Michael Grieves), relevant concepts and models have been applied in a wide variety of ways [1,2], and they are of most use when an actual real-world physical system or process (a physical twin) is changing over time and when measurement data correlated with this change can be captured [3]. Physics-based modelling has been the main approach for digital twin implementations, where numerical simulation models are combined with sensor data for real-time monitoring, predictive maintenance, and performance optimization.

Digital twin implementations for marine aquaculture systems and farmed fish are still in the research stage [4–6], where interactions between the fish, marine environment and productions systems (fish farm structures) need to be addressed. Atlantic salmon (*Salmo salar*) is currently one of the most significant farmed finfish species in marine aquaculture, and most of its production is

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conducted in flexible net cages (open net pens) that are placed in floating fish farms moored to the seabed or the shore. These cages can deform when subjected to water currents and waves, altering the available space (cage volume) for the fish, the ambient water flow and production environment [7]. The loss of cage volume has been shown to affect fish growth and mortality rates due to reduced oxygen and increased stress levels in the fish, particularly when the stocking density is high [8]. The current and wave environment, in itself, can also cause stress to the fish, as the fish have to swim faster and expend more energy to avoid contact with the net enclosure and other fish [9]. There are no existing simulation models able to account for these interactions, while being efficient enough for real-time digital twin implementations. Relevant numerical tools have been developed with the focus on the modelling of hydrodynamic loads [10–15]) and structural analysis of fish farms [16–18], which are usually computationally intensive. Although it might be possible to extend these models for the simulation with fish, this would presumably lead to a more computationally intensive model as it would then have to compute the physics of the system with high accuracy, while also considering the relatively rapid dynamics on fish behaviour and resulting effects on the hydrodynamic characteristics [19]. [20] presented a multipurpose modelling framework [21], based on which an integrated model of fish and cage was introduced. This simplified model is able to simulate cage responses and fish swimming behaviour in real time, which offers new possibilities for digital twin implementations.

With respect to data assimilation [22] and relevant estimation techniques, features such as fish behaviour and biomass distribution are notoriously difficult to quantify using conventional solutions based on statistical methods such as Kalman filtering [23] and nonlinear observer techniques [24]. It is also difficult to assimilate numerical simulation models of flexible net cages that consist of many interdependent system states (typically in the order of 10^3 after simplification of the netting structure) with the sensor data that typically cover a small part (less than 1%) of the total system states. A compromise to this is to use limited sensor data to improve the estimation of some dominant environmental or structural parameters, such as waves and flow field alterations around the cage that are difficult to measure, but correlate with the measured cage responses [25]. Besides that, the combination of physics-based models and data-driven approaches (machine learning/artificial intelligence) has shown to be a promising direction for various digital twin implementations [26–28].

In this study, the integrated fish and cage model [20] and the corresponding data assimilation method [25] were extended for the digital twin implementation, where the metocean buoy, load shackle, accelerometer and depth/pressure sensor data were fed into the simulation model for real-time monitoring of cage responses, net deformations and mooring loads. In the meantime, the fish swimming behaviour and biomass distribution were modelled according to the previous field observational data [29]. A remote sensor network and communication system has also been tested, which was, in general, found to be suitable for real-time applications in fish farms.

2. Materials and methods

2.1. Simulation models

A typical open net cage consists of a floating collar, a sinker tube, weights and a net pen that contains the fish. Several net cages may be connected to a common mooring frame within one fish farm. Thus, a complete net cage system also includes various mooring ropes/cables/chains, buoys and coupling plates [30]. All these components can be modelled in the simulation framework, FhSim, which allows a high degree of flexibility to combine different mathematical models, numerical solvers and estimation techniques for time-domain representation of a complex system [20,21]. An individual-based model of Atlantic salmon [31] has also been implemented and integrated with the cage model in FhSim, which is able to simulate full-scale fish populations (e.g., 200,000 individuals) in real time, and consider the spatial and temporal fish behavioural responses towards the cage, feed, temperature, light, prevailing water

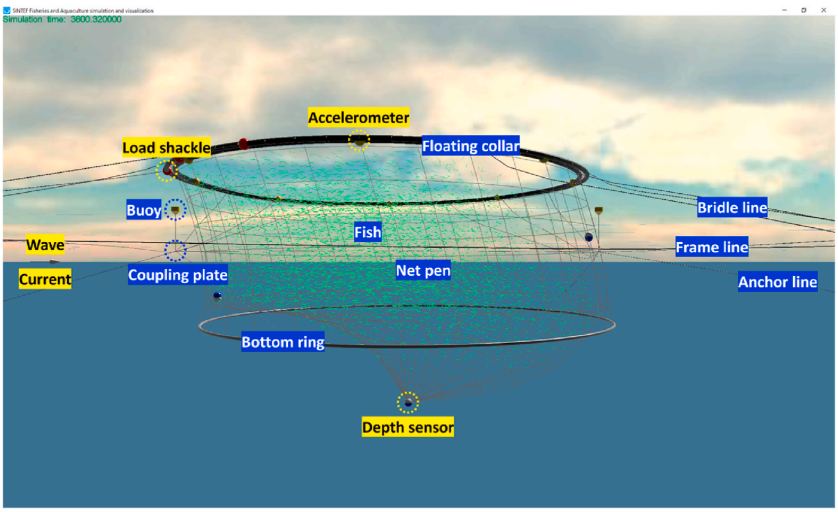


Fig. 1. An example of the simulated fish and net cage system in FhSim.

currents, waves and other individuals. Fig. 1 shows an example of the simulated fish and net cage system in FhSim, using the models that have been validated in previous numerical and experimental studies [25,30–33]. For the present digital twin implementation, the same simulation models were used but set to be adaptable according to relevant sensor inputs:

1) The sea environment model was continuously updated according to the metocean buoy data (current and wave) or the online metocean forecast, and adapted by comparing the simulated and measured cage responses (accelerometers on the floating collar) and net deformations (depth sensors on the net pen).
2) The complex stiffness behaviour of fibre ropes [34], e.g., dynamic stiffness during loading and unloading processes, was continuously evaluated and adapted by comparing the simulated and measured mooring loads (load shackles on the bridle lines).
3) The increased or decreased net solidity due to biofouling [18,35] or net cleaning [36] and the resultant screen force model [10] were evaluated and adapted by comparing the simulated and measured total mooring loads and net deformations.

2.2. Real-time data collection

The wireless sensor network (WSN) is regarded as a revolutionary information gathering method and the key technology for Internet of Things (IoT). The WSN architecture is built with a base station and sensor nodes that can be used in various real-time applications to perform varying tasks like collection, processing, analysis, storage and mining of data. Compared with wired solutions, WSN features easier deployment and more flexibility in devices. Some wireless sensors (e.g., depth sensors, accelerometers, dissolved oxygen and temperature sensors) have been tested at the aquaculture site of SINTEF ACE full-scale laboratory facility (operated by Salmar: one of the world's largest producers of farmed salmon) for the digital twin implementation, as well as a sensor network built by using a flow-based development tool (i.e., Node-RED) for wiring together hardware devices, APIs (application programming interfaces) and online services.

The message queuing telemetry transport (MQTT) is an ISO standard publish-subscribe-based messaging protocol that has been widely used for IoT. It is designed for connections with remote locations and devices with constraints or limited network bandwidth. It is light weight, open, simple, and runs over a transport protocol (typically TCP/IP: Transmission Control Protocol/Internet Protocol) that provides ordered, lossless, bi-directional connections. These characteristics make it ideal for real-time applications in fish farms. Fig. 2 illustrates the wireless sensor network and a communication system built upon MQTT and 4G that has been tested at SINTEF ACE and found to be suitable for real-time digital twin implementations.

2.3. Module integration

An interface for assimilating sensor data into the numerical simulation model was developed and embedded in a high-level, general-purpose program (i.e., Python) which can connect to the sensor network through the MQTT messaging protocol and transfer data to FhSim based on the TCP client-server implementation. The simulation models in FhSim have been validated against the model-scale experimental data where the relevant input parameters (e.g., current, wave, net solidity and mooring line stiffness) were controllable. However, a full-scale sea cage that is in use might be different from the original design or specifications, considering e.g., the load history and biofouling. The measured current and wave from a metocean buoy might also be different from the actual situation, as it is usually deployed several hundred meters away from the cage. When deviations were found between the simulation outputs and measurement data, the relevant input parameters were adapted by using a Proportional-Integral-Derivative (PID) controller. For instance, the deviations between simulated and measured positions of the net at different depths (see e.g., in Fig. 1) can be used to evaluate the alterations of the water flow from the measuring point to the cage and adapt the resultant current velocity profile and screen force model. This approach had been verified in the previous study [25] for real-time monitoring of net deformations. In the present study, it was extended for the monitoring of the floating collar in waves where the deviations between simulated and measured responses were used to evaluate the alterations of the waves. The deviations between simulated and measured mooring loads (mooring line tensions) were also used to evaluate the alterations of the stiffness of each bridle line due to the dynamic loading process.

For each time step t, the implemented PID controller calculates the deviation, $e_i(t)$, as the difference between the simulation output ($i = 1, 2, \ldots n$) and the measurement data (see e.g., in Figs. 1 and 3), and applies a correction $\dot{r}_i(t)$, i.e., rate of change, to the relevant

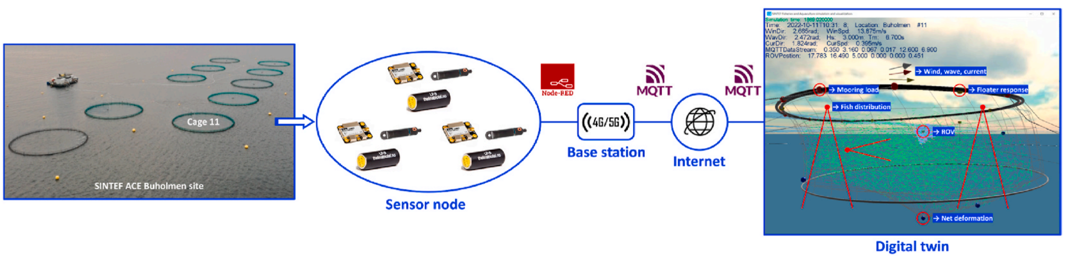


Fig. 2. Wireless sensor network and communication system for real-time data collection and digital twin implementations.

input parameter:

$$\dot{r}_i(t) = K_p e_i(t) + K_i \int_0^t e_i(t')\mathrm{d}t' + K_d \frac{\mathrm{d}e_i(t)}{\mathrm{d}t} \tag{1}$$

where K_p, K_i, and K_d are the coefficients of the proportional, integral, and derivative terms, respectively. The PID controller is set with integral saturation for preventing the integral term from accumulating above or below pre-defined bounds and an up limit (e.g., percentage of the original input parameter) for the applied correction. In this way, the measurement data can be assimilated into the simulation model for representing an actual fish cage, while not using too many sensors and heavy computations for fluid−structure interactions.

A thorough description of the real-time simulation model and the PID implementation for data assimilation can be found in Ref. [25]. Fig. 4 shows an extended configuration for the present digital twin implementation, where the same simulation model and additional sensor data (i.e., accelerometers and load shackles) were used. As the simulation model itself has been validated in previous numerical and experimental studies, it would be able to reproduce the measured net displacements, floating collar responses and mooring loads when the actual environmental and structural parameters were used in the simulation. However, it is notoriously difficult to obtain the exact input parameters for the current, wave, net solidity and mooring line stiffness in actual situations, considering the wake effects from the fish farm and other obstacles [7], the influence of biofouling on the net [35] and the complex stiffness behaviour of fibre ropes [34]. Herein, the resultant outputs (i.e., net displacements, floating collar responses and mooring loads) and the PID controllers were used to continuously correct/adapt these input parameters, such that the simulation would coincide with the field measurement data.

3. Field deployments and monitoring results

3.1. Monitoring sensors and setup for the digital twin

Fig. 5 shows the layout of a full-scale fish farm (SINTEF ACE Buholmen site) and setup of the sensors on a selected cage (diameter: 50 m; net solidity: 0.21) for testing and verification of the digital twin implementation. A metocean buoy was deployed 400 m away from the cage that was equipped with the monitoring sensors. The depth cell size of the metocean buoy was set to 3 m, and the measured current velocities (profile) at 4 m, 16 m and 31 m depths were used. There were totally eight accelerometers (#1–8 as shown in Fig. 5) installed on the floating collar (evenly distributed) of the cage and five load shackles (#1–5 as shown in Fig. 5) installed between the floating collar and the bridle lines on the upstream side where the prevailing water current was coming from. The depth sensors were installed at three different layers, i.e., four at 7 m depth, four at the boundary of the cylindrical part (15 m), and one at the bottom (31 m) of the net pen. One from each layer (#1–3 as shown in Fig. 5) was used in the digital twin.

The current and wave data were fetched every hour from the metocean buoy, while the depth sensor data were logged every 4 min. Much higher sampling rates could be used for the load shackles (4 Hz) and accelerometers (8 Hz). However, only the calculated 1-min average values and standard deviations were used in the digital twin, in order to reduce the communication time (using 4G) between the digital twin and the remote sensor network (i.e., 80 km away). The original high-frequency load and accelerometer data were still saved locally and used for comparing with the simulation results after the sensors were retrieved from the field. The sampling rate and relevant pre-processing of sensor data are summarised in Table 1.

3.2. Monitoring results and verifications

The monitoring sensors were deployed in the field for more than one month (Jan. 18 to Mar. 05 in 2020). Fig. 7 shows the measured current and wave data which were representative for a relatively harsh period of the year. The significant wave height and the current velocities measured at three different depths (4 m, 16 m and 31 m) were used in the digital twin for the monitoring of net deformation, cage response and mooring load. As mentioned above, these input parameters could be adapted when relevant simulation outputs deviated from measurement data. Fig. 7 shows the adapted current velocities and wave hights in a period of 12 h (03:00 to 15:00 on Jan. 23), when the maximum current velocities (about 0.4 m/s) were measured and the waves were also high (about 1.5 m). An up limit of 20% was set for the applied corrections to all the input parameters, so they would not be very different from the measured current, wave and initial structural parameters (i.e., net solidity and mooring line stiffness). An non-adaptive setup was also made for

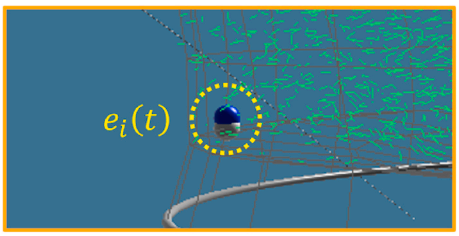


Fig. 3. An example of the deviation between the simulated (lower) and measured (upper) vertical displacements of the net.

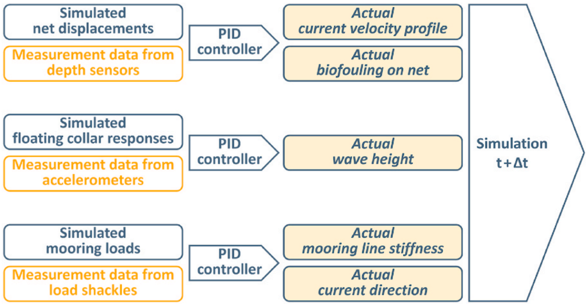


Fig. 4. Data assimilation configuration for the digital twin.

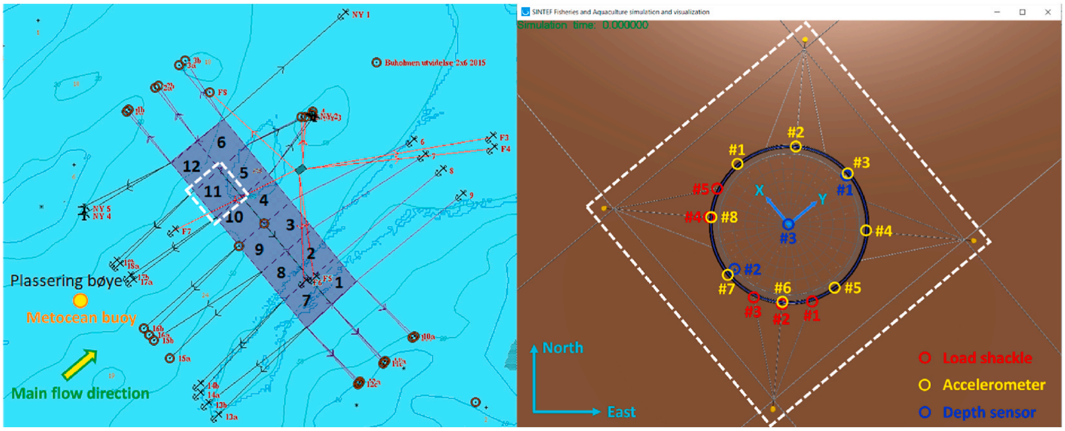
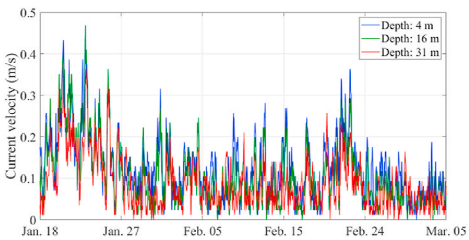


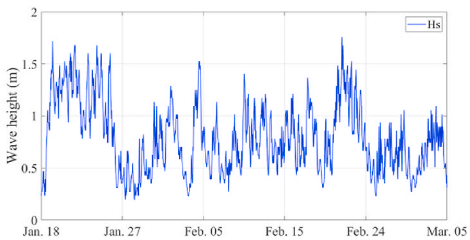
Fig. 5. Layout of the fish farm (SINTEF ACE Buholmen site) and setup of the sensors in the digital twin for real-time monitoring of cage responses (Accelerometer #1–8), net deformations (Depth sensors #1–3) and mooring loads (Load shackle #1–5).

Table 1
Sampling rate and pre-processing of sensor data.

Monitoring sensor	Sampling period/rate	Pre-processing
Metocean buoy	1 h	No
Depth sensor	4 min	No
Load shackle	4 Hz	1-min moving average
Accelerometer	8 Hz	1-min standard deviation



(a) Current velocities at three different depths



(b) Significant wave height

Fig. 6. Measured current and wave from the metocean buoy.

illustrating how the simulated cage and environment might be different from the actual situations that were continuously changing over time, and what could or could not be captured by the simulation model without data assimilation (non-adaptive model).

The non-adaptive model was found to underestimate net deformations (i.e., vertical displacements #1–3 at three different depths: 7 m, 15 m and 31 m) during the 12-h period, and it was partly attributed to the increased net solidity (e.g., due to biofouling). This was

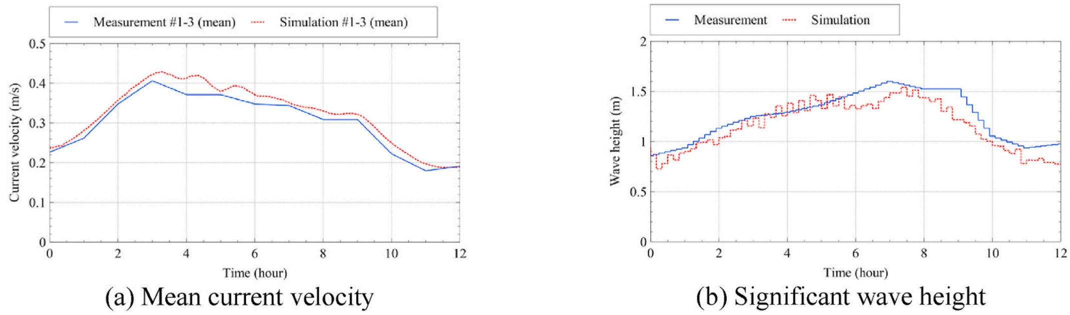


Fig. 7. Applied corrections to the current and wave measurements in a period of 12 h (03:00 to 15:00 on Jan. 23) when the maximum current velocities were measured (as shown in Fig. 6).

considered in the adaptive setup according to the cumulative deviation of simulated net deformation from measurement data. The possible alterations of the current from the measuring point (i.e., 400 m away) to the cage and changes during each sampling period (i. e., 1 h) were also evaluated according to the instant deviations between simulated and measured net deformations. As shown in Fig. 8, the simulated net deformations were eventually coincident with measurement data. The amplitude of simulated cage responses (i.e., vertical displacements of the floating collar) was comparable to the measurement data (8 Hz original data), even though no corrections were applied to the waves. It is also evident (as shown in Fig. 9) that improved results could be obtained by using the adaptive model, where the simulated response amplitudes were very close to the measurements. The sum of simulated mooring loads (i.e., #1–5) was comparable to the measurement data, however the load within each mooring line could not be captured by the non-adaptive model. This was because the distribution of the total load among each mooring line was very sensitive to the configuration of the cage and mooring system. A small change of the stiffness or stretched length of one mooring line could change the overall load distribution. The assessment of the load within each mooring line also requires very accurate measurement of current and wave directions which is notoriously difficult. In the adaptive model, corrections were applied to both the mean current direction (up to 15°) and the stiffness of each mooring line (up to 20%). As shown in Fig. 10, the simulated mooring loads were eventually coincident with the measurement data (1-min moving average). It should be noted that the adaptive model was not intended to capture all the instantaneous amplitudes of the loading process, but just the mean load within a certain period (e.g., few seconds to few minutes depending on the real-time capability of the data collection and communication system).

4. Discussions

4.1. Instrumentation requirements for real-time monitoring of net deformations

In the present study, the metocean buoy and the measured current velocities at three different depths (4 m, 16 m and 31 m) were used for the monitoring of net deformations. However, in most cases only the average or surface current data are available (e.g., from the online metocean forecast that is free to use for all the aquaculture sites in Norway). Fig. 11 shows the estimated current velocity profile where only the uppermost layer (4 m) of the metocean buoy data were used, as well as the depth sensors (#1–3 at the 7 m, 15 m and 31 m layer, respectively). The net deformation results (Fig. 11b) were found to be similar to the previous setup where the measured current velocities at three different depths were used (Fig. 8b). The multiple depth sensors installed at the same layer of the net pen were also found to get similar data of vertical displacements, therefore only one from each layer was used in the digital twin. Fig. 12 shows the measured displacements from four of the other depth sensors (i.e., #4–5 at the 7 m layer and #6–7 at the 15 m layer). The corresponding simulation results were found to follow the measurement data even though they were not used in the adaptive model.

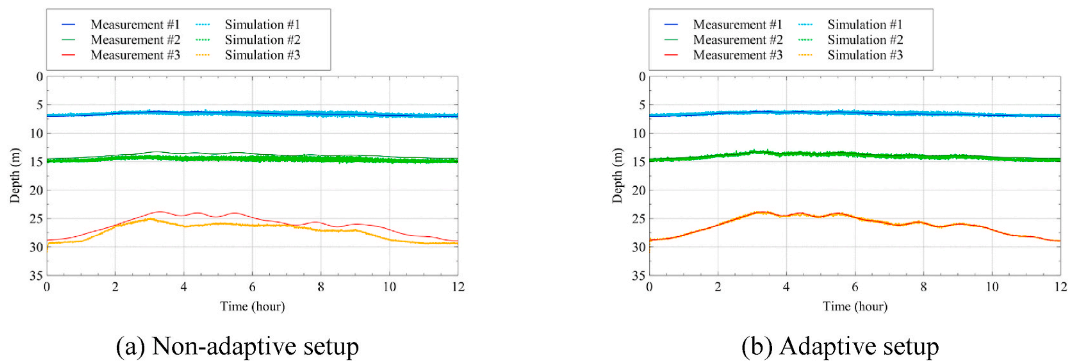


Fig. 8. Comparison of the measured and simulated net deformations.

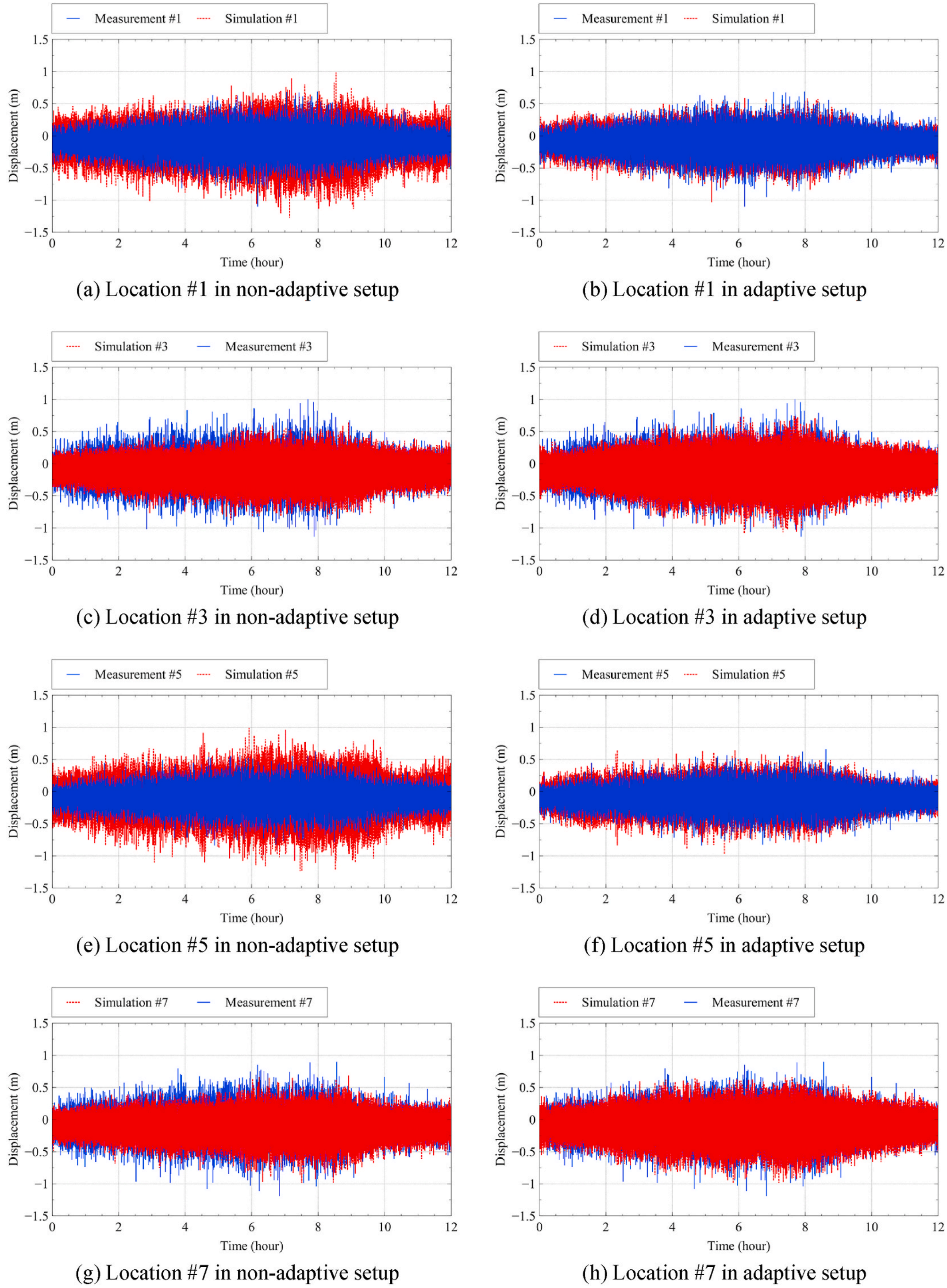
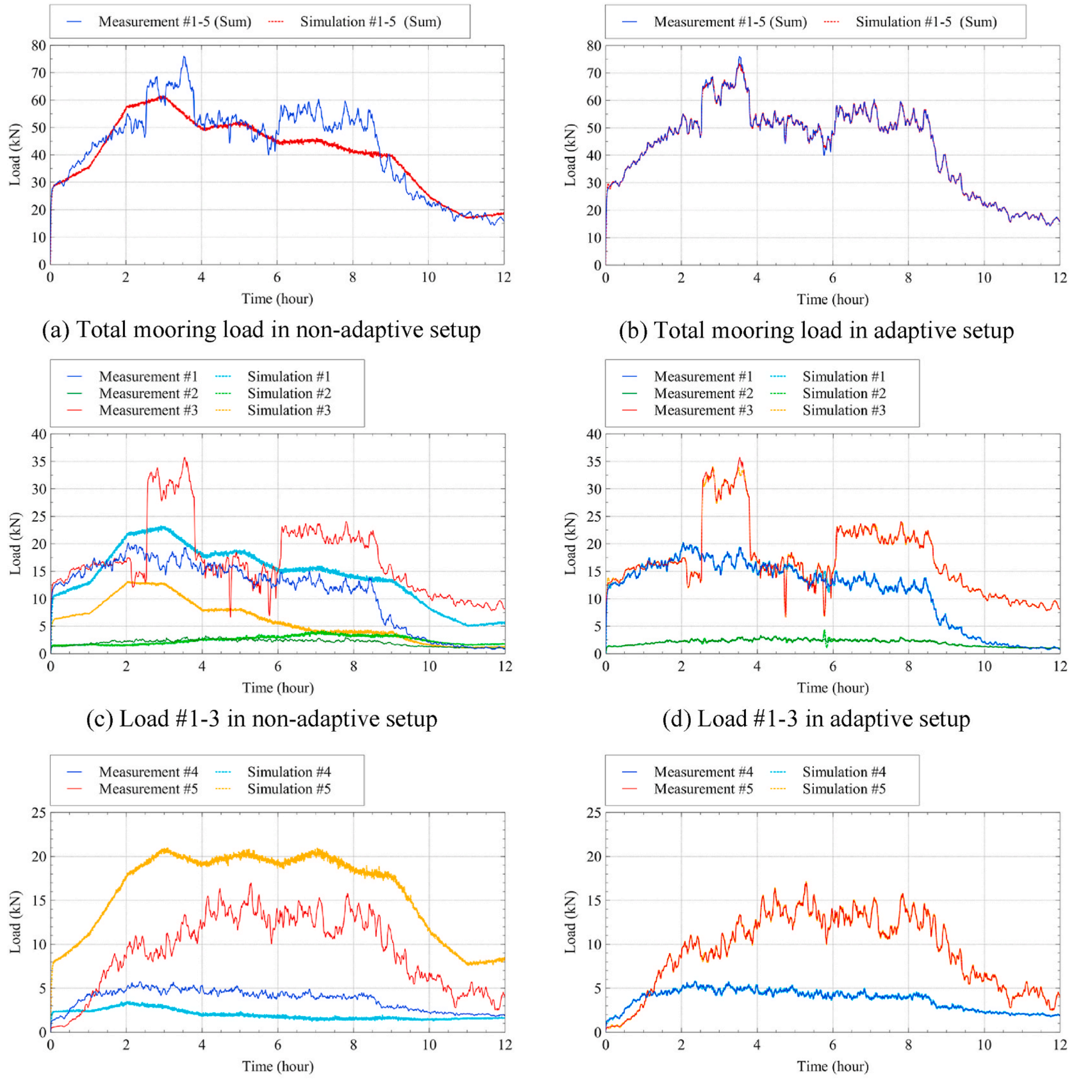


Fig. 9. Comparison of the measured and simulated floating collar responses.

This indicated that three to four (e.g. an additional layer between 15 m and 31 m) depth sensors would be adequate for the monitoring of net deformations and cage volume reductions (Fig. 13). However, each of them must be well calibrated and installed at a place with less interferences from the net and other structural components and equipment, especially during net cleaning and crowding (e.g., for sea-lice treatment) operations.



(a) Total mooring load in non-adaptive setup

(b) Total mooring load in adaptive setup

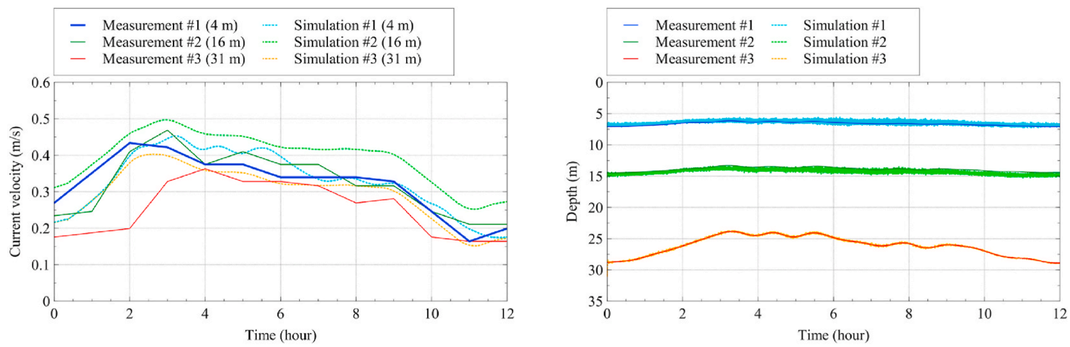
(c) Load #1-3 in non-adaptive setup

(d) Load #1-3 in adaptive setup

(e) Load #4-5 in non-adaptive setup

(f) Load #4-5 in adaptive setup

Fig. 10. Comparison of the measured and simulated mooring loads.



(a) Applied corrections to current measurements

(b) Net deformations

Fig. 11. Applied corrections to the current velocity profile where only the uppermost layer (4 m) of the metocean buoy data were used and comparison of the measured and simulated net deformations.

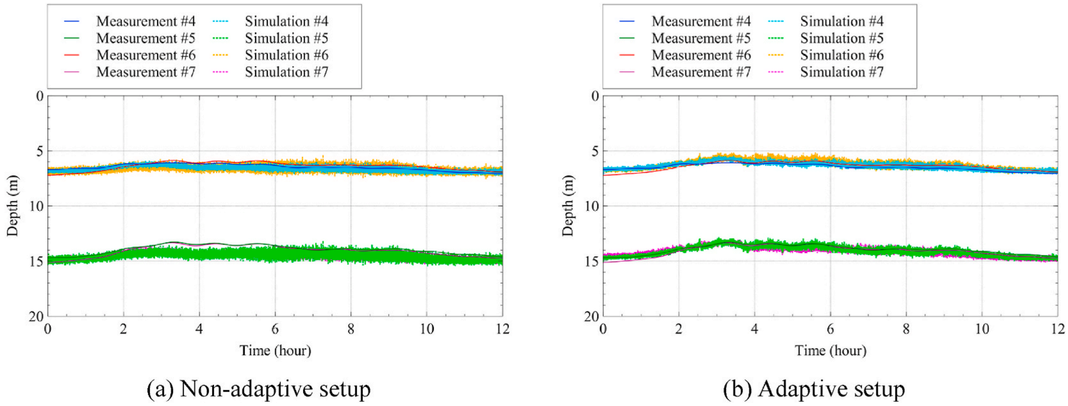


Fig. 12. Comparison of the measured and simulated net deformations from four of the depth sensors that were not used in the digital twin.

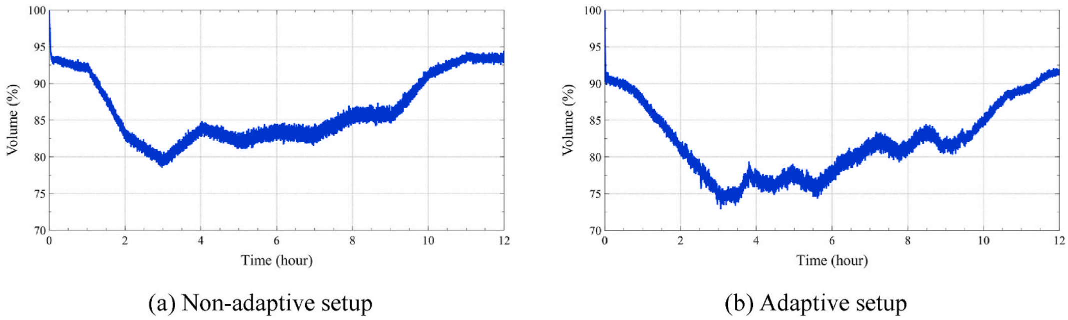


Fig. 13. Calculated reduction of cage volume.

4.2. Instrumentation requirements for real-time monitoring of floating collar responses

In the present study, the calculated standard deviations of floating collar responses within a certain period (e.g., 1 min) were used for the evaluation and correction of the waves acting on the cage, instead of using the original accelerometer data (8 Hz). The reason for this was to reduce the communication time between the digital twin and the remote sensor network which could affect real-time applications. There were totally eight accelerometers installed and evenly distributed around the floating collar. Fig. 14 shows the calculated standard deviations of floating collar displacements when different numbers (one to eight) of accelerometers were used in the digital twin. Through the comparison, four accelerometers were found to be adequate for the overall match (relative error <5%) between the simulation results and measurement data, while the instant deviations could be slightly different at different time and when different configurations were used. However, the adaptive model was not intended to capture all the individual amplitudes of cage responses, which would require phase-resolved real-time wave measurement or prediction data (see e.g., Ref. [37].

4.3. Instrumentation requirements for real-time monitoring of mooring loads

As shown in Fig. 15, the measured loads from two mooring lines (i.e., #1–2) were used in the adaptive model, while the measurement from the third one (i.e., #3) was not used. The comparative results indicated that the digital twin could hardly match all the load measurements, especially when an unexpected change occurred (e.g., in the period of 2–4 h). In order to capture this kind of individual loading processes, all the mooring lines might need to be equipped with sensors. Less measurement data (e.g., one load shackle towards each corner of the mooring frame) would be required, if only the total mooring loads (see e.g., in Figs. 10a and 15b) are concerned.

4.4. Instrumentation requirements for real-time monitoring of fish behaviour

In the present study, no dedicated sensors were used for fish monitoring, but the fish behavioural responses to current, wave and cage deformation were modelled (Fig. 16), according to the field observation that the fish were trying to avoid hitting the net when they were drifted by current and avoid the surface of the water column in large waves [29]. Fig. 17 shows the simulated fish distributions where the available space for the fish was reduced due to cage deformation in current and waves, and they were moving towards the current [38] in order to avoid being pushed to hit the downstream side of the cage. The calculated stocking density and fish

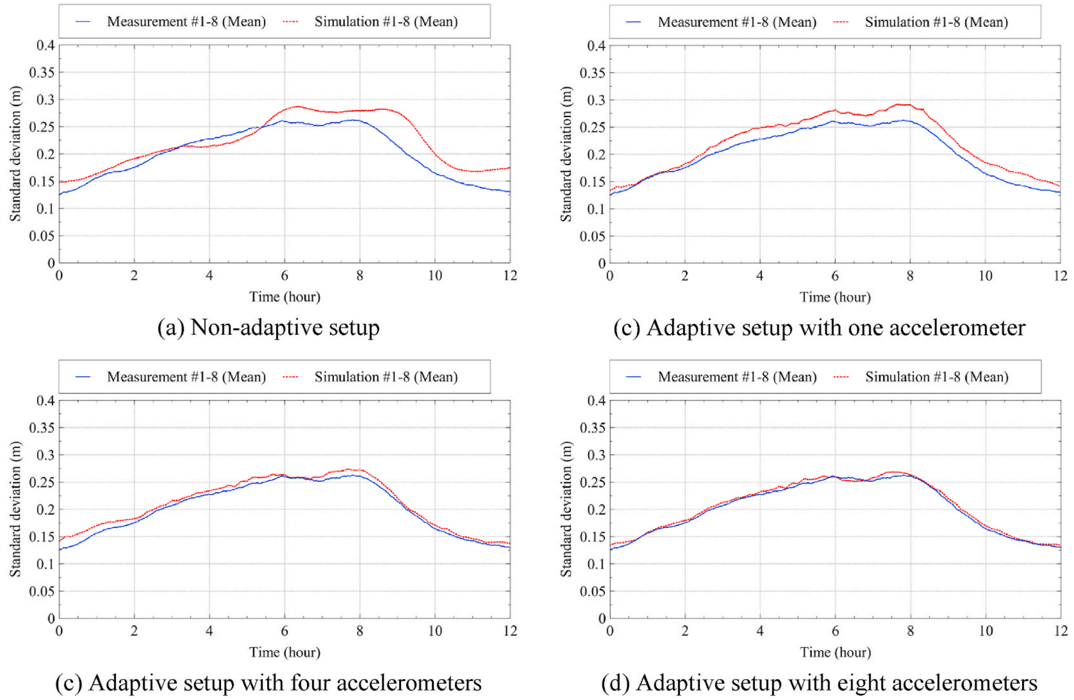


Fig. 14. Comparison of the standard deviations of measured and simulated floating collar responses.

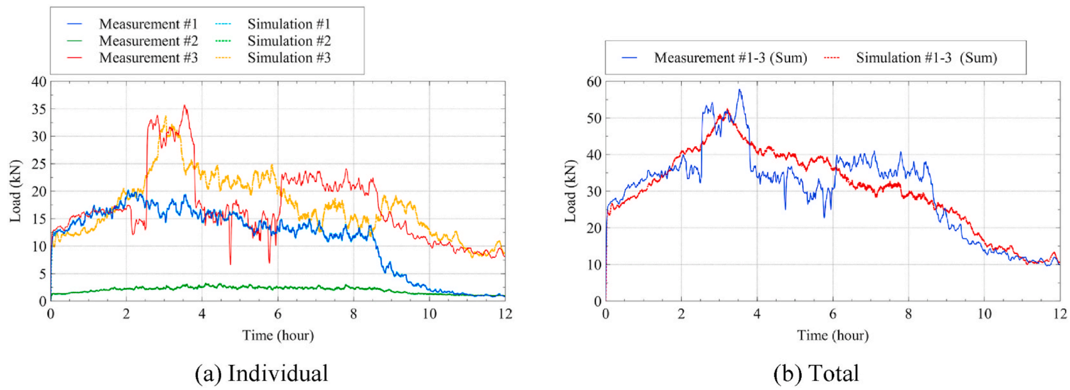


Fig. 15. Comparison of measured and simulated mooring loads.

swimming speed (mean and maximum), considering the effects of current, wave and cage deformation, are two important indicators for the monitoring of fish welfare on a daily basis (Fig. 16). Dedicated environmental sensors are required for the monitoring of other influencing factors such as water temperature, light, dissolved oxygen and salinity which were not the focus of the present study. Cameras, echosounders and acoustic biotelemetry tags [39] can also be used to collect relevant data such as fish size, skin status, sea-lice infection level, individual swimming activity and biomass distribution. However, none of these sensors and technologies can alone provide a holistic view of the fish in cages. The combination of the present digital twin implementation and data-driven approaches based on machine learning/artificial intelligence [40] is a potential solution for integrated environmental, structural and biological monitoring on full farm scale with a number of cages and the contained fish.

5. Conclusions and future work

An integrated digital twin solution has been introduced and tested at a full-scale aquaculture site for real-time monitoring of flexible net cage systems. A remote sensor network and communication system was developed and found to be suitable for the digital twin implementation, where the most commonly used sensors and technologies (i.e., online metocean forecast, metocean buoy, depth sensors, accelerometers, load shackles and embedded 4G modules) were exploited for the structural monitoring. In the meantime, the

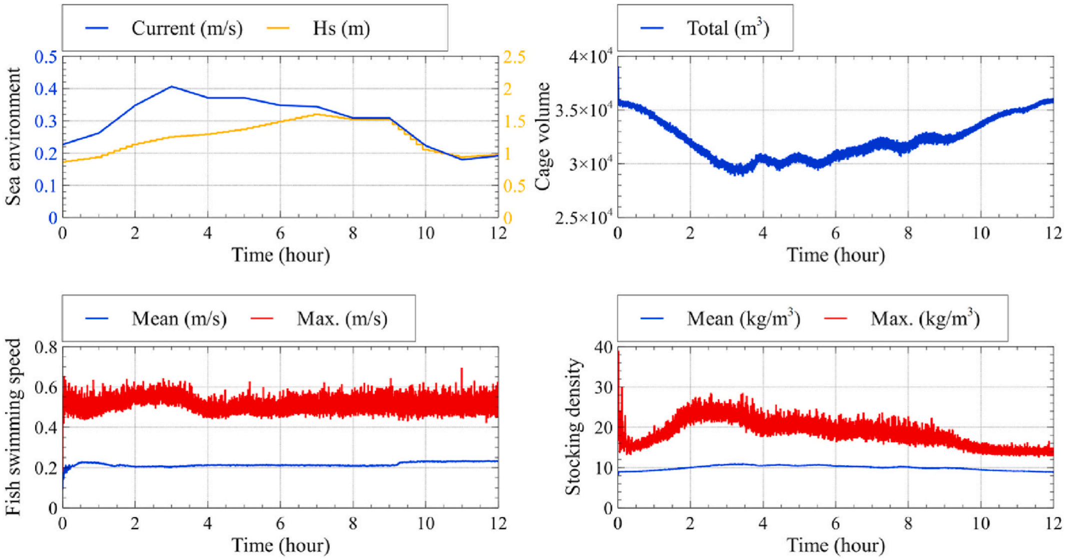
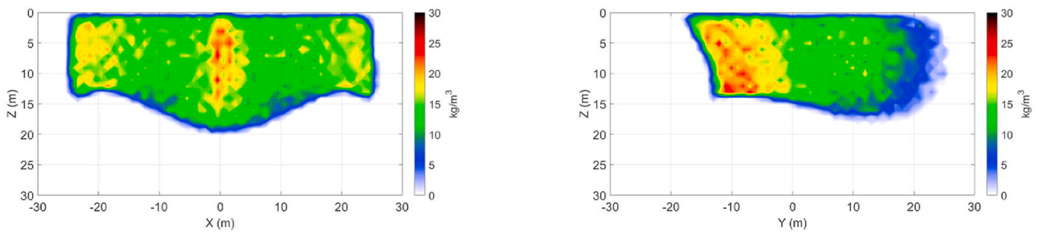


Fig. 16. Simulated fish behavioural responses to current, wave and cage deformation.



(a) Perpendicular to the prevailing current direction (b) Along the prevailing current direction

Fig. 17. Simulated fish distributions in the cage (within the period of 2–4 h).

fish swimming behaviour and biomass distribution were modelled according to relevant field observational data.

The required numbers and configurations of sensors for the monitoring of net deformations, floating collar responses and mooring loads were evaluated, based on a possibly maximum number and combination of sensors that could be tested for a flexible sea cage at the commercial aquaculture site. The present data were insufficient for a comprehensive quantitative analysis where a considerably longer time frame and the robustness of the data and the remote sensor network itself should be considered. Due to harsh environment, hardware limitation and unexpected interferences, the data collected by sensors within the system can be faulty or inconsistent. Therefore, sensor fault detection, isolation and accommodation [41] is an important feature to be considered for instrumentation and data management.

The combination of the present digital twin implementation (physics-based) and data-driven approaches (machine learning/ artificial intelligence), i.e., hybrid modelling and analysis [28] for integrated environmental, structural and biological monitoring on full farm scale, remains a specific goal for future implementations. Practical use cases will be developed and tested, such as predictive cleaning and maintenance of the net, optimization of the feeding schedule, remote control of an underwater vehicle in the cage and automated path planning. A holistic digital twin solution will build on the continuous implementation of new features/techniques. And it is aiming to facilitate the realisation of the Precision Fish Farming concept [39] that has been introduced to link technology and automation principles with the practical aspects of aquaculture operations, thereby contribute to moving commercial aquaculture from the traditional experience-based to a knowledge-based production regime.

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.

Data availability

The authors do not have permission to share data.

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