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Intelligent Fish feeding through Integration of ENabling technologies and Circular principle

Grant Agreement (GA) No: 818036

D2.5 iFishIENCi Technology Packages

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1 Introduction

iFishIENCi aims, among other things, to develop solutions for continuous and real-time monitoring of feeding-related fish behaviour and environmental conditions (water quality), in different production systems (**Fish-Talk-to-Me** capability - **FTTM**). the Fish-Talk-to-Me project innovation which integrates conventional and emerging technologies for enabling continuous control on fish behaviour, growth, physiology, welfare, health & environmental microbiome. FTTM is further integrated into a flexible IoT framework including analytical capability, the so-called **iFishIENCi Biology Online Steering System (iBOSS),** to be provided to the market as a solution that significantly improves production control and management for all fish aquaculture systems. iBOSS intends to maximise feed utilisation through smart feeding, providing continuous monitoring of fish behaviour, health and welfare and reducing response times to aberrations. In addition, iFishIENCi targets circular principles and zero waste by qualifying new and sustainable organic value chains for feeds, and valorisation of by-products.

The present deliverable “D2.2 - technology packages” first provides an overall description of the iBOSS, before presenting specific deployments conducted as part of the piloting activities (WP3). For each selected deployments, recommendations for future developments are discussed based on the lesson learned from the pilots.

2 General description of iBOSS

2.1 Introduction

The **iBOSS** product is a set of interoperable components allowing to build custom solution fitting particular farmer needs. This intends to avoid vendor lock-in, in which farmers can get locked when dealing with proprietary solutions. It indeed allows the farm management system to evolve, integrate new components, and to share data, so long as these components provide the same standardized interface.

The solution, of which specific technical details are provided in the iFishIENCi deliverables D2.2-D2.4 (https://ifishienci.eu/media/publications/), is built around a data core which connects data suppliers (such as sensor connected or cloud platforms from 3rd party providers), data consumers (such as dashboard, mobile applications, etc.) and data processors (such as machine learning models, fish simulator, etc.). Most of these components are running on a web server, which can either run in the datacentre of a cloud provider or can be deployed locally (on premise) when required or if preferred. In addition, devices (iBOSS edge) can be deployed in the field to cover functionals requiring local connectivity, especially for sensing and actuating.

These different components are described in the following sections.

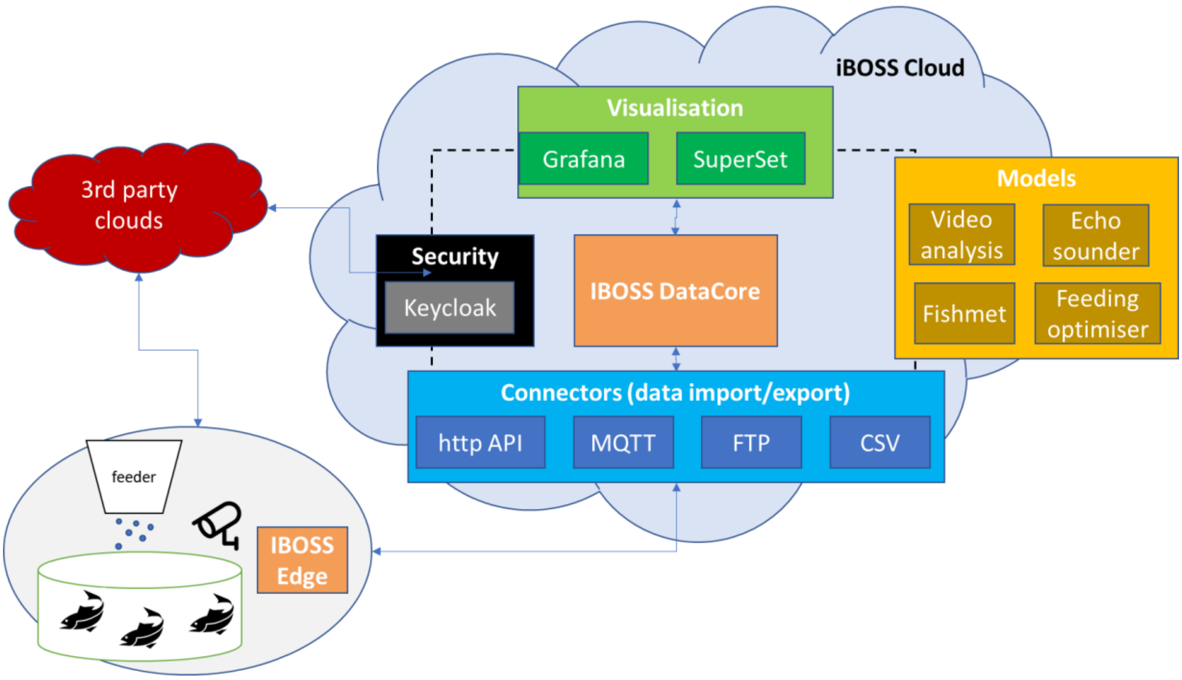


Figure 1 : iBOSS cloud components overview

2.2 iBOSS DataCore

iBOSS DataCore is a ETSI NGSI-LD compliant context broker. NGSI-LD defines a restful API publishing, querying, and subscribing to information together with a meta-information model made to connect and interoperate domain specific data models. The iBOSS DataCore is published as an open-source component named [Stellio under the Apache 2.0 licence](). It has been accepted as a generic enabler of the FIRWARE foundation catalogue.

The data model adapted by the iBOSS core in the context of aquaculture is fully published in open-source license on the FIWARE Smart data model platform ([link]()). The work done there enhances the design, the development, and normalization of data models for the aquaculture domain.

2.3 Visualisation

Two open-source components have been tested and integrated for visualization and analysis of data available in the iBoss DataCore: Grafana and Superset.

2.3.1 Grafana

The platform integrates the Grafana solution, open-source software specialized in the visualisation field. It is mature, very widespread, extremely flexible, thanks to a very complete plugin system which allows it to connect to very diverse data sources as well as to benefit from numerous widgets representing this data.

It offers in particular:

- Detailed user management, which allows to manage access rights to the various dashboards (administration, editing, reading), as well as an official extension allowing authentication to be based on an OAuth2 provider
- Complete graphic customization (logo, colours, etc.)
- The configuration and logging of automatic alerts on value thresholds, which can be sent to a wide choice of channels
- The display of real-time or historical data, and this in a very efficient way, even on complex dashboards
- Display of tabular data from different data sources, including REST APIs
- The provision by default of all the display widgets expected for this type of tool: simple text, statistics, gauges, tables, graphs, interactive maps, images with overlay, etc.

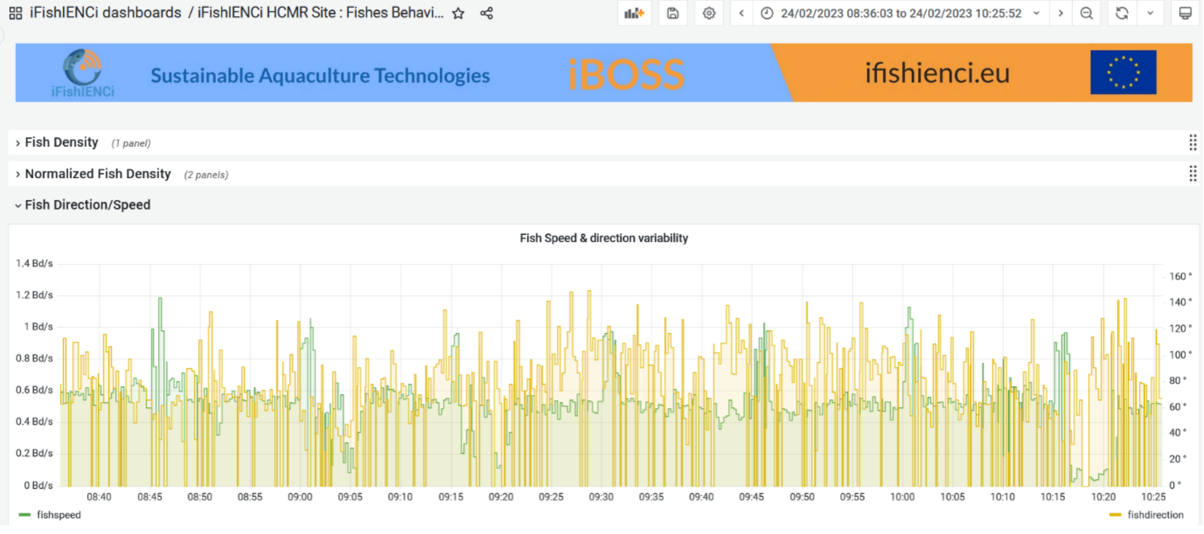


Figure 2: Grafana based visualisation.

2.3.2 Superset

Data analysis can be performed by the Superset tool which natively offers the following main features:

- Rich catalogue of visualizations, including map visualizations based on Mapbox and deck.gl
- Possibility of integrating data from a large number of databases or from CSV or Excel exports
- Ability to organize data in comprehensive dashboards, and to define dynamic filters
- Ability to export data in image or CSV formats
- Ergonomic and intuitive interface (and above all not requiring any particular technical knowledge) making it possible to create and finely configure all visualizations
- An authorization system allowing fine control of read, write and administration access to the platform in general, and to dashboards in particular
- Ability to generate reports and raise alerts.

2.4 Connectors

2.4.1 General connector

iBOSS can provide a bidirectional connectivity with a number of different protocols. In the iFishIENCi project, the main used connectors have been HTTP, MQTT, FTP and .CSV connectors. To ease the ingestion process, Apache Nifi has been used. This open-source data collection and validation module provides tools and an environment for:

- The creation and visual management of a directed graph of processes, generally by composing a set of processes that already exist in the catalogue (which contains nearly 400)
- A very complete existing catalogue of processing allowing native integration of a REST API (with or without authentication), processing of CSV, Excel, JSON or XML files, or even access to files stored on FTP servers
- The versioning of the processing graphs with the traceability of the modifications made to each graph, as well as the author of each modification
- The possibility of importing and exporting processing graphs
- The possibility of automatically executing, at predefined regular intervals, processing flows
- The development of coherent and loosely coupled components that can simply be reused by different processing tools
- Management of errors during processing, with the possibility of configuring specific actions when they occur (subsequent test, sending a notification, etc.)
- The possibility, during processing, of querying a database for the detection of duplicates and of applying specific processing depending on the case
- Automatic and detailed monitoring of all actions performed during processing
- Securing exchanges and the possibility of defining detailed authorizations
- The possibility of applying validations to the data processed, in particular via the definition of JSON or CSV schemas
- Monitoring of all processing via a dashboard
- Sending alerts triggered on the lack or invalidity of data

Moreover, it is a tool designed natively for extensibility and therefore offers all the functionalities necessary for the development and integration of specific processing components.

Via the processing chain administration interface made available by NiFi, the customer also retains autonomy in their daily adaptation and in the addition of new file processing.

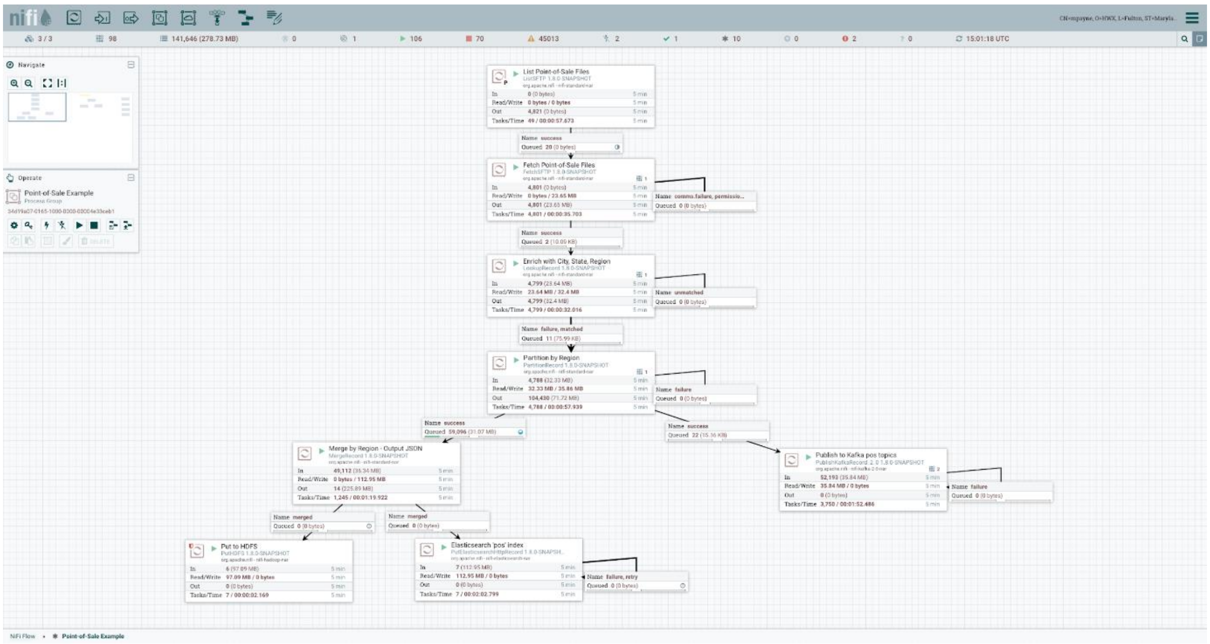


Figure 3 : Example of the definition of a complete processing chain in Apache NiFi

2.4.2 CVS Exporter

Aquaculture data such as water quality parameter and fish behaviours are important data and may be used by Scientifics for trainings or any other use. Within the project, an interface to export data stored in iBOSS as a .CSV file has been developed.

This interface allows the easy selection of NGSI-LD entities and their attributes as well as selecting a range of time for time-series to be exported.

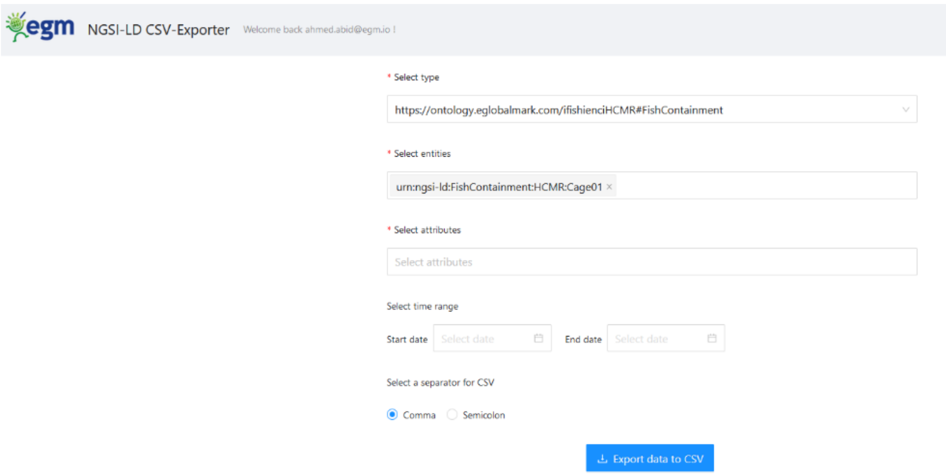


Figure 4 : iBOSS Exporter interface

2.5 iBOSS Edge

Two main versions of iBOSS Edge have been developed in the project context to adapt to the local requirements. These are:

- **Feeding Inspector**: monitor feeders installed on tanks.

- **Feeder Controller**: In addition to the Feeding Inspector functionalities, it is possible to schedule feeding programs as well as interrupt feeding processes.

2.6 Models

The AI Control of the iBOSS Smart feeding system is based on an automated decision-making system (ADMS) using water quality data, behavioural data and predictive data, as input. An AI algorithm has been trained for providing the capability of determining a single decision to either reduce feeding, increase feeding, stop feeding or keep on distributing the planned amount of feed. The decision is transferred to the feeder, through the iBOSS interface, and thereby controlling the feeding conditions and optimizing the feeding to obtain the best feed conversion rate (FCR).
The ADMS is planned to be able to adapt and optimize its decision-making continuously, as the changes to the system, resulting from the feeding operation, affects the input data. Effectively creating a feedback loop.

2.6.1 Behavioural model

The video analysis component collects a real time video stream of the fish (either from an underwater or out-of-water camera) and uses deep-learning algorithms to measure the behaviour of the fish in real time. These measurements are used to better understand how the fish anticipate the feeding and react to it, but they are also used to adapt the feeding directly: if the fish seem very hungry then they should be fed more, and if they don't eat much, they should be fed less. The video analysis was developed in two very different environments: a RAS and an open cage.

The behavioural models are described in the deliverable 2.4 (section 3.1 and 3.2) and with further details in section 3 and 4 of this report, for Open cages and RAS respectively.

2.6.2 Predictive model

The FishMet digital twin is intended to help with finding optimal feeding strategies that enable to optimise growth with minimal waste (smart feeding). FishMet is a simplified, digital representation of a fish built using computer-aided design and computer simulation. FishMet can be integrated with other (e.g., AI-based) models.
The FishMet digital twin is a numerical model composed of virtual components and software modules operating on different levels. It is engineered to be able to communicate with iBOSS. Each component of the digital twin is therefore built to be integrated with iBOSS and the outside world: the fish farm automation system, the decision support system, and the prediction/scenario modelling system. FishMet is therefore developed to use common application programming interface (APIs) for interoperability with other components.
A comprehensive description of the model is available as part of the iFishIENCi deliverable D1.4 (https://ifishienci.eu/media/publications/).
The integration of FishMet within iBOSS is comprehensively described in the deliverable D2.4.

2.6.3 Feeding optimiser

The iBOSS combines information from the above-mentioned sources to optimize the amount of feed distributed to the fishes. For this information to take effect on the physical feeders, the iBOSS needs to steer the feeders in either direction (feed more or feed less).
In the OxyGuard Commander Feeder Control, an "Activity factor" is designed specifically for the purpose of adjusting the amount of feed in accordance with an intelligent observation of the fish. Increasing the activity factor, will distribute more feed and vice versa. Effectively, changing the active to inactive ratio (or duty cycle) of the feeder (see deliverable D2.4 for further details). Traditionally,

this intelligence has been in the form of a human decision, but with the use of AI, specific models, and appropriated data collection (sensors, cameras, etc.), the same knowledge has been transferred to the iBOSS Artificial Intelligence system.
The same software that pushes data from the site to the iBOSS, can retrieve data from iBOSS to manipulate the feeder's activity factor.

3 iBOSS deployment in open cages (HCMR demo-site)

The pilot-scale farm of HCMR (that is located at Souda, Crete) is used for monitoring the European Seabass feeding behaviour. A circular cage of 40*m* diameter and 9*m* depth is selected for the experiment (Figure 5). The cage is cylinder-shaped with up to 8m depth and has a cone that closes the cage at 9m.

Figure 5: Circular open-cage used at Souda, Crete.

To achieve better control of the feeding, different technological equipment is used for the integrated monitoring of the cage, i.e., for environmental monitoring and behavioural monitoring. More specifically, water quality parameters are collected using sensors and behavioural parameters are collected using underwater cameras and echosounder. Additionally, a trial was organized with tagged individuals for monitoring their individual behaviour around feeding times using telemetry.

3.1 Technology package at HCMR demo-site (Fish-Talk-to-Me package at HCMR)

The technology installed and the type of data collected are presented in the following paragraphs.

3.1.1 Environmental monitoring

1 OxyGuard and BiOceanOr sensors are deployed on the cage and are capable to send data online and to facilitate constant monitoring. pH (OxyGuard K01SVPLD Light Duty pH probe), DO and temperature (OxyGuard D40C4 Pacific DO probe for Dissolved oxygen and temperature and BiOceanOr oxygen and temperature Optical digital sensor Titanium probe) and salinity (BiOceanOr conductivity digital sensor) sensors are used for constant monitoring (Figure 6). The DO sensors are located at three different depths, i.e., at 2, 4 and 6m, as shown in Figure 2. The HTTP protocol is used for the communication between the sensors and the iBOSS, and the parameters are presented at the online platform (Figure 7). The data that are collected to the iBOSS are planned to feed machine learning models to detect changes in the parameters that could affect fish energy demands and thus, the feeding schedule.

Figure 6: Setup of the environmental sensors at the pilot scale farm.

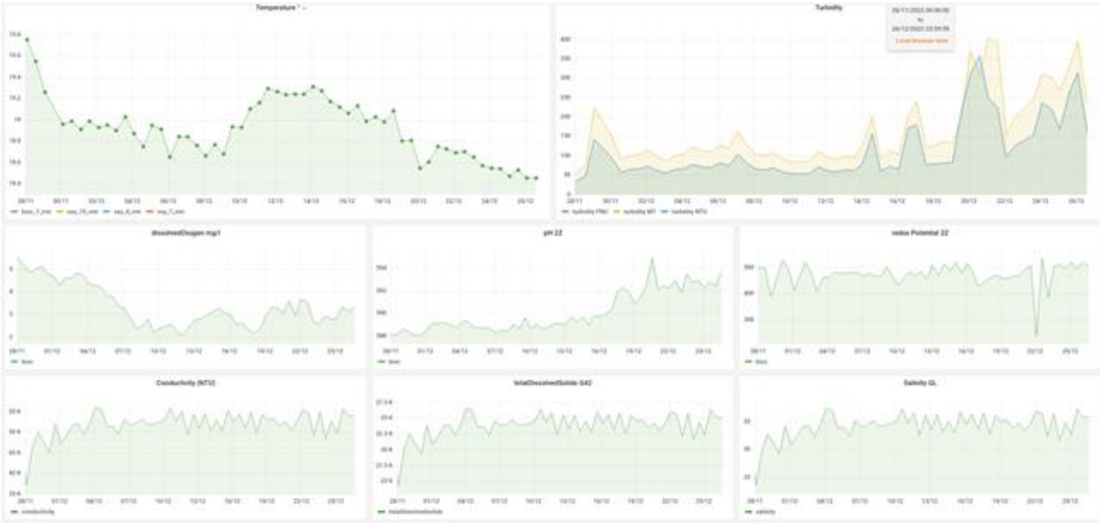


Figure 7: Online monitoring of the environmental parameters as shown on the iBOSS platform.

3.1.2 Automatic feeder

An automatic feeder is located at the centre of the cage. More specifically, a microcomputer (rpi , Rasberry4 - model B) is used as a node and is controlling a simple motor (feeding motor, 12V). To enable remote control of the feeder the MQTT communication protocol is used. To test satiation levels, the feeder is activated at specific times and for specific duration according to the experimental protocol that is explained below.

3.1.3 Behavioural monitoring

Video camera: A submerged network camera (Fyssalis v3.1; Figure 8) capturing at 10 fps is used for monitoring and video recording during daylight hours. The camera is positioned at 4-5 *m* depth using a gyroscopic gimbal stabilizer to ensure it pointed upwards. The videos are transferred via streaming and were analysed using a custom-made fish identification and tracking algorithm based on YOLOv5 and DEEPSORT. Parameters such as the fish speed, the polarization, and the horizontal distribution (also called as feeding index) of the fish group are estimated using these algorithms.

Figure 8: The submerged network camera used at the cage.

Echosounder: A SIMRAD EK 15 (single beam) is installed in the same cage as of the camera and the water quality sensors. The echosounder provides information on the distribution of the fish, a parameter related with the feeding behaviour as shown for salmon. European seabass individuals approach the surface during feeding and therefore monitoring variation in the vertical distribution of the fish around feeding times can facilitate the detection of the anticipatory behaviour as well as the satiation levels of the fish. The data are pushed to the iBOSS cloud and are available online as a component of the iBOSS.

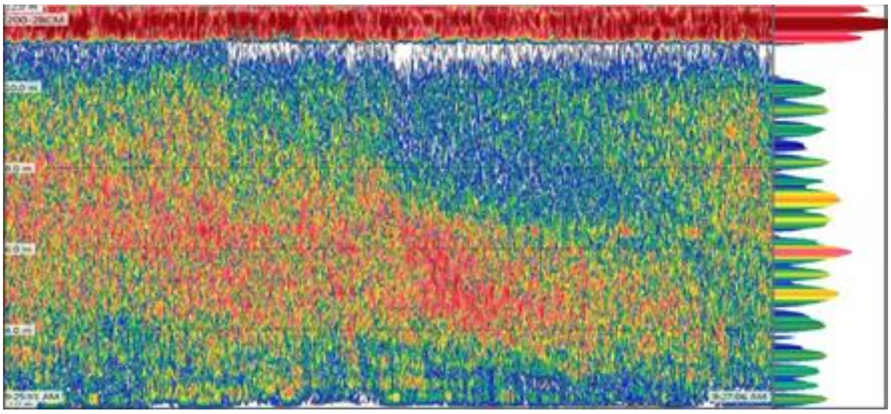


Figure 9: Vertical distribution of the fish as retrieved from the echosounder data.

Telemetry: The vertical distribution and the swimming activity as well as the temperature could also be measured by an array of three acoustic receivers (TBR700, Thelma Biotel Ltd.). The three receivers were placed 2.5m deep through anchors on ropes from the floating ring of the sea cage. The GPS position (N, E in decimal degrees) formed a triangle: (35.48011◦,24.112◦), (35.48006◦,24.11209◦), and (35.48◦,24.11196◦). 24 individuals got tagged with a low-power transmitter (ADT-LP7, Thelma Biotel Ltd., Figure 6), which was programmed to send signals for depth and position every 30-90 (mean 60) seconds, and alternately temperature and activity. The activity is measured in m/s^2 using a three-axis accelerometer in each tag which uses the root mean square over the three acceleration axes. The 24 transmitter tags were evenly distributed among the available frequencies (67kHz, 69kHz, 71kHz) to minimise overlapping of signals.

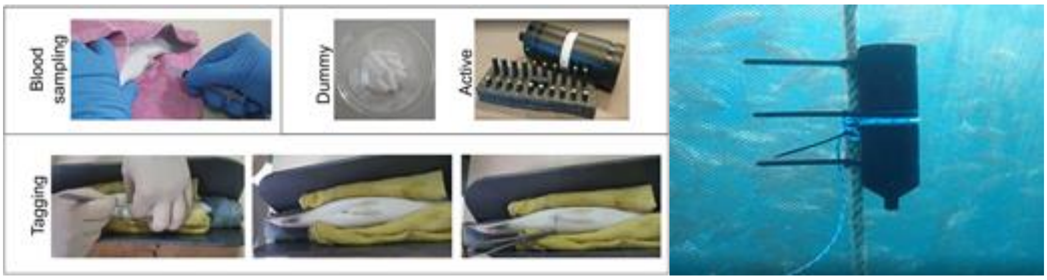


Figure 10: Telemetry tag implantation procedure (left) and setup (right).

3.2 Performance of the smart feeding AI algorithm

Each monitoring system is used to extract slightly different information around the feeding period. The parameters of the environmental sensors are used to feed AI-models that could associate the changes in temperature, oxygen, and turbidity with changes in behaviour and determine satiation levels. The normal ranges of the environmental parameters are previously defined as: T = 14-28 ºC, DO >40-50% saturation. As the species from the study are euryhaline (i.e., tolerate wide range of salinity) the salinity parameter was not considered as a significant factor that would affect feeding behaviour.

The acoustic telemetry tags were used to detect the food anticipatory behaviour of European seabass and together with the data collected from the other sensors (cameras, echosounders) to detect changes in the anticipatory behaviour for different feeding schedules and environmental conditions.

Lastly, the cameras are used to detect satiation levels, i.e., to infer the threshold values of the activity parameters tested. In addition, they could also enhance and complement the information around food anticipation from the telemetry studies.

3.2.1 Cameras

To define satiation levels in European seabass species using cameras, different feeding trials were carried out, with the aim of detecting changes in two different swimming behavioural parameters, i.e., the fish swimming speeds and the fish horizontal activity (relative to the camera), also called as feeding index. The main objective is to associate the potential detected changes in these parameters with increased satiation levels and decreased appetite. To achieve this, we modified the following parameters related to feeding: the feeding mode (i.e. if the fish were fed manually or automatically), the feeding time (if the fish were fed in the morning or in the afternoon), the feeding rate (i.e. if the fish were fed once, twice or three times daily) and the feeding quantity (i.e., if the fish would receive normal, reduced, excess feed or no feeding at all). The detailed experimental procedure followed is shown in

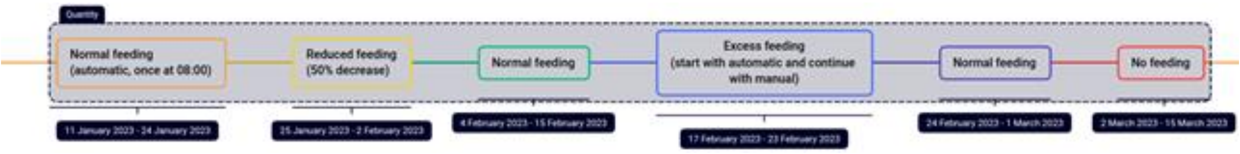


Figure 11.

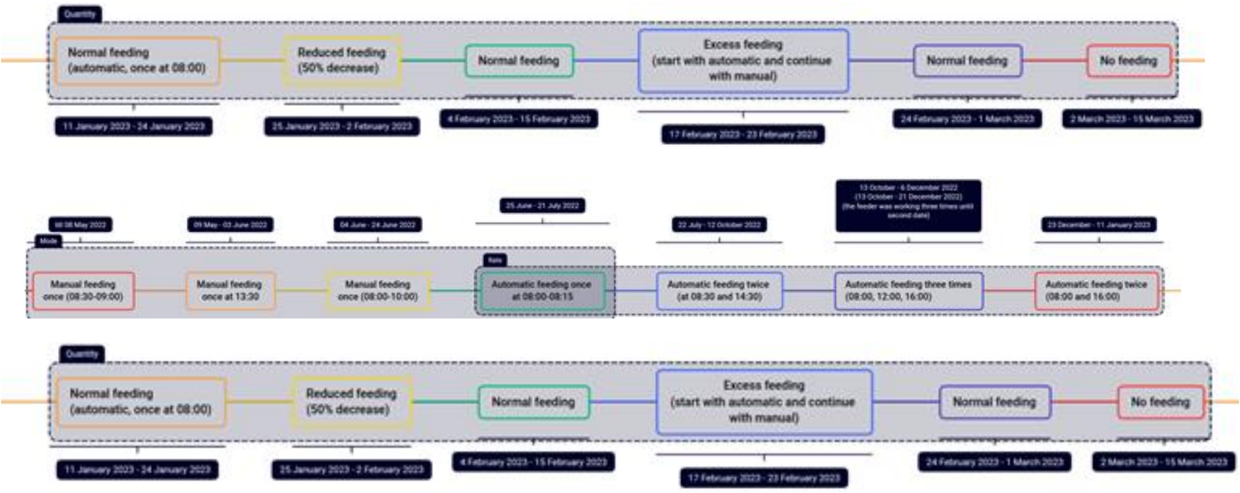


Figure 11: Timeline of the experimental protocol followed.

The videos are consecutively used to detect the fish swimming behaviour using computer vision techniques and artificial intelligence models (YOLOv5 and DEEPSORT). The swimming performance parameters that we test are the fish activity, expressed as the average swimming speed, and the feeding index, which is expressed as the horizontal distribution (relative to the camera view) of the group. The group polarization is also tested. As the feeding duration changes depending on the feeding schedule, the time of both signals has been normalized so that the signals are aligned, and the feeding starts at time = 0 minutes. The first two parameters show significant variation around feeding times, as previous observations confirm, and thus, their variations should be tested under different feeding scenarios, and they could potentially be used as indicators of hunger and satiation and could help to control the feeding.

3.2.2 Telemetry

The monitoring window for this experiment was two days after putting the fish into the sea cage, from 26.05.2021 to 06.06.2021. The transmitters were thereafter deactivated. The fish were fed once a day between 8:00 and 10:00 (manually). Cameras and echosounders were not installed at this period. Commercial food pellets were used for feeding. For analysis, we split the sea cage into three depth segments: The upper water column ranged from 0-3m depth, the mid-water column ranged from 3-6m depth, and the lower water column ranged from 6-9m depth.

Variables such as the activity and the vertical positioning of the fish were extracted and analysed. We were able to extract exactly a one-time locomotor-based food anticipatory activity (FAA) window per day which last longer than 120 minutes (per the description of our method more windows were possible). Since the time windows all reach into the feeding period, they are marked as FAA time windows from their beginning up to the feeding period which starts at 8:00. FAA activity starts on average at 06:21 ± 00:52. The peak in seasonal (periodic) influence is at 8:40, and lowest at 22:40, respectively (see Figure 8, yellow line). DBSCAN (Density-based spatial clustering of applications with noise) was used in the vertical-temporal analysis to identify high-density areas, meaning a high number of transmitter signals in the same vertical area during short time periods. The method was used with the standard parameter ϵ = 0.5 and a chosen number of minimal samples of 300. In sea cage terms the choice of ϵ translates to the measure that for example two points closer than 0.5m depth distance and no time difference or points with half an hour time lag and no depth difference will have the Euclidean distance of 0.5 and therefore considered neighbours. The parameter "minimal samples" describes the minimal number of points required in the ϵ-neighbourhood of a point for it to be a so-called "core point". The point itself is always in its own neighbourhood.

Food anticipatory behaviour

Telemetry analysis showed that fish have a strong anticipatory behaviour around feeding times, and this is expressed in both the vertical direction (food anticipatory positioning or FAP

Figure 12, left) but also in the fish activity (food anticipatory activity or FAA,

Figure 12, right)[1]. In addition to that, the analysis showed that the food anticipatory positioning precedes the food anticipatory activity. It seems that the actual positioning near the surface precedes possible recordings of increased activity (over 0.5 quantile). In addition, FAP is increased in the afternoon suggesting that FAP can provide insight into not just the entrained food anticipation in the morning, but also other biological patterns as the FAB in the evening as foraging behaviour in E. seabass.

[1] Chen IH, Georgopoulou DG, Ebbesson LOE, Voskakis D, Lal P and Papandroulakis N (2023) Food anticipatory behaviour on European seabass in sea cages: activity-, positioning- , and density-based approaches. Front. Mar. Sci. 10:1168953. doi: 10.3389/fmars.2023.1168953

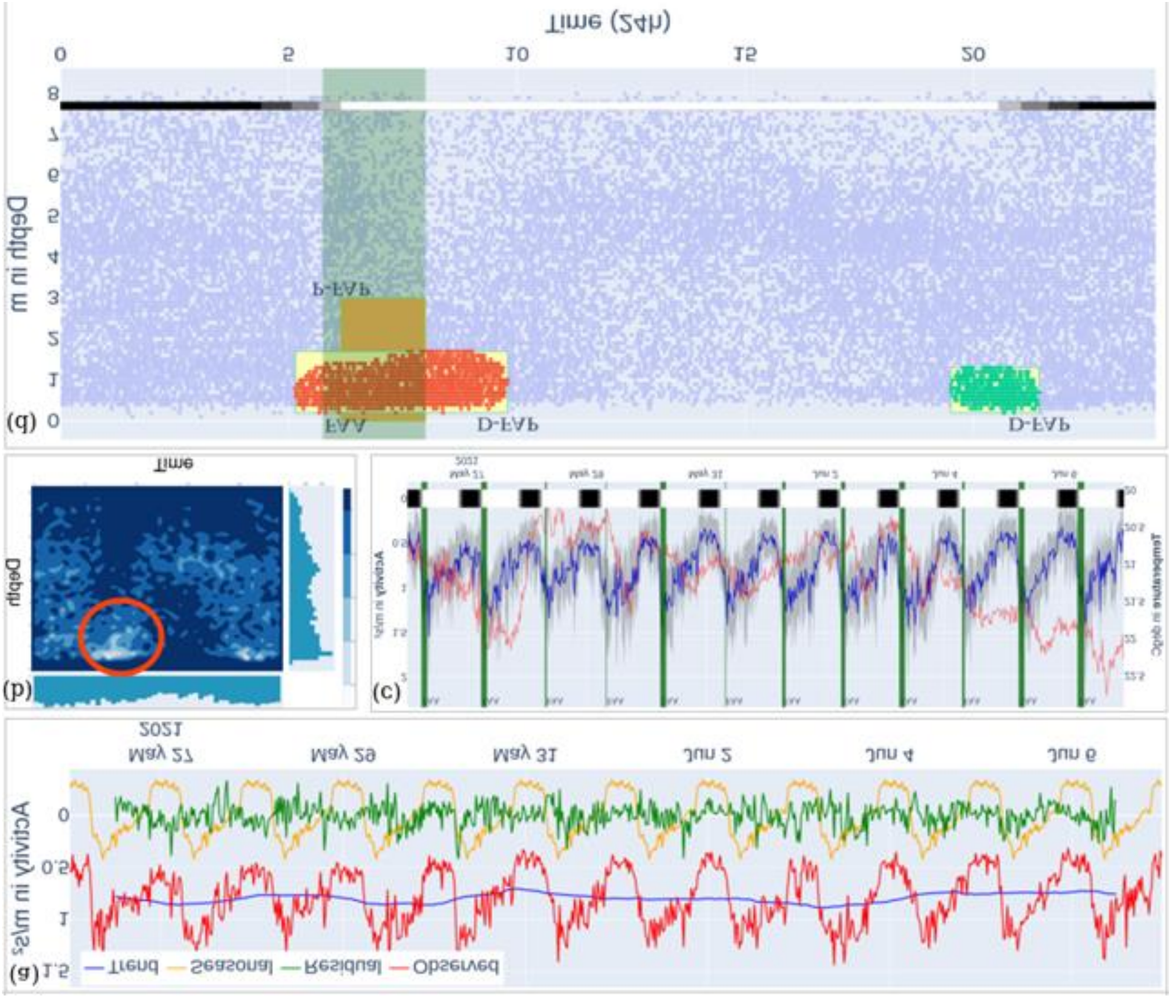


Figure 12: (a) Seasonal decomposition of the activity signal, (b) vertical distribution of the fish for different times of the day and (c) activity profile for the total period of the experiment, (d) DBSCAN clustering result showing the FAP clusters in red and green and highlighted the duration of the FAA.

3.2.3 Swimming behaviour related to feeding using cameras

The following results are preliminary and show how the group activity and the feeding index vary for different feeding frequencies and at different times of the day. The feeding index, i.e., the aggregation of the fish around the feeder is shown in Figure 13 for different feeding times and different feeding frequencies. The feeding index parameter increases significantly at the start of the feeding. In addition to this, it is apparent from the figure that the fish show a stronger response to feeding if the feeding frequency is one time daily in contrast with the response they show when the feeding is taking place more times in a day. The intensity of the response is depicted in the highest value of the feeding index after the start of the feeding.

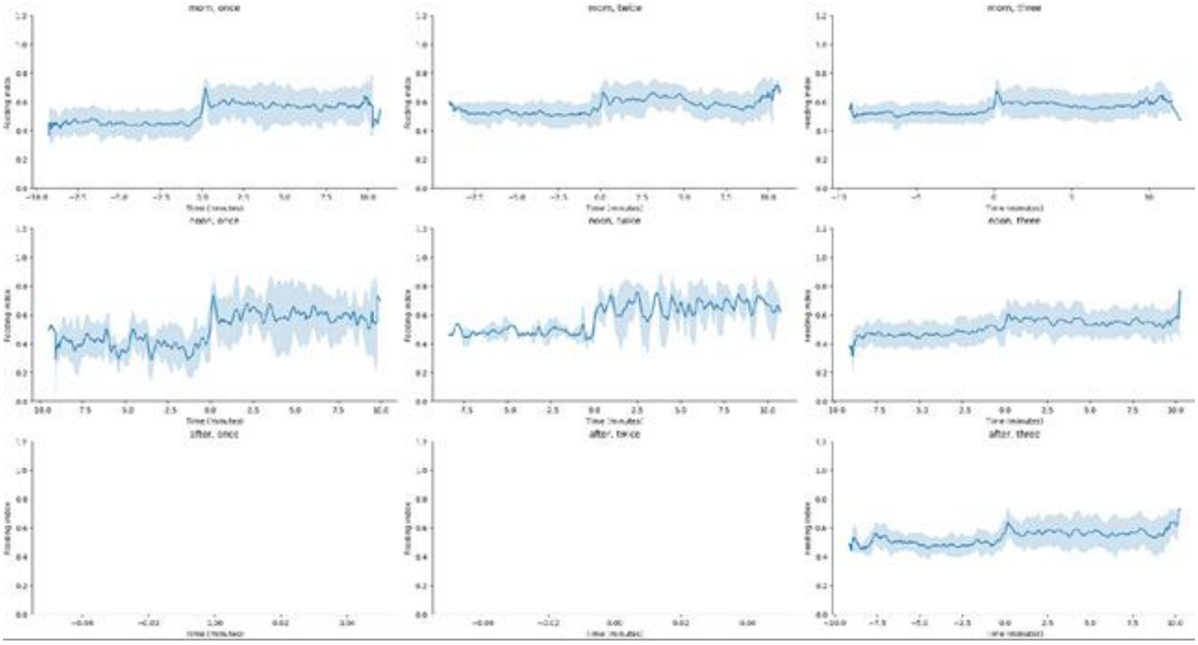


Figure 13: Feeding index across time for different times of the day and different feeding frequencies. The time of the signal has been normalized so that the feeding starts at time = 0 minutes.

The group activity is shown in Figure 14. As in the case of feeding index, there is also a significant difference in the activity of the fish between different feeding schedules. More specifically, the activity is significantly increased if the fish receive food once in a day in contrast with the case in which they receive food three times. The activity is maximal at the onset of the feeding and gradually decreases in most of the cases. In addition to this, when the fish are fed three times in a day, their activity remains at similar levels irrespectively of the time of the day.

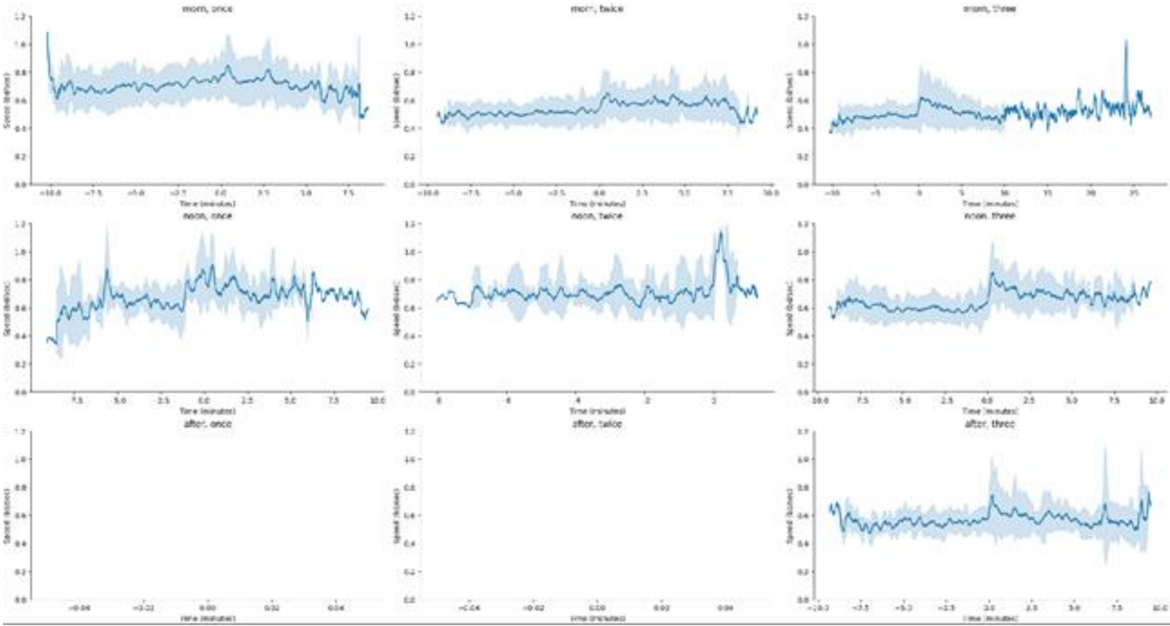


Figure 14: Average speed across time for different times of the day and different feeding frequencies.

The above results clearly show that the variation of the feeding schedule can affect the behaviour of the fish. Fish seem to have a stronger response to feeding if they are fed once daily. The stronger response would be an indication of increased appetite.

3.3 Recommendations for further developments

Here we have presented the set-up of the equipment used, the methodological approach and some preliminary results from the initial feeding schedule, i.e., we analysed how fish behave if they are fed once, twice or three times. During the demonstration trial we plan to analyse how fish respond to different food quantities by keeping the feeding frequency stable. These results will help define when the fish are satiated and provide us possible thresholds that may allow us to better control feeding. Regarding telemetry, a new trial will account for different feeding schedules and will be associated with the observations taken from the camera and echosounder data.

Furthermore, an analysis correlating the environmental data (i.e., T and DO) with the fish activity (speed and feeding index) is undertaken to provide a better insight in the fish behaviour.

Regarding the set-up of the different equipment used, the installation was easy and straight forward without any significant problems. The operation also during the period (almost a year) was without serious problems. There were periods where the data collection was interrupted because of network failure that were associated with stormy weather particularly during winter. Although gaps in data series is generally undesirable, the periods with data gaps were short and did not cause any serious problems in the operation neither in the subsequent analysis. Improvements in the network and use of alternative solutions may resolve this problem.

Regarding the equipment used, the sensors from both partners (OxyGuard and BiOceanOr) were proved reliable requiring basic maintenance for proper operation. The same is true for the camera and the image analysis algorithm. The echosounder data were properly collected and the transformation software for transferring to iBOSS was proven reliable. However, the narrow single beam echosounder used has shown to provide limiting information on the behaviour and in particular the feeding behaviour of E. seabass. An updated, more sophisticated equipment (e.g., multibeam) may be considered in future setups, especially in the case of larger cages than the one used at HCMR, and with a proper assessment of the cost-benefit.

4 iBOSS deployment in RAS (Smart-RAS)

4.1 ABT demonstration

4.1.1 Experiment setup

The demonstration held at ABT site was performed in Atlantic salmon (*Salmo salar*) at a size of about 13 grams and lasted for 13 weeks. A total of 400 fish were randomly placed in two tanks and fed at 2.22% of live biomass per day with commercial feed (Start alevin, 2mm, Alltech Coppens). The feed was delivered four times per day (09:00, 11:30, 14:00 and 16:00) by automatic feeder in one tank and by hand in the second, which was used as control. Each feeding event lasted for a total of 15 minutes and was comprised of 3-second feeding pulses, spaced by about 1 minute. The activation and deactivation of the feeder are sent to the iBOSS via MQTT.

4.1.2 Expected feeding behaviour

In the RAS, the fish tend to swim in a circle by default. When a feeding starts, they rush towards the feed, then have a chaotical behaviour for a few seconds, before slowly returning to the baseline behaviour. We try to measure the swimming speed of the fish, as well as these two patterns: rotating and converging towards the feed.

The goal of this experiment is to identify a few metrics that are representative of the behaviour of the group of fish and use these metrics to evaluate the time it takes for the fish to be satiated and return to rest. Anticipatory activity can also be detected. At this stage, the measurements can be analysed by hand from one day to the next, in order to adapt the feeding quantity and pattern.

The data does not have to be sent to the iBOSS in real time, but it should carry the correct timestamps, so it can be correlated with the feeding pulses.

4.2 Technology package at ABT demo-site

The Smart Ras system used during the demonstration at ABT site is presented in the Figure 15. The recirculating aquaculture system as described in the deliverable D2.4 (https://ifishienci.eu/media/publications/) is monitored through a OxyGuard Pacific unit, functioning as the central data collection and control. In addition, multiple water quality probes (DO, T°, pH, ORP), high-definition cameras and automatic feeders (Arvotec T-Drum 2000) were installed as shown below.

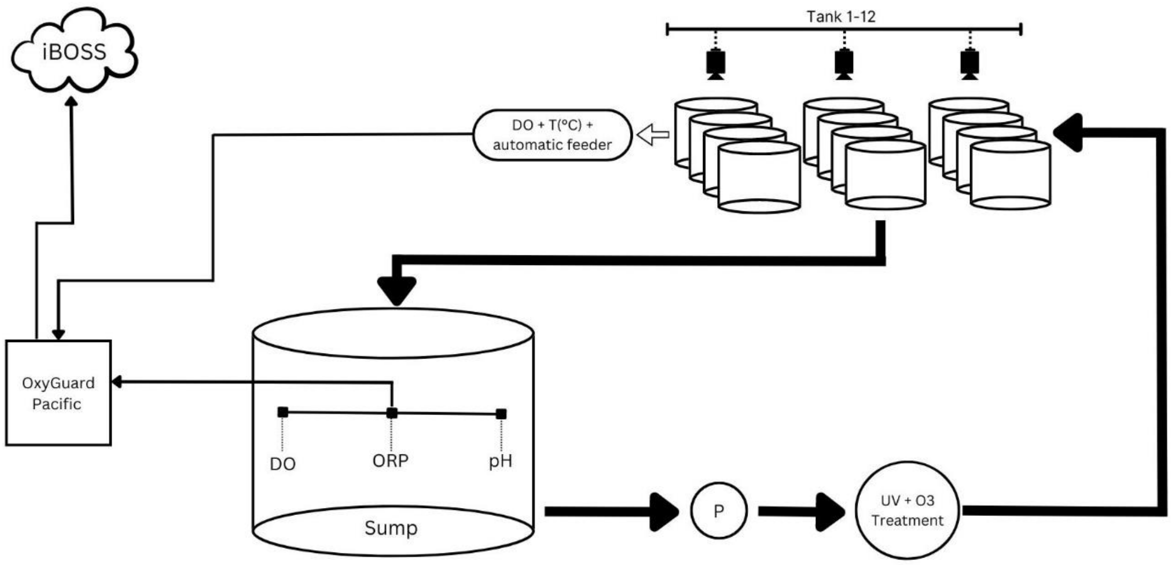


Figure 15 : Diagram of Smart RAS system at ABT used for the demonstration

4.2.1 Realtime monitoring of the fish behaviour

The only sensor used to monitor the fish behaviour is an IP camera placed above the tank, running at 25 frames per second. This device has a few constraints. Firstly, we do not have access to the depth of the fish: we only get a two-dimensional information, so only horizontal speed can be measured. Secondly, the camera is subject to the reflectance of the surface of the water: when the fish are highly agitated, it becomes very difficult to see the fish beneath the rough surface. Finally, we could have tagged individual fish to help us track them, but we chose not to do so, in order to develop a solution that could be applied in production.

The first image below (Figure 16) is a screenshot of the video captured by the IP camera, when the fish are at rest. The second image (Figure 17) is taken at the beginning of the feeding: we can see that it is very difficult to distinguish individual fish in the right area of the image, where the feed pellets were dropped (the feeder is the blue device on the top right of the screen).

Figure 16: Screenshot of the fish at rest

Figure 17: Screenshot of the fish during feeding

4.2.2 AI-model for fish behaviour

Fish detection

Detection of the fish was performed using YOLOv5, a deep-learning object detection model implemented in Python. After training the model on trout trial videos in 2022, it was evaluated on the salmon trials in 2023.

In principle, each individual fish needs to be detected on each frame of the video, so it can be tracked, and its speed measured. However, the goal is to estimate the behaviour of the whole group of fish, so it does not matter if there are a lot of non-detected fish.

In practice, when the fish are highly agitated during feeding, the detection rate drops significantly because the generated surface foam (white water) makes the fish virtually invisible to the camera placed over the surface. There are about 100 fishes detected at rest (out of 400), as illustrated in the first screenshot below (Figure 4.1.1.3.a), and with a minimum between 20 and 40 during the feeding (Figure 4.1.1.3.c) The second screenshot (Figure 4.1.1.2.b) shows that right after the pellets are dropped, the fish are better detected far from the feeder, where the water is clearer: there seems to be few fish at the bottom right of the screen, where there should be many (as a side effect, the pipe is wrongly detected as a fish, but this has no impact). This introduces a bias, because we only see the fish far from the action, so the maximum speed is likely to be underestimated. This also has an impact on the other metrics, as will be discussed hereafter. However, the activity of those surrounding fish can be considered as a proxy of the swiftest fish near the feeder. 20 seconds after the pulse, the clarity of the water is deteriorated on the whole surface, so few fish are detected.

(a)
(b)
(c)

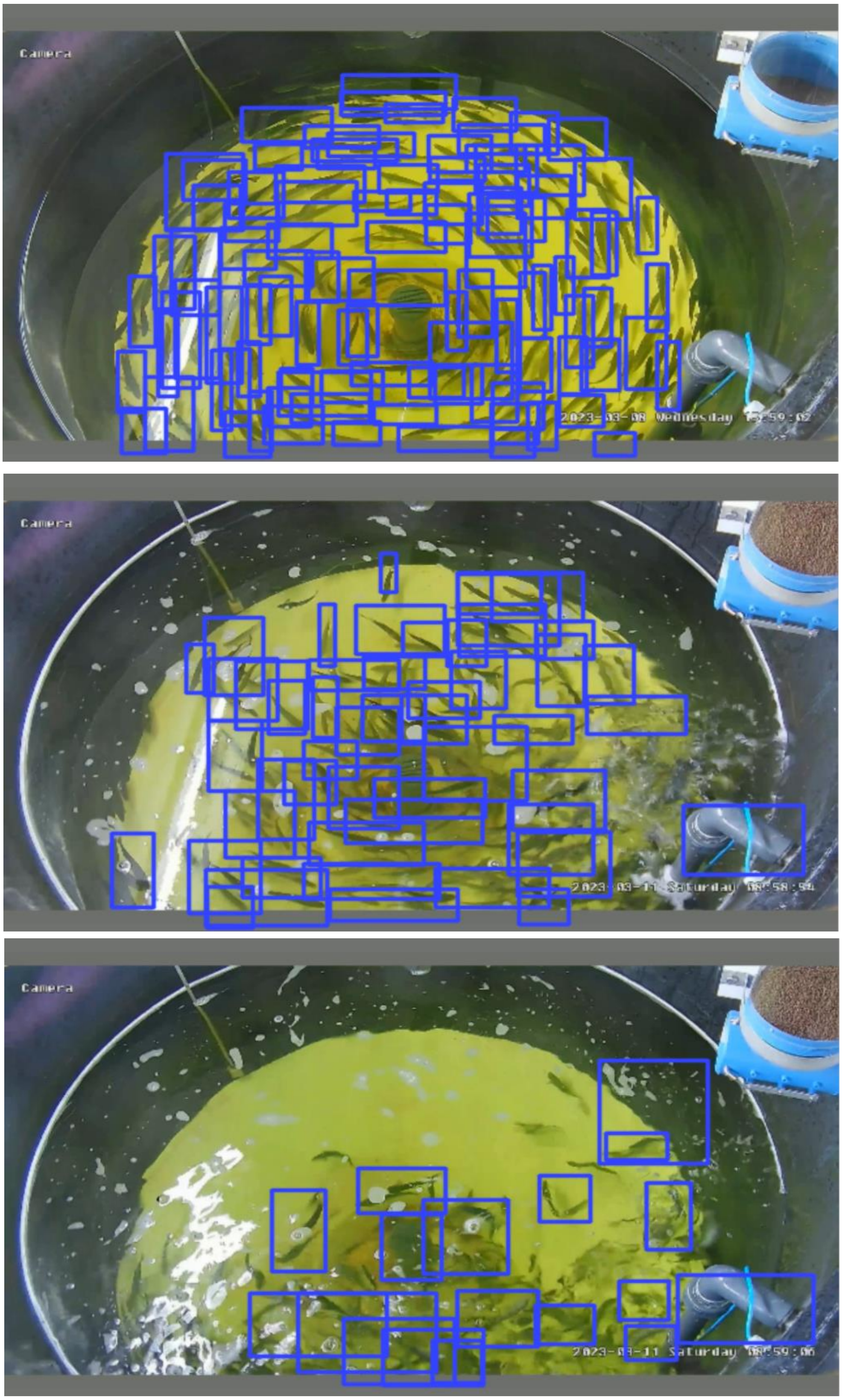


Figure 18: (a): Screenshot of the fish detected individually, at rest; (b) Screenshot of the fish detected individually, at the beginning of the feeding; (c) Screenshot of the fish detected individually, after 10 seconds of feeding: the whole surface is agitated, few fish are detected.

Fish tracking

Fish tracking was done using Norfair, a Python library which implements a tracker using Kalman filters. Figure 19 is a representation of the tracking, where each individual fish speed is represented as an arrow (the underlying image was dimmed for visibility).

Having a fraction of the fish detected is not an issue, however, proper tracking is critical. The fish can reach top speeds of 3 to 5 body lengths per second, so the processing requires a minimum of 12 frames per second (every other frame) to track them, which is a computational constraint. Indeed, without a powerful GPU, it is not possible to process 12 frames per second in real time. Therefore, the videos are recorded, then processed offline (30 minutes of video are processed in 4 hours on ABT's Xeon computer).

Figure 19: Fish tracking example

Computation of metrics and data sent to iBOSS

Four metrics are sent to the iBOSS: the speed, the rotation, the convergence and the number of detections.

Speeds - Firstly, the speed of the fish is measured in *body length per second* (bl/s). The diagram below (Figure 20) illustrates the computation: it shows the detection box of a fish (natively measured in *number of pixels*), and the speed arrow measured by the tracker (natively *number of pixels per second*). The speed of the fish in body lengths per second is computed as:

$$Speed_{bls} = \sqrt{\left(\left(\frac{dx}{x}\right)^2 + \left(\frac{dy}{y}\right)^2\right)}$$

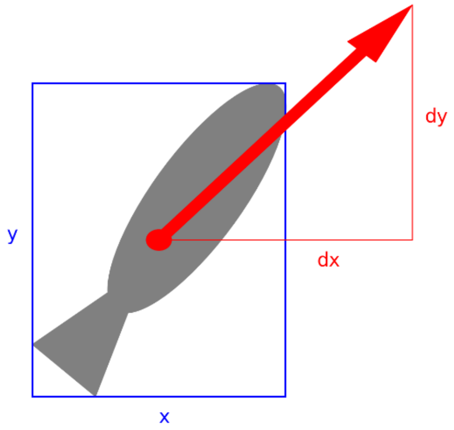
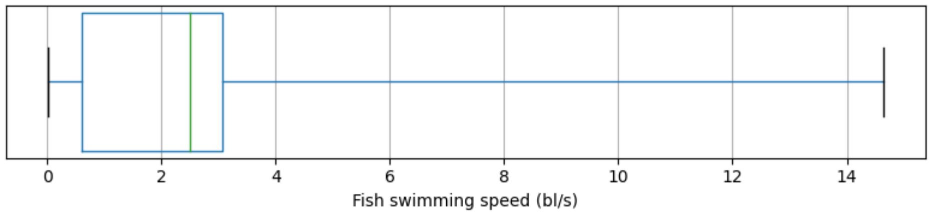


Figure 20: Speed computation in bl/s

Individual speeds are measured, but they cannot all be sent to iBOSS. There are too many, and there may be tracking mistakes due to fish disappearing below the surface or below other fish. In addition, simply averaging them would lose a lot of information, because the speeds are very heterogeneous. Therefore, we chose to send three statistics on the distribution of the speeds: the first quartile, the median, and the second quartile. These three statistics are sent to iBOSS.

Example: if the swimming speeds are distributed this way:



- 25% between 0.0 bl/s and 0.6 bl/s,
- 25% between 0.6 bl/s and 2.5 bl/s,
- 25% between 2.5 bl/s and 3.0 bl/s,
- 25% between 3.0 bl/s and 15 bl/s

Then the statistics sent to iBOSS are 0.6 bl/s (first quartile), 2.5 bl/s (median) and 3.0 bl/s (second quartile). The maximum value (15 bl/s) is not sent, because it is probably a measurement error.

Rotation and convergence - We have access not only to the value of the speeds, but also their directions. These cannot be directly averaged in a meaningful way given that the fish swim in a confined cage and not as a school in an open environment, but we computed two metrics to try to capture the behaviour: the rotation (based on the physical notion of curl) and the convergence (based on the physical notion of divergence), see Figure 21 for an example. Convergence is normalised, 1 is a very high value of convergence, typical values reach around 0.5. Rotation is also normalized, and its sign identifies the direction of rotation. A rotation of -1 is a fast rotation clockwise, and a rotation of +1 is a fast rotation counter clockwise.

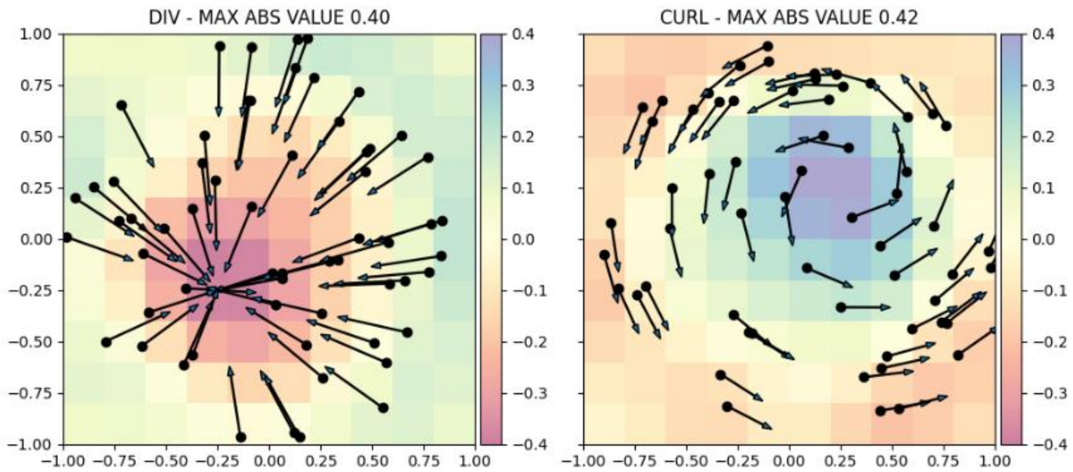


Figure 21: Illustration of convergence ("DIV") and rotation ("CURL") metrics based on fish speed

What follows is a more technical explanation of the computation of the rotation (curl) and the convergence (divergence).

The frame is divided into a 30 by 30 grid, and curl and divergence are computed at each node of the grid. Only the maximum value is then reported.

For one node, each fish is assigned a weight based on its distance to the node (the closer the heavier), then, taking the node as a reference point, we take the average of the products between the position vectors of the fish and their speed vectors (scalar product for the divergence, and vector product for the curl). Finally, we take the cube root of the result as a trick to flatten extreme values and emphasise groups, then we normalize it by the weighted average of the speeds.

Number of detections - Finally, a safety metric is kept, which measures how many fish are being detected. This gives a confidence level on the other metrics. Typically, the more the fish are agitated, the fewer fish are detected, because of reasons mentioned above (white water and fish superposition). Indirectly, the number of detections is therefore also a good indicator of fish activity.

Note on abandoned metrics – Some other metrics have been considered, such as the maximum density of fish. It could have been very helpful to quantify the fact that the fish tend to aggregate around the feeder during the feeding and get something similar to the "feeding index" in the open cage HCMR trial (see section 3.1). However, this is not possible due to the limitations described above: given that the fish are mostly detected in calmer areas, the density around the feeder seems to decrease during the feeding. This is why it cannot be used.

Examples

Figure 4.1.1.7.a represents an example of scenario, where the fish were initially rotating (clockwise, rotation is negative) the first ten seconds, probably because they had eaten already, then food was dropped in the tank, so the fish rush towards it (convergence is high, and the number of detections dropped), but quickly the fish started rotating again, they were not very hungry.

Figure 4.1.1.7.b is another example, where the fish were at rest in the beginning (low speed), probably starved, then food was dropped, and they all started moving much faster, with a peak in convergence, and the number of detections dropped and remained low because this time, they were very agitated, very hungry.

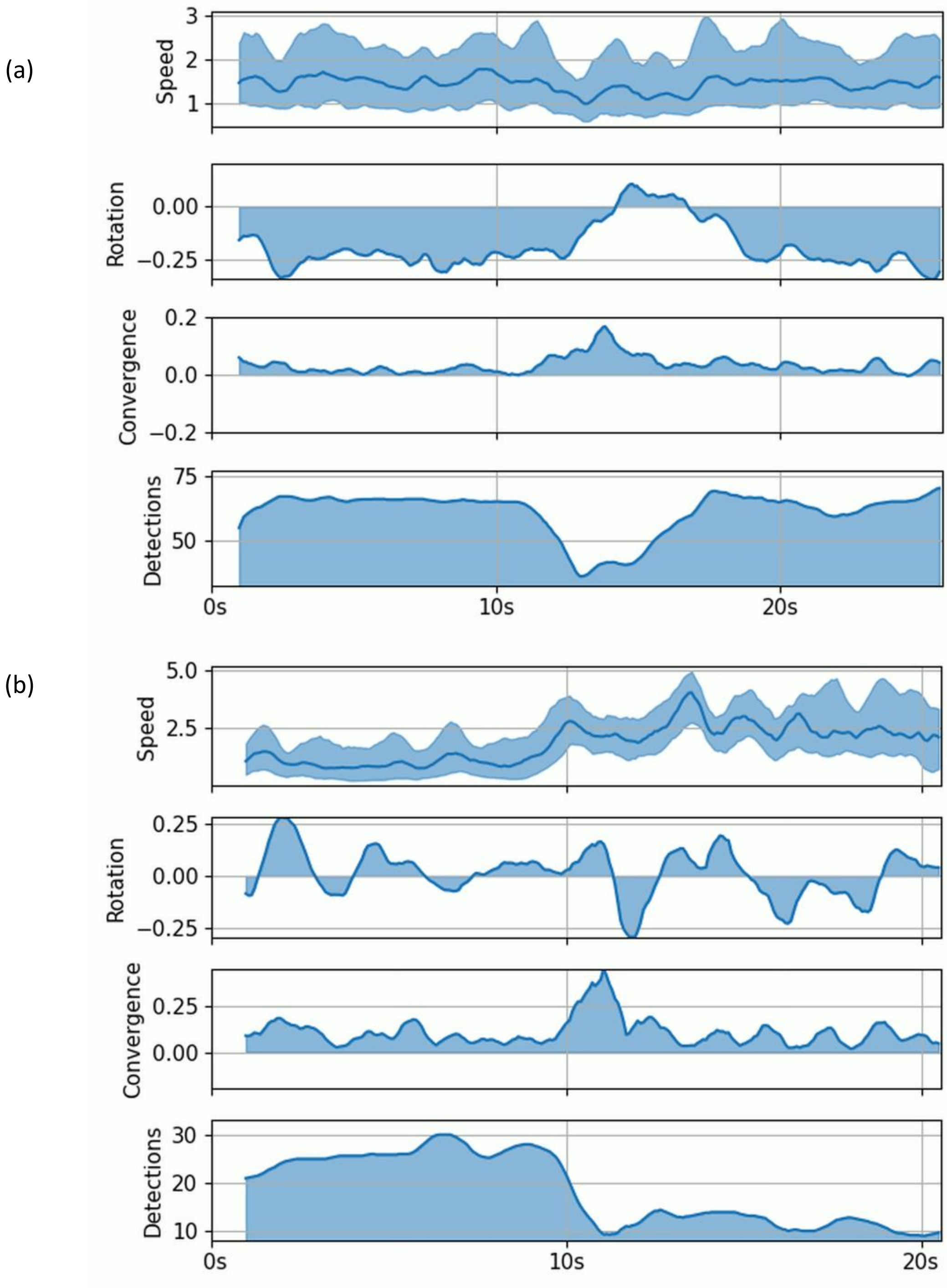


Figure 22: (a) Metrics during fish feeding – rotation then convergence; (b) Metrics during fish feeding – rest then convergence

Timing of the recording and processing

Given the fact that the detection and tracking are too computationally heavy to be run in real time, it is not possible to track the fish around the clock (in addition, it would be a waste of computational resource and power). Therefore, the recording is only set to start 10 minutes before the beginning of the feeding. In principle, we do not know in advance when the feeding will start, so to achieve that, the video is read continuously with a 10-minute buffer which is emptied as it goes along by discarding the oldest frame, then when the feeder sends its activation signal, the oldest frame is grabbed to be recorded instead. Then, the end of the feeding is declared when 10 minutes have elapsed without any feeding pulse, and the recording continues for another 20 minutes. The diagram below (Figure 23) illustrates the pipeline.

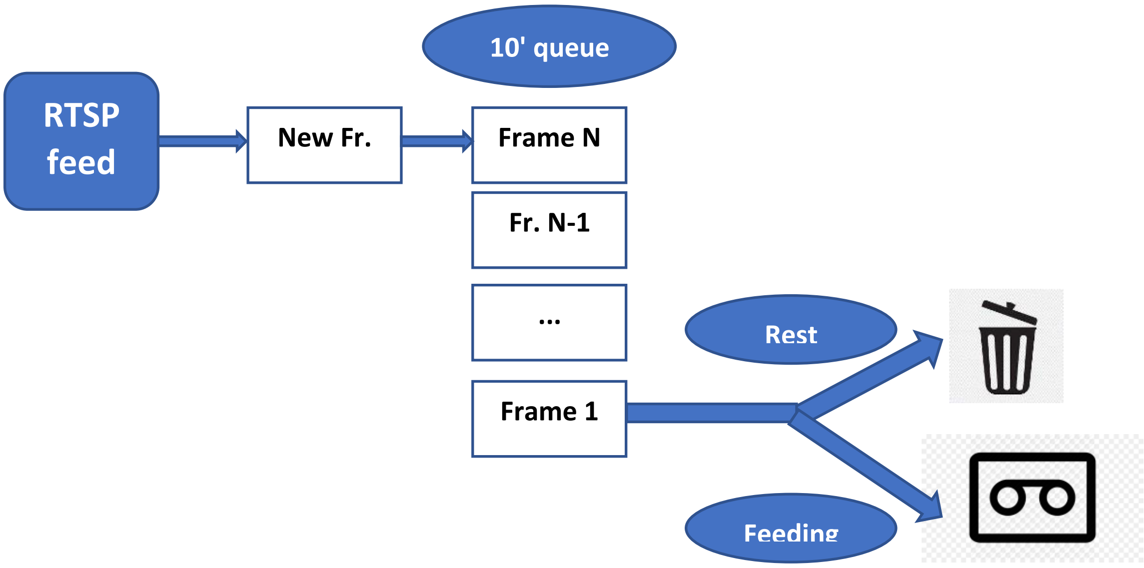


Figure 23: Pipeline from RTSP feed to record

The second step is to process the recorded video, offline. This consists in the detection, tracking, and computation of the metrics. The heavy work is done in detection and tracking, so in order to run it as efficiently as possible and not have to wait for the computation of the metrics, this last brick is done in parallel, as illustrated in the following diagram (Figure 24).

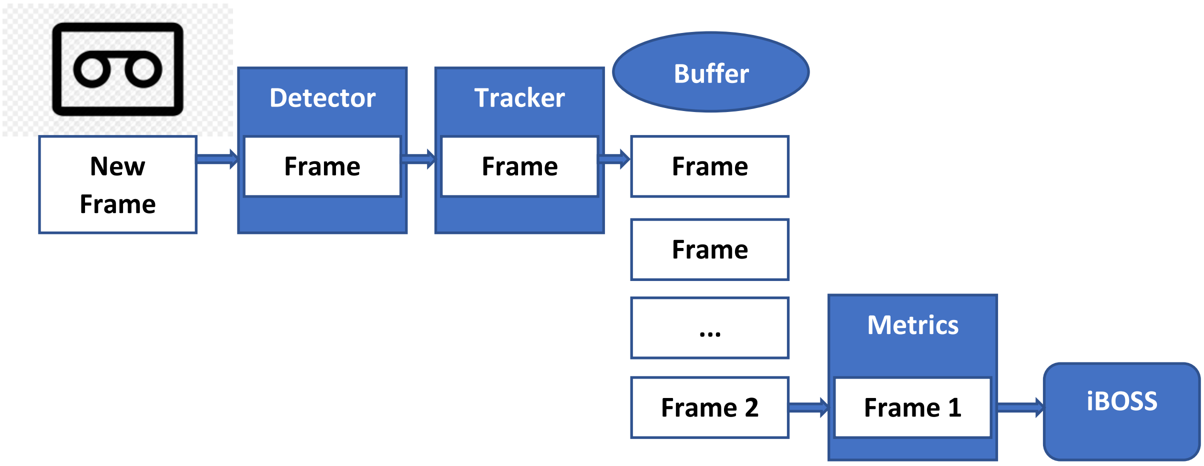


Figure 24: Pipeline from record to metrics sent to the iBOSS

The full pipeline runs continuously on ABT's Xeon computer onsite, in a Ubuntu virtual machine. It is a Python script, launched with the process manager PM2, and it restarts every morning at 08:00.

4.2.3 Performance of the smart feeding AI algorithm

The **fish detection model** was calibrated on a previous trial with rainbow trout that were significantly larger that the salmons: they were only 44 fish in the tank. The calibration consisted in manually annotating 148 frames with boxes around each fish (for a total of 3741 annotated fish) and evaluating the capacity of the model to detect the fish on 20 other unseen images (456 fish). We reached a precision of 82% and a recall of 87% on the validation dataset ("precision" is the percentage of model detections that correspond to actual boxes, and "recall" is the percentage of real boxes that were detected). This is a good score, considering that the manual annotation itself probably did not do much better, because often, during the feeding, some fish are invisible even to the human eye.

It was established that 400 small fish in the tank is closer to real life production situations. One of the challenges was to evaluate the capacity of the detection model to generalise to scenarios that it did not encounter during its calibration. In addition, we did not have the resource to annotate new salmon images to recalibrate the model.

The results were satisfying. Out of 400 fish, the model detected about 100 at rest, as detailed in the previous section "Fish detection". We noted, however, that as opposed to the trout, the salmons seldom adopted a rotating behaviour before or after feeding, so it was difficult to evaluate the relevance of the rotation metric.

The computational challenges that arose during the salmon trial, related to running the processing on live footage, unfortunately did not allow the collection of a very diverse set of results, so at this stage we have not used the video analysis to understand the variations in fish behaviour in relation to the hour of the day, their density, appetite or feeding regime.

More detailed results from the demonstrations are to be found in the deliverable D3.4 (https://ifishienci.eu/media/publications/).

4.3 Possible improvements of the AI-controlled feeding

There are several ways this fish behaviour analysis pipeline can be improved.

4.3.1 AI-models

The **tracking model** is the first that could be improved by changing the detection task: instead of looking for a rectangle box around the fish, we could try to detect body parts, like the head or the tail. This would make the computation a bit heavier, but it could greatly improve tracking, because fish swimming close by would be less likely to be mistaken for each other, from one frame to another.

Secondly, the **detection model** would benefit from feedback by the tracking model. Indeed, it is much easier to detect a fish when one knows where it was on a few previous frames, even for a human agent. Then, the rotation and convergence metrics are difficult to calibrate, and if they are not well calibrated, they are just noise. It would be good to make them more robust, in order to reuse the algorithm more easily.

Last but not least, with a stronger computational resource (a GPU), the processing could be done in real time, enabling applications at a much shorter time scale, like automatically stopping the feeder when the fish have stopped eating.

4.3.2 Smart feeding implementation

Feeders are controlled by an OxyGuard Commander Feeder control, which is already implemented at ABT. The controller engages the Avro-tec feeders to distribute feed. The controller is designed to manage a feeding regime set up by the farmer and handles when to engage the feeder to distribute the planned amount of feed throughout the set feeding regime.

As an example, if the farmer wants to feed 20 kg of feed today but only from 8:00 to 10:00 and from 14:00 to 16:00, the controller calculates how much it should engage the feeder to distribute the 20 kg evenly over those intervals. Tomorrow the farmer will feed 22 kg, but in the same time interval, so the controller will recalculate to suit the request. The daily increase in feed amount can also be handled by the controller but only following a predetermined daily increase. The farmer will have to correct for fish appetite and similar effect.

In order for the Feeder controller to adapt to changes in the fish appetite, a smart feeding approach is implemented. A measure of appetite is derived from the behaviour analysis done by the camera, described in the previous section. This appetite measurement (called Feeding score) can be used to change how much feed should be made available for the fishes during the feeding intervals. The feeding score is available in iBOSS.

In order to change feeding amount from feeding score, the Feeder control was connected to OxyGuards Cobália Farm Management cloud in order to communicate the changes. Cobália sends statistics (i.e., fed amount used) from the Feeder controller to iBOSS and receives the new Feeding score from iBOSS (Figure 25). The feeding score is then sent through to the Feeder controller. The demonstration of the technology is described in the public deliverable D3.4 – D15 Demonstration Performance (KPIs) for recirculating Aquaculture System.

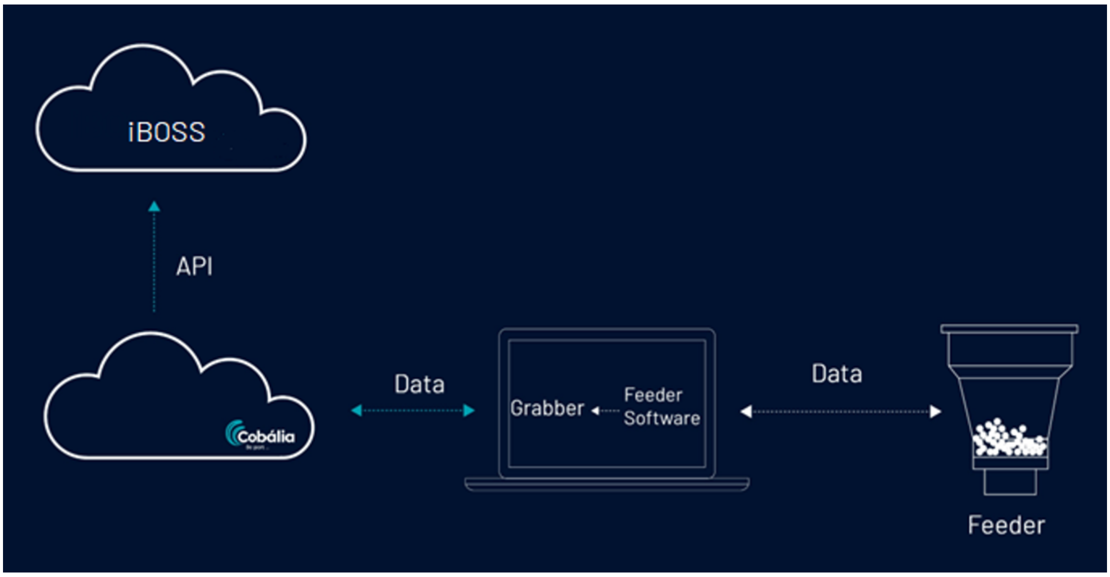


Figure 25: Interface iBOSS-Cobália-feeder, in the context of the ABT Smart RAS.

4.3.3 Connecting iBOSS to the feeders

During the final demonstration, one feeder was actively controlled by iBOSS and utilised to feed the fish according to the feeding score. iBOSS successfully retrieved the feeder status and the camera monitoring data throughout the demonstration. Data were displayed in a dashboard and were used for the calibration of the feeding score. The feeding score was exposed on the API of the iBOSS, to be retrieved by the feeder, to adjust the amount of delivered food. This amount was also monitored by the iBOSS on an hourly basis (more detailed to be found in the deliverable 15 - D3.4).

5 iBOSS deployment in flow-through systems and Pond

5.1 GYE demo-site

The GYE site has been used for rearing and selecting African catfish. No sensors nor iBOSS were deployed to the system. However, we share here some thoughts and recommendations on the use of FTTm and iBOSS in the context of early-phase rearing.

In the case of African catfish, the breeding conditions significantly differ from those of species kept in other intensive systems. This is primarily due to its supplementary respiratory organ, which makes it less sensitive to water quality. The fish are kept at much higher densities (up to 200 kg/m^3). The quantity of feed provided is also much higher, accompanied by very intensive feeding behaviour. Therefore, the water quality parameters for African catfish aquaculture often fall outside the measurement range of commonly used sensors. it would therefore be necessary to develop specific sensors adapted to the specificities of the species.

The oxygen level typically ranges between 0-1 mg/l, and the lack of oxygen does not pose a problem for the fish. They often come to the surface to take in atmospheric air. The pH typically falls into a low range of 5.5-7. The total ammonium nitrogen can reach up to 80 mg/l, NO_2- can reach 8 mg/l, and NO_3- can even reach several hundred mg/l. The African catfish cope well with such conditions and do not refuse feeding. The critical level of these nitrogen forms is much higher. It would therefore be necessary to develop a specific measurement and alarm system adapted to the specificities of the species.

The level of floating matter is also very high, which drastically reduces visibility. As a result, camera systems used to observe underwater and/or surface events are not applicable. A camera system could only be used to monitor floating feed signals on the water surface and thus measure feeding intensity. Perhaps the number of breaths during atmospheric air breathing could also be monitored. Additionally, the high level of Chemical Oxygen Demand (COD) and Biochemical Oxygen Demand (BOD) results in these values being very high. Furthermore, due to the high nutrient content, large amounts of saprophytic, typically anaerobic bacteria proliferate, which poses a significant problem for the maintenance and operation of various sensors due to biofilm formation. Based on previous experiences, the sensors need to be mechanically cleaned at least daily.

However, it should be noted that the above statements only apply to breeder, juvenile, and market-size fish, as the generally accepted guidelines are applicable during larval and early fry rearing (until the supplementary respiratory organ starts functioning). Thus, sensors and cameras developed for other species may work well in these stages.

5.2 Laos demo-site

The experimental activity in Laos (conducted by Vitafort) was organised into two main phases to implement responsible, consistent, and scientifically-well based feeding trials. As part of WP1 a small-scale experiment was carried out to identify the most promising feeds and feed supplementations. These promising formulas and concepts were tested later in the frame of semi-industrial scale trial (WP3).

The small-scale experiment was carried out at the premises of the Namxuang Aquaculture and Fisheries Development Center, (NAFDEC) which is operated by the Ministry of Agriculture and Forestry in Laos. The fish stock was divided into 3 groups, one group was accommodated in 3 pcs of 0,8 m^3 containers and 200 fingerlings were reared in each container.

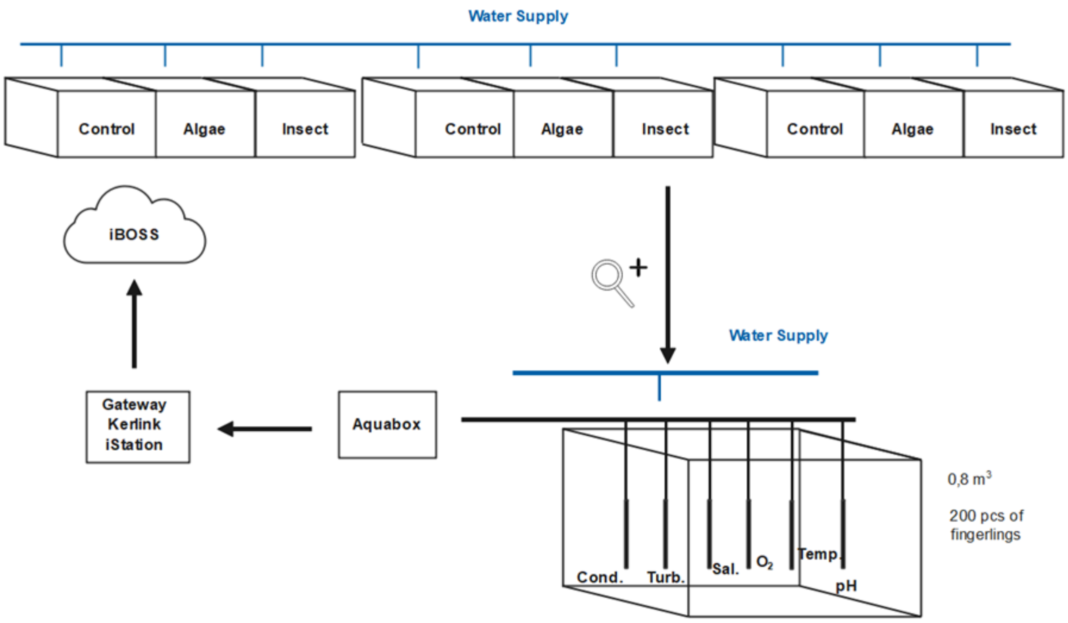


Figure 26. Diagram of the WP1 small-scale experiment setup.

In WP 3, the proposed location of the experiment was a farm operated by a Hungarian-Laos joint venture company named Aquatic Development Company Ltd. (ADC). For the feeding trials, a net cage system was used in a tropical freshwater lake. Each system consisted of 4 cages of 45 m^3 each. The water supply of the lake was provided by the Namhoum reservoir. The fish stock was divided into 4 groups, one group occupied 2 cages.

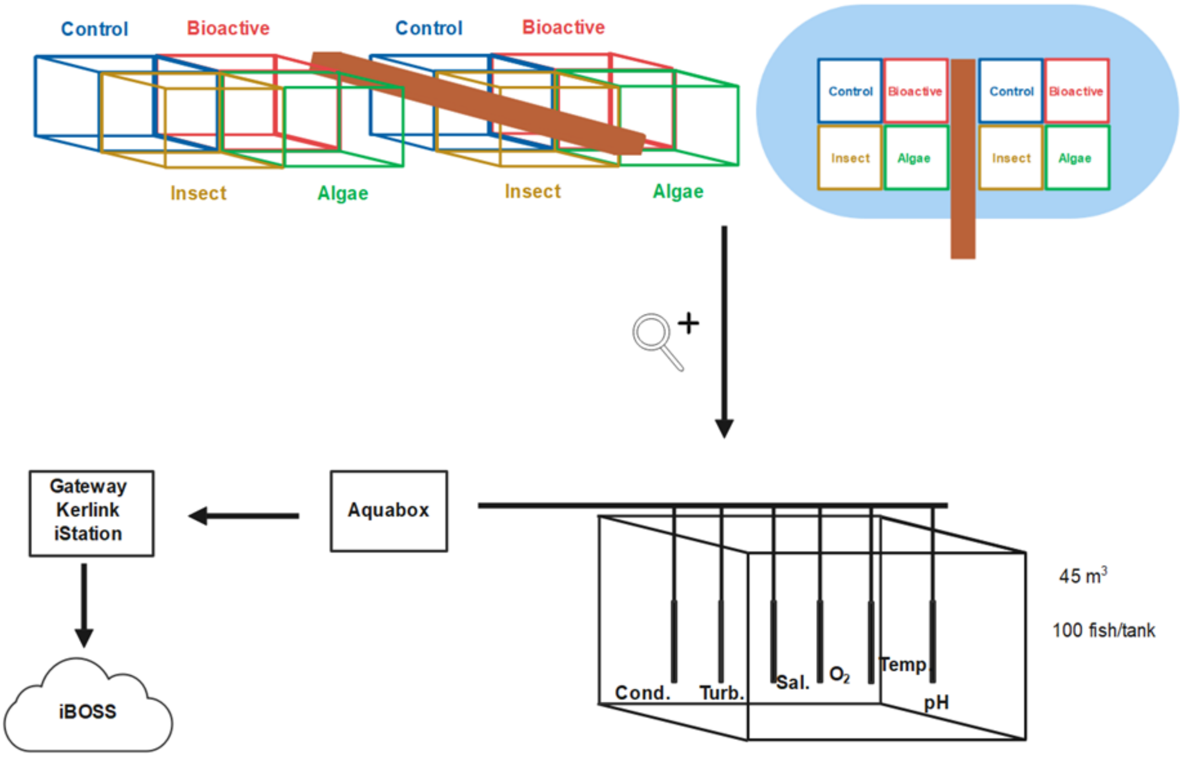


Figure 27. Diagram of the WP3 semi-industrial scale experiment setup.

5.2.1 Technology package at Laos demo-site

Vitafort received a water quality package (Aquabox) from BiOceanOr with several probes (salinity, O_2 level, pH, temperature, turbidity, conductivity), and a Gateway Kerlink iStation. This setup was used to monitor the water quality parameters and to push them to the iBOSS server, every 20 minutes. To ensure the stable internet connectivity we chose Unitel, which provided the best internet access for the task. The package did not contain cameras or other technology.

5.2.2 Lesson learned

Vitafort used the deployed technology to monitor the environment and optimize the fish production by providing the best possible water quality for the animals. The recorded parameters were checked daily by the professionals. During the WP1 trial it was observed that in some cases the turbidity value or the O_2 level were the same even though the water was refreshed in the container. Based on this experience the colleagues started to regularly clean the probes, during the WP1 and later the WP3 experiment, so the recorded parameters were correct and followed the actual changes of the water quality.

As the basic monitoring system package was operated successfully, Vitafort sees further opportunities to test other components of the system both in a flow-through and a pond environment, to get more data and a deeper understanding of the fish's needs. With the integration of a camera system fish behaviour can be monitored in the context of hunger and water quality, while an automatic feeder can provide the necessary amount of feed based on the fish behaviour and the farm management's decision.

5.2.3 Ways of improving the AI-controlled feeding

To improve the operation of the basic system and ensure that the recorded data is reliable, the integration of a warning mechanism in the online system, which alerts the manager if a value reaches the limit or a dynamic parameter remains the same for a longer period, would be a useful upgrade. Furthermore, a special cover could be applied in the probes, so the contamination cannot stick to the sensors.

6 Conclusions and Way forward

In iFishIENCi a "Biology Online Steering System" (iBOSS) framework has been jointly developed between the project partners (NORCE, HCMR, ABT, Covartec, EGM, BiOcenOr, OxyGuard, UiB), for feeding optimisation in different production systems (i.e., open-cage and RAS). It is based on the development and integration of three main components:

1. A capability for real-time monitoring fish behaviour and water quality under production (Fish-Talk-to Me - FTTM)
2. Models supporting decision-making and automatic steering of feeding. AI-based video/image processing (deep-learning) and analytics, and predictive modelling of fish-feeding (FishMet – digital twin of Salmonids)
3. An open IoT framework for integration of technologies (monitoring sensors, feeders), management of FAIR data (iBOSS cloud) and Edge computing

Two prototype versions of the iBOSS have been developed, answering the specificities of production systems (i.e., Open-cage and RAS). A version for flow-through semi-closed containment system (Egget by Ovum AS - https://www.ovum.no/) is under development in cooperation with Ovum AS.

The project has successfully demonstrated the capability to develop robust real-time indicators of feeding behaviour, further used for the control and optimisation of feeding systems.

The first prototypes of the iBOSS may of course be improved in many ways:

- For the FTTM: specific sensor packages could be set-up to answer specific challenges and peculiarities of a production system, also adapting low-cost sensor aspects to optimise the uptake of the iBOSS globally. In particular, technological solutions for better operational monitoring of the environmental microbiome (in RAS and S-CCS) should be further investigated.
- For the IoT platform: expansion of the I/O interfaces to increase compatibility with existing systems may be looked at on a case-by-case basis. Further development of the visualisation interface and the related tools will be considered, in tight dialogue with end-users.
- For the analytical capability: The FishMet model should be adapted to more species, not least Seabass and catfish which are two highly consumed fish globally. For the behavioural models one could improve robustness (reduce false-alarm) by improving the integration of data on environmental conditions in the AI-model.

The partners of the project are up to the challenge and have, for many, already integrated this in their exploitation plan.

At the end of the project, the innovations and findings of iFishIENCi are clearly opening new ways of controlling production, with many exploitation routes:

- **Feeding control and optimisation**: iBOSS is an open, flexible and adaptative concept ready to be taken up by fish-farmers. It can be implemented as an "overlayed" platform that integrates existing technologies (sensors, feeders) already installed at a farm, and provide decision-making for feedings. It can also be propose including a set of tested and robust sensors for water quality and fish behaviour, if required by the end-user.
- **Other applications**: iFishIENCi FTTM and IoT platform may have many other applications apart from feeding control. Indeed, if in iFishIENCi we focused on indicators of feeding behaviour, one can use the same approach and technology for developing other AI-based

models for automatic detection/assessment of other fish behaviours related to health and welfare, to be used in welfare control and production optimisation more generally. We believe that the iBOSS concept and components are generic enough for envisaging a smooth and reasonably easy transposition of the current system to other applications, meaning that, when the IoT platform with appropriate sensors are installed, iBOSS will be capable, with limited efforts, to propose new AI-models dedicated to specific applications and/or challenges at the production site.