Intelligent Fish feeding through Integration of ENabling technologies and Circular principle

Grant Agreement (GA) No: 818036

D13 Demonstration Performance (KPIs) for Marine Open Systems

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1 Introduction

Aquaculture growth demands better and optimized control. Feeding is one of the primary factors that can have significant impact on the cost (more than 40% of the total cost is for feeding), the welfare of the fish (stressed fish due to underfeeding, overfeeding, competition etc) and the environment (feed waste). Efficiency and cost in aquaculture depend largely on feeding, making it crucial to optimize feeding strategies to reduce feed loss and improve fish health and welfare. Intelligent feeding control that utilizes behavioural changes and growth status is gaining attention as a useful tool for improving husbandry practices.

In the frame of iFishIENCi one of the objectives was to develop and test two main tools/technologies in this direction. These are Fish-Talk-To-Me and the iFishIENCi Biology Online Steering System, iBOSS platform.

The Fish-Talk-To-Me is based on the development of appropriate methods of monitoring fish behaviour or physiology (without human intervention) in order to determine fish requirements and to link them with husbandry activities particularly feeding.

The iBOSS is a platform that collects and analyse information from fish monitoring and their environment allowing actions for better husbandry practices.

The overall objective therefore was to provide a decision support tool to improve feeding process in cage farming by collecting online data/information using intelligent sensors and by providing rules allowing automated actuation of systems (i.e., feeders) in a farm.

For the HCMR-Open Cages demonstration, both technologies were developed and tested. As described in public deliverable 2.5 the iBOSS platform was installed and operated in the pilot farm collecting data from environmental sensors and also from fish behaviour ones. Furthermore, specific algorithms were developed to allow control of the feeder depending on predefined values/ thresholds.

For Fish-Talk-To-Me, a combination of tools for monitoring the feeding behaviour (cameras, echo sounders and telemetry tags) were used to investigate different characteristics of swimming behaviour and its variations in relation to feeding aiming the selection of appropriate parameters to serve as decision indicators and the quantification of thresholds for transferring these parameters' values to iBOSS.

For continuously monitoring the feeding behaviour an online/real-time intelligent system was developed i.e., to automatically detect and track fish, and detect the feeding and feeding progression.

In addition, two behavioural-based indicators were investigated, speed and the feeding behavioural index (a newly defined metric), across different feeding scenarios using E. seabass as model species. The findings suggest that fish exhibit distinct behaviour patterns in response to various feeding situations, and both the speed and feeding behaviour index can identify threshold values that correspond to satiation levels, facilitating controlled feeding.

The Norwegian Open-Cage demonstration with Atlantic salmon has had repeated delays due to access to commercial facilities, COVID, technology readiness and conflict of interest for commercial partners. Following these delays, we were able to deploy iBOSS in Ovum´s open cage system mid-July 2023. Here the ability of iBOSS to adapt external iFishIENCi technical providers, Imenco and Guard through Oxyguards Cobalia, to allow real-time monitoring of the cage environment in iBOSS was demonstrated.

Presently the testing of Fish-Talk-To-Me behavioural models for Smart Feeding is ongoing, developed by HCMR for European seabass (see above), it is being determined whether this can be adapted for Atlantic salmon using Imenco´s standard feeding cameras. The demonstrations of iBOSS and Fish-Talk-To-Me in Atlantic salmon production demonstrates that the potential to deploy the flexible iBOSS cloud-based platform, adapting existing hardware and employing the Smart feeding AI from behaviour to water quality will greatly advance the fragmented systems that are often used today.

2 HCMR – Open Cage

2.1 Key Performance Indicators

Feeding control in cages represents the main objective of the work performed in this demonstration. In order to achieve this, a large number of parameters should be considered that describe in an accurate manner the environment of the rearing, the physiological status of the individuals and in particular their metabolic state, their developmental phase and their general status.

The daily consumption of delivered feed is today still mainly calculated based on the "hypothetical/estimated" biomass of each cage considering also factors based either on empirical/production data or theoretical scientific information based on feeding needs under ideal laboratory conditions. In any case, parameters related to different juveniles' quality, the nutritional value of commercial feed, daily changes in environmental conditions, health, and stress of the population from the management of the farm are hardly or not considered. In economic terms, this determines the viability of a farm. In addition to the direct economic benefits of optimizing the consumption of fish feed, there are benefits related to the health and quality of the final product and the protection of the farmed environment.

Results from experimental farms have shown that the best production performance is achieved when a population is fed at optimum levels that subsequently result in optimum growth rate, feed conversion factor, quality, and health of farmed fish. Cage-reared populations show different species-specific feeding behaviour and mobility (speed, acceleration, dispersal within the cage) when they need feed, during feeding, at the first signs of satiation and at satiation. And even though existing commercial systems allow online monitoring of the farm environment (e.g., from OxyGuard and Bioceanor) and others providing a good estimation of the fish size and its distribution (e.g.,[1]) there are no available tools for continuous online monitoring of the fish behaviour and in particular the feeding behaviour in cages. One way to achieve this is by monitoring individual and group swimming patterns, especially in response to external factors like feeding. Furthermore, no system exists that integrates all these parameters allowing for a better control of feeding.

The KPI described in the DoA was the potential difference in growth performance and the relevant changes in production cost using the smart feeding technology developed during the project. Due to the complexity of the collection and analysis of the data, particularly for the feeding behaviour, the

[1] D. Voskakis, A. Makris, N. Papandroulakis, 2021. Deep learning based fish length estimation. An application for the Mediterranean aquaculture. IEEE Oceanic Engineering Society, San Diego Sept 20-21, 2021. DOI: 10.23919/OCEANS44145.2021.9705813

planned level of readiness was not reached that would allow the running of a full-scale trial using the tools developed.

Therefore, a different set of KPIs were considered, showing the steps achieved towards intelligent feeding in cages. These were:

- The development of the "Fish-talk-to-me" technology for open sea-cages incorporating environmental and behavioural data.
  - The functionality of the behaviour monitoring algorithm.
  - The definition of metrics that correspond to different satiation levels.
- The long-term operation of the iBOSS platform for data collection.
  - The ability for online control of feeding based on data collected in the farm.

Although the full operation of the system was not demonstrated the different consisting components are demonstrated to be operational in pilot scale.

2.2 Demonstration Methodology

The equipment and the general methodology applied is provided as summarized below. A more detailed description of the methodology particularly on the image and data analysis is also presented.

The demonstration trial was implemented at the pilot scale cage farm of the HCMR (Souda Bay, Crete) which is certified as an aquaculture facility from the national veterinary authority (GR94FISH0001). A group of European seabass of 220 ± 30g body weight at a stocking density of 5.2kg m^{-3} was reared in circular polyester cage of 40m perimeter and 9m depth. The cage form is cylinder-shaped up to 8m depth and has a cone that closes the cage at 9m. More than 10,000 individuals were held in the cage in total.

The monitoring system included sensors for monitoring dissolved oxygen (DO), temperature (T), salinity and pH together with a submerged camera, and an echosounder to monitor fish activity. A SIMRAD EK 15 (single beam) was installed providing information on the distribution of the fish, a parameter related to the feeding behaviour.

A submerged network camera (Fyssalis v3.1) capturing at 10 fps was used for video recording during daylight hours. The camera was positioned at 4m depth using a gyroscopic gimbal stabilizer to ensure it pointed upwards. The videos were collected using RTSP streaming.

In Figure 1 a view of the cage farm is shown together with a graphical representation of the experimental set-up.

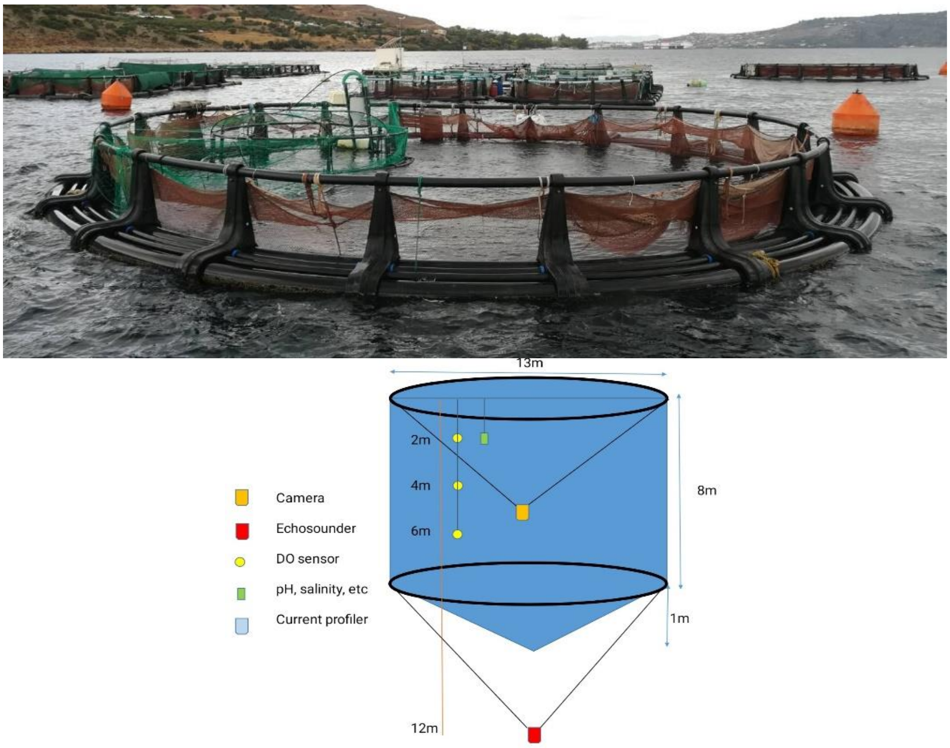

Figure 1. Experimental site and setup.

2.2.1 System Testing

Fish were recorded for a duration of approximately a year following different feeding scenarios as shown in Figure 2. Four different feeding parameters were controlled for: the feeding mode (if the fish are fed manually or using an automatic feeder), the feeding frequency (if the fish are fed once, twice or three times), the feeding time and the feeding quantity (if the fish are fed using normal quantity, reduced quantity (50% less than normal), excess quantity (using 150% of the normal) and no feeding at all. Each feeding treatment lasted for a period of 7-10 days.

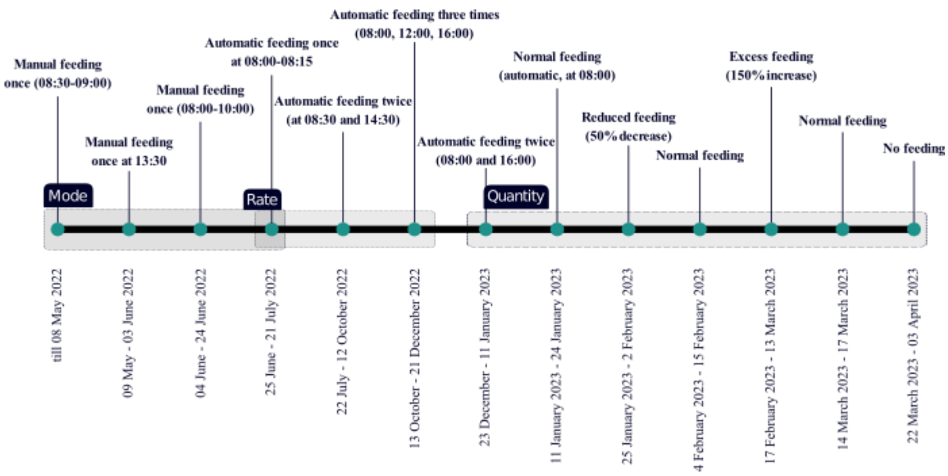

Figure 2. Experimental timeline and planning.

The experimental protocol was approved by the Ethics Committee of the IMBBC and the relevant veterinary authorities (Ref Number 32257 09-02-2021) in accordance with legal regulations (EU Directive 2010/63).

2.2.2 Video Analysis

We focused the swimming behavioural analysis on two different levels, the individual level and the group level. At the individual level, previously existing models were trained for the detection and tracking of individual fish in the cage. At the group level, computer vision techniques were used to extract group level swimming performance parameters, such as the group cohesion/density and the group synchronization. All algorithms used for both, the video and data analysis were developed in Python (v3.9).

2.2.2.1 Individual level video analysis (deepsort and YOLOv5)

YOLOv5 was used to detect the fish in the videos, after training the model with 1000 annotated images of individual fish. To associate each detected fish between frames (i.e., to track the fish) the DEEPSORT algorithm was applied excluding the appearance-based association parameter. All training and video analysis was run on a desktop computer at the HCMR with the following specifications: Intel Core i9-10900F 2.8 GHz CPU, 32GB RAM and NVIDIA GeForce RTX 3060Ti Gaming X8G LHR GPU. The YOLO bounding boxes of each individual fish was used to detect when fish change their direction. For this, the rate of change of the box long axis length/short axis ratio was estimated.

2.2.2.2 Group level video analysis (polarization, feeding index etc)

During strong polarization events the fish align, and this is captured in an image and quantified using image gradients, which are defined as the directional change in image intensity. By using Scharr operator and the arctan function the histogram of this direction of change could be extracted. By observing the changes in the distribution of the directional change, thresholds could be manually defined and could be used to conclude if fish were polarized, and in which direction relative to the camera.

During feeding events, E. seabass shows a strong reaction, i.e., their inter-individual distances decrease significantly, and the fish are crowded around the feeder. This behaviour lasts during feeding, and it does not appear as such in different behavioural events. Taking advantage of this distinct behaviour that E. seabass exhibits during feeding, a new metric was defined called Feeding Behaviour Index. When the high density exceeded a threshold, a crowding event was assumed as feeding.

2.2.3 Data analysis

2.2.3.1 Clustering - Gaussian mixture models

The feeding behavioural index was automatically grouped into four different clusters related to get some insight into the feeding behaviour changes in time. The function GaussianMixture() from the scikit-learn library of Python was used.

2.2.3.2 Change point detection

Change point detection analysis was run using Python to automatically detect significant changes in the feeding behavioural index signal. The library ruptures in Python were used for off-line change point detection. This package provides methods for the analysis and segmentation of non-stationary signals. Implemented algorithms include exact and approximate detection for various parametric and non-parametric models. The function Dynp() was used which finds the (exact) minimum of the sum of costs by computing the cost of all subsequence of a given signal. It is called "dynamic programming" because the search over all possible segmentations is ordered using a dynamic programming approach. The changes of the start and the end of the feeding needed to be found and for this reason, it was decided that the number of changes should be two.

2.2.3.3 Motion Asymmetry

To compare the speed and feeding behaviour index across different feeding scenarios the time the feeding starts was set as t = 0. The time of the feeding can serve as a reference axis that can be used to test the behaviour around these time periods. It is therefore interesting to test how the parameters change relative to the start of the feeding. In other words, how symmetric the behaviour of the fish is around the feeding times can be detected by setting the start of the feeding as the axis of asymmetry. The asymmetry parameter was therefore defined as:

$$A(t)=f(t) - f(-t)$$

Where f(t) is the signal of interest (the speed or the feeding behaviour index) at any time “t” ($t \in [0, \infty)$). For any given time “t”, if this difference is positive, this means that the activity of the fish is higher at “t” seconds after feeding than “t” seconds before feeding. This metric can be very useful to study the qualitative behaviour of the fish.

2.2.3.4 Feeding index prediction using a custom neural network

A custom-made neural network was built to predict the feeding behaviour index after 1-5 seconds of the current time. The network was built using Keras and Tensorflow library in Python and consisted of three input layers, one hidden and one output layer. 11,000 input feeding behaviour signals were used of 300 frame duration to train the network.

2.3 Demonstration Results

The installation of the different components and tools for the demonstration was easy and the operation of all systems was without significant problems during the demonstration period. Issues related with the internet connectivity during bad weather periods were confronted without significant effects on the operation of the whole system.

2.3.1 Data collection and storage

All data sets were collected locally by sensors and other tools and were wirelessly transferred and stored in the iBOSS platform being available for further analysis. Behavioural data were transferred to the iBOSS using HTTP communication protocols.

2.3.1.1 Environmental data

The operation of the environmental sensors (T, DO, pH etc) was constant from both systems tested (Oxyguard and Bioceanor). Regular maintenance of the sensors ensured proper data collection.

The iBOSS platform was collecting online the relevant data (shown in Figure 3) allowing a constant overview of the farm status.

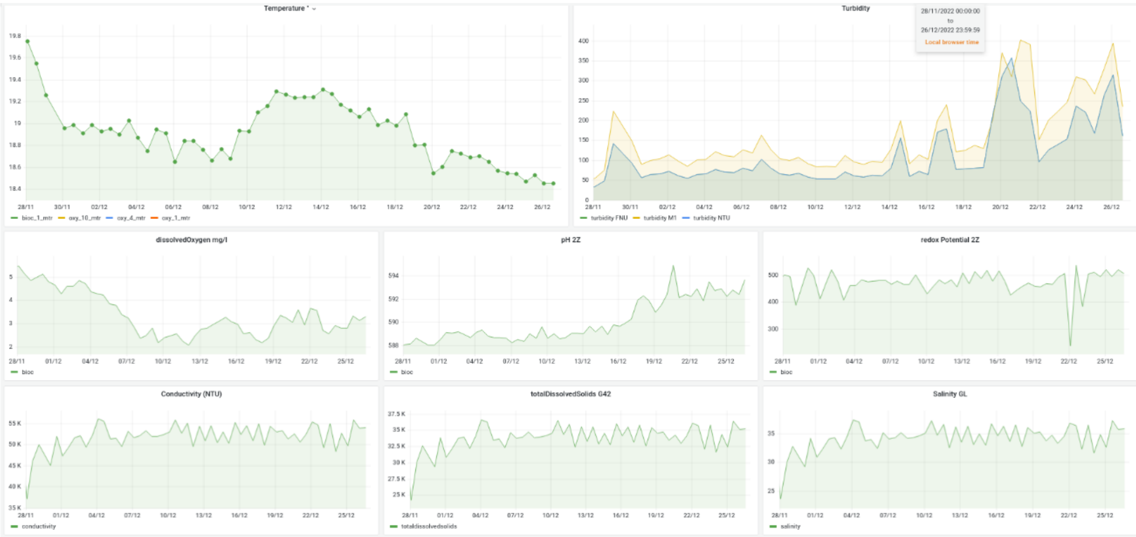

Figure 3. Environmental data collected in the iBOSS platform.

The preliminary analysis of the resulting data sets showed the expected seasonal pattern of temperature and the correlation with the dissolved oxygen concentration (Figure 4).

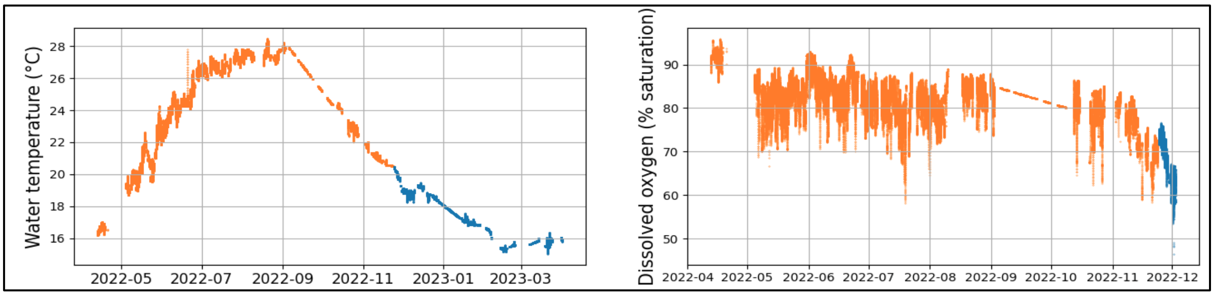

Figure 4. Seasonal pattern of T and DO during the evaluation period.

2.3.1.2 Behavioural data

The different tools used for behavioural data collection were also properly operating during the trial.

2.3.1.2.1 Echosounder

European seabass individuals approach the surface during feeding and therefore monitoring variation in the vertical distribution of the fish around feeding times (Figure 5) could facilitate the detection of any anticipatory behaviour and potentially also the satiation levels of the fish. The data were initially collected locally but specialized algorithms allowed the integration of the relevant data sets to the iBOSS.

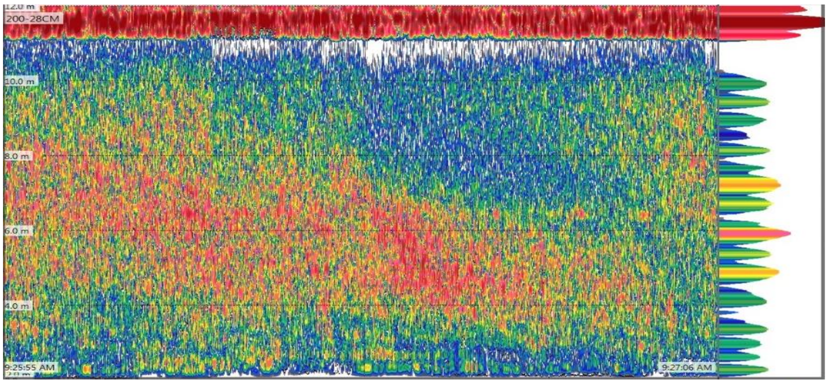

Figure 5. Vertical distribution of the fish as retrieved from the echosounder data.

The type of the equipment used however in this trial (single beam) and therefore the resolution in time and depth available in the collected data sets did not allow a detailed analysis that would provide useful information for feeding control.

2.3.1.2.2 Data from Motion monitoring

For the first time datasets with information on the fish motion (speed and direction) were collected for long periods of time during photophase. A typical data set with the mean individual speed is shown in Figure 6 where feeding period is also shown with the expected excitation during the event.

Figure 6. Mean values of individual speed during a period of six days.

2.3.2 Data analysis

2.3.2.1 Environmental - behavioural data correlation

As the collected data sets were for first time combining environmental and behavioural data, a first analysis was performed for possible correlations and potential changes in behaviour depending on changes in some critical environmental parameters, namely T and DO.

Figure 7 shows the distribution of the behavioural (above) and environmental data (below) between 12-04-2022 and 01-04-2023. The fish speed data set is divided into two phases: a “summer” period (between April 2022 and the end of November 2022) when fish are moving faster and a “winter” one (between the end of November 2022 and April 2023). Regarding fish direction (upper right graph) the fish are globally more aligned during the winter period.

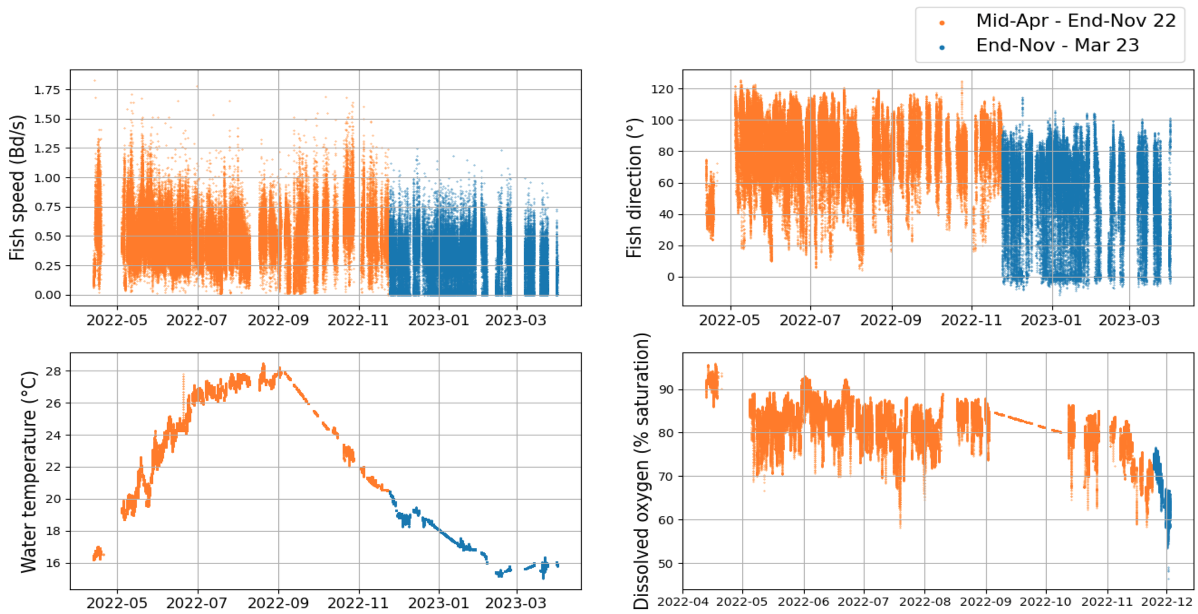

Figure 7. Fish speed and direction together with Temperature and DO during the demonstration period.

As a change in the fish speed curve for the summer period is observed, the data was analysed further assuming that an optimal temperature that maximizes the fish speed may exist. Indeed, it was observed that when the water temperature increases to a certain value, fish speed increases too. But when the water temperature continues to increase over this value, fish speed begins to decrease until the water temperature gets closer to the optimal value.

For this, the correlation was calculated between distance to optimal water temperature and fish speed for different values of candidate optimal temperature. A graphical representation of the results is shown in Figure 8.

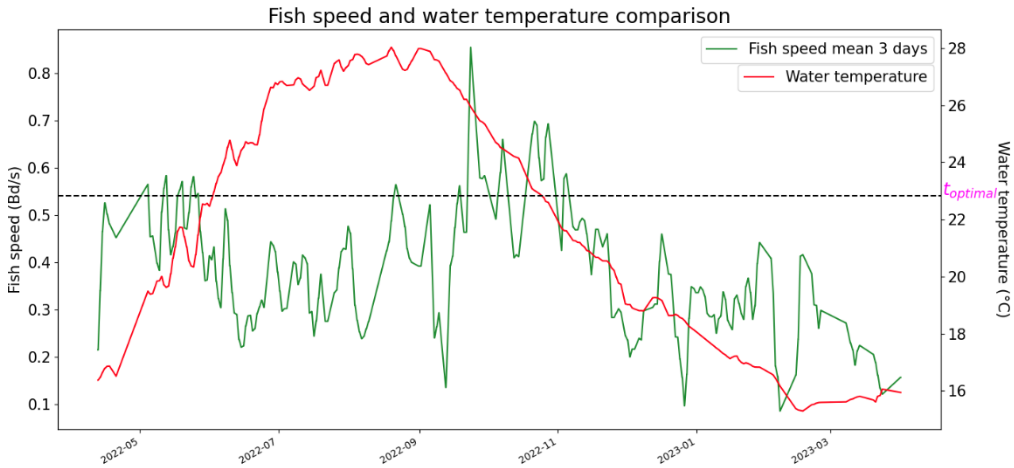

Figure 8. Definition of "optimal" temperature for E. seabass motion.

It is indeed interesting that such an analysis provided an optimal temperature value, at 23°C, that is close to the one defined in different experiments and is known from the literature[2].

2.3.2.2 Fish motion data analysis

From observations, we can distinguish at least three distinct movement patterns, the swarm behaviour, the polarized behaviour and the milling behaviour. The first one is usually apparent when fish are in a quite state (Figure 9, i), the second mainly appears as a response to a perceived threat (Figure 9, ii), and the last one appears when feeding is taking place (Figure 9, iii).

[2] Guy Claireaux, Christine Couturier, Anne-Laure Groison; Effect of temperature on maximum swimming speed and cost of transport in juvenile European sea bass (*Dicentrarchus labrax*). *J Exp Biol* 1 September 2006; 209 (17): 3420–3428. doi: https://doi.org/10.1242/jeb.02346

Figure 9. Variation in the swimming patterns of the European seabass in cages: i) Swarm behaviour, ii) Polarized behaviour, iii) Milling behaviour during feeding.

2.3.2.2.1 Polarized behaviour and turns

No significant difference was found in the number of turns and polarization events between feeding and non-feeding periods. This suggests that these two parameters (shown in Figure 10) are not informative around feeding times but could be useful metrics to quantify other behavioural responses, e.g., responses related to a perceived threat, such as predator attack etc. Further investigation is required.

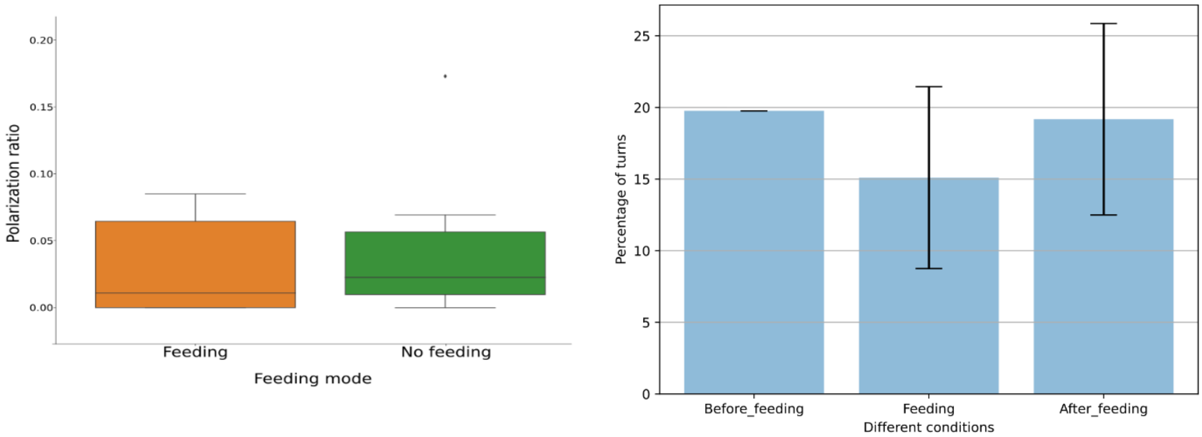

Figure 10. Variation in the swimming patterns of the European seabass crowd in cages: i) Swarm behaviour, ii) Polarized behaviour, iii) Milling behaviour during feeding.

2.3.2.2.2 Individual speed

There was a significant change in fish speed before and after feeding was initiated while there were differences in fish speed depending on the different feeding conditions tested. The differences were both in intensity and duration of the excitation (i.e., the period of increased activity) and depend also on the feeding conditions. In Figure 11, the mean individual speed is shown depending on feeding frequency and time of feeding for a time interval of 10 min before and after feeding.

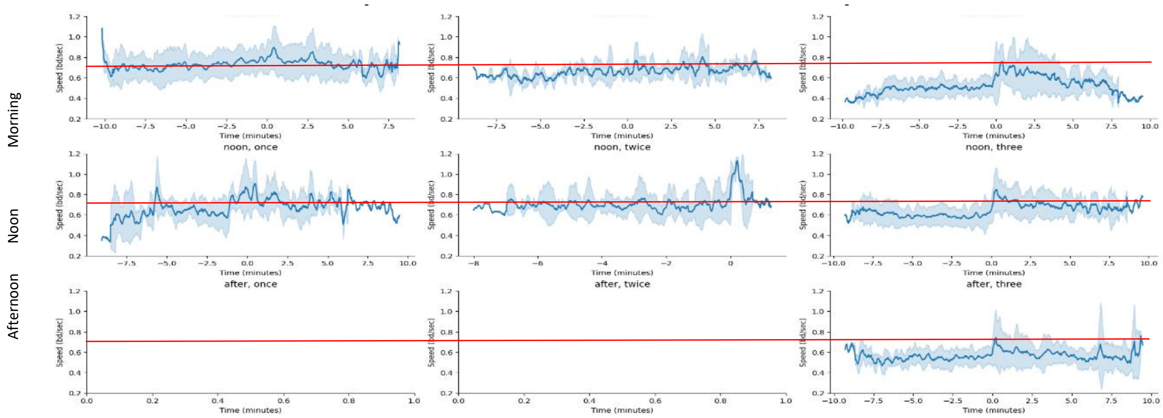

Figure 11. Mean individual speed (solid blue line) and standard deviation (cyan area) for different feeding times (morning, noon, evening) and feeding frequency (once, twice or three times per day).

Fish respond to both feeding time and frequency of feeding. When fed once during the morning, considered as standard feeding practice, and therefore serves also as control, fish were excited before feed delivery anticipating for feed, but the excitation was stronger when the single meal was delivered in the noon. As expected, fish speed and therefore excitation was lower when meal was delivered twice indicating probably reduced hunger levels. Fish activity was further reduced when multiple meals are delivered. While mean speed was almost continuously below 0.6 body lengths sec^{-1} when 3 meals were delivered it was almost continuously above 0.7 body lengths sec^{-1} when fed once in the morning.

A significant outcome of the demonstration was the observed changes in fish activity (increase or decrease) relative to the start of the feeding. And these changes differ depending on the feeding rate applied.

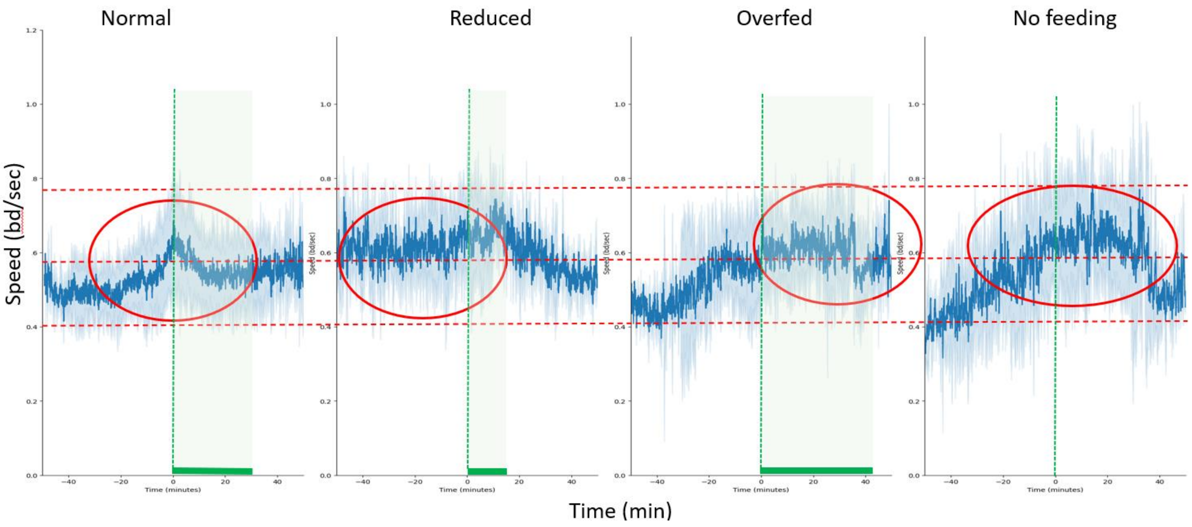

Figure 12. Mean individual speed (solid blue line) and standard deviation (cyan shaded area) for different feeding rates (normal, reduced, overfed, no feeding). The green shaded area represents the period of feeding. t = 0 is the start of the feeding.

In Figure 12 the average speed changes around the feeding start (t=0) which is shown. When normally fed (i.e., the delivered quantity is according to the applied feeding plan) individuals present a gradual increase in their speed that maximizes when the feeding starts followed by a gradual decrease. The speed, thus, exhibits a rather symmetrical pattern relative to the start of the feeding. This behaviour, that expresses the anticipation for feeding following habituation, may represent the standard pattern expected by E. seabass and matches well with observations made by farmers.

Under the reduced feeding period fish showed a higher activity before feeding (almost 0.1 body lengths sec^{-1} difference from the respective activity before feeding in the normal trial) while during feeding they remained excited until feeding stopped. This behaviour before feeding could be attributed to higher hunger levels.

On the contrary when overfed, fish expressed lower anticipatory activity, they showed a response during feeding by increasing their speed and after feeding their activity remained asynchronous without any gradual decrease. When no feeding was provided the mean speed showed an increase around the time the fish were used to expect feeding. However, the standard deviation is larger suggesting that the daily behaviour of the group deviates significantly from the average behaviour during fasting.

2.3.2.2.3 Speed asymmetry round feeding events

There is a distinct pattern of asymmetry of the speed values between the different feeding scenarios (Figure 13). When fish are fed normally the asymmetry is stable and close to 0, suggesting that the activity of the fish is symmetric around feeding time. In contrast, when fish are fed with reduced and excess feeding there is asymmetry in the activity around feeding times and the asymmetry is different between the reduced and the overfeeding. When fish are fed with reduced quantities show an increased activity prior to feeding in comparison to the overfeeding behavior, where fish show an increased activity after feeding. During no feeding, there is no specific pattern of asymmetry.

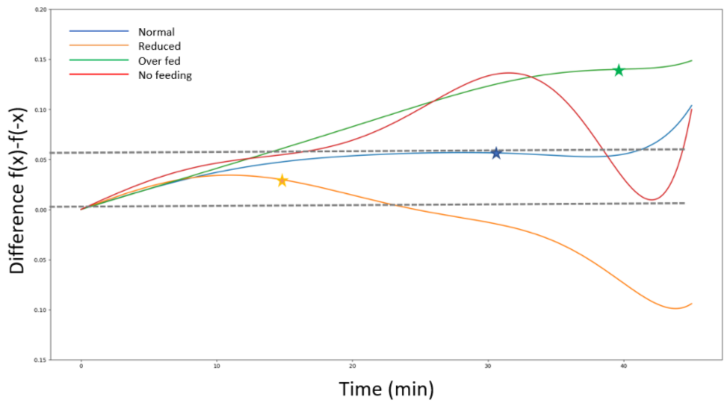

Figure 13. Asymmetry of the speed for different times and different feeding quantities. The start of the feeding is the axis of symmetry.

2.3.2.2.4 Feeding index

The "Feeding behaviour index" appears to be a sensitive parameter that variates for the different feeding trials (Figure 14).

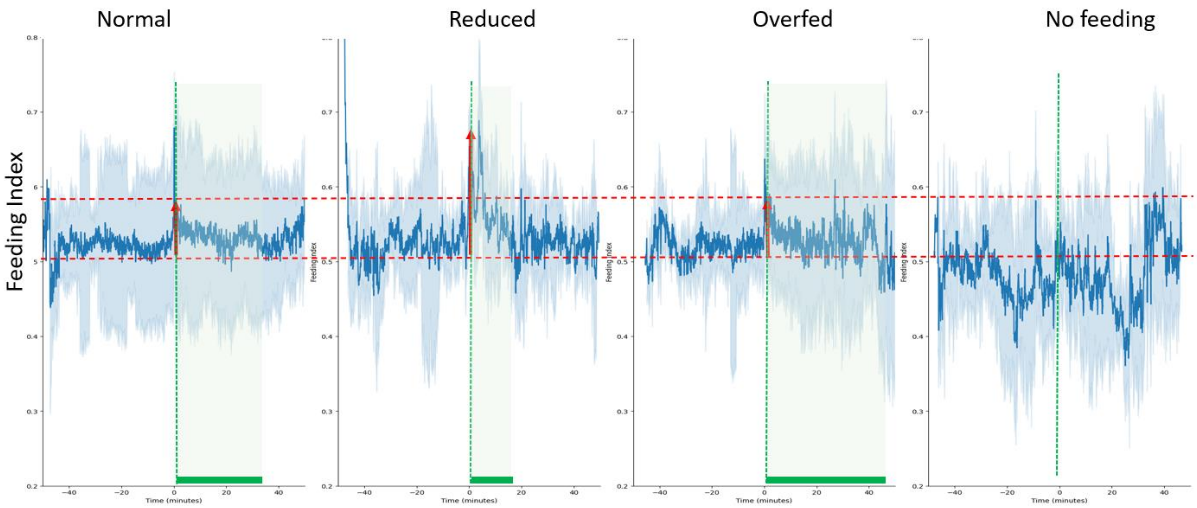

Figure 14. Feeding behaviour index in time for different feeding quantities.

During normal feeding, fish show an increased activity that decreases as time progresses. At the start of the feeding, the fish respond and increase their density abruptly, this appears as an increasing step. The excitation step is significantly larger when fish are fed with reduced quantities. When fish are overfed the excitation is smaller than that from both, the reduced and normal feeding trial. The duration of the excitation of the feeding behaviour index was larger during reduced feeding than in the normal, excess and no feeding, as shown in Figure 15.

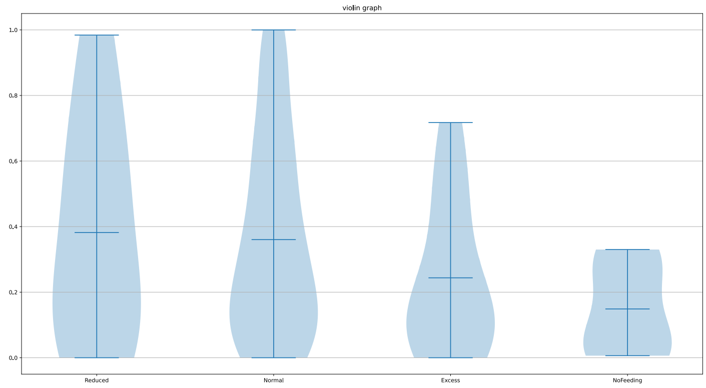

Figure 15. Duration of the excitation of the feeding behaviour index (expressed in ratio) for different feeding quantities.

Figure 16 shows the results from the gaussian mixture models, i.e., the clusters that appear for the feeding behaviour index and for the different feeding trials.

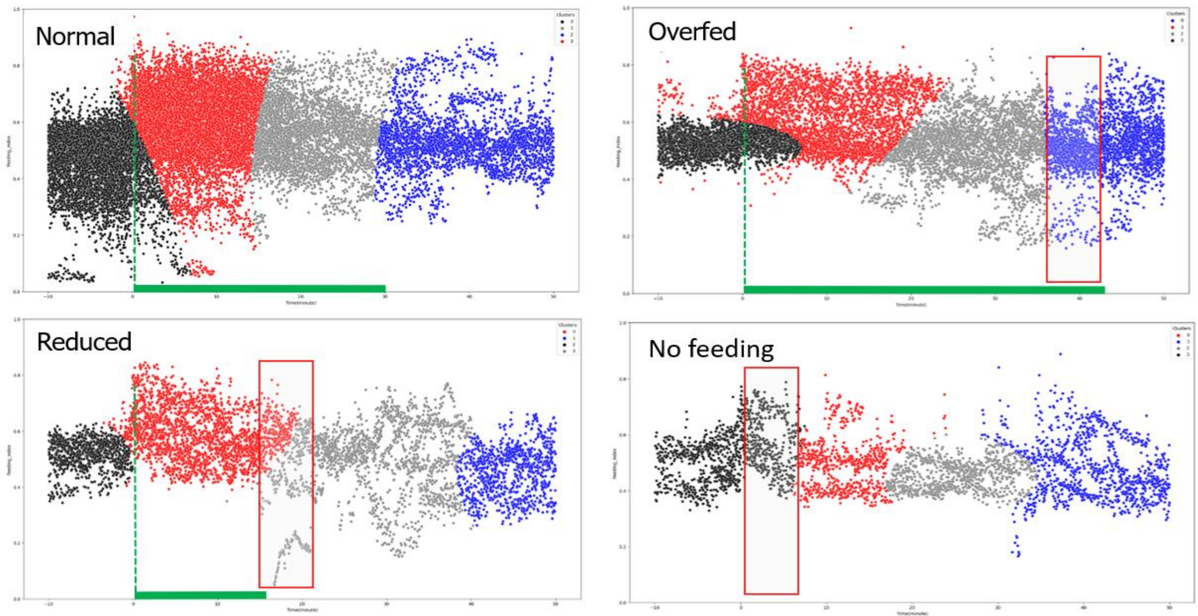

Figure 16. Feeding behaviour index in time for different feeding quantities.

For the normal feeding trial, we see that the black cluster corresponds to the behaviour that appears just before feeding (pre-feeding cluster). The red and the grey clusters describe the behaviour at the start of the feeding and close to the end of the feeding. The blue cluster shows the behaviour after feeding (post- feeding behaviour). It is interesting to notice that during overfeeding, the post feeding cluster appears during feeding progresses, indicating a decrease in the activity before feeding stops. The opposite happens during reduced feeding, i.e., the feeding clusters appear also after the feeding has stopped, suggesting that the fish remain active and possibly they are not satiated. Last, during fasting, the pre-feeding cluster is apparent even, after the time that the fish are used to expect feed.

The results of the prediction of the feeding behaviour index are shown in Figure 17, where the blue line shows the actual measurement, and the orange line shows the prediction. In all feeding trials, the model can successfully predict the feeding index value and the error of the prediction is 0.044 ± 0.036.

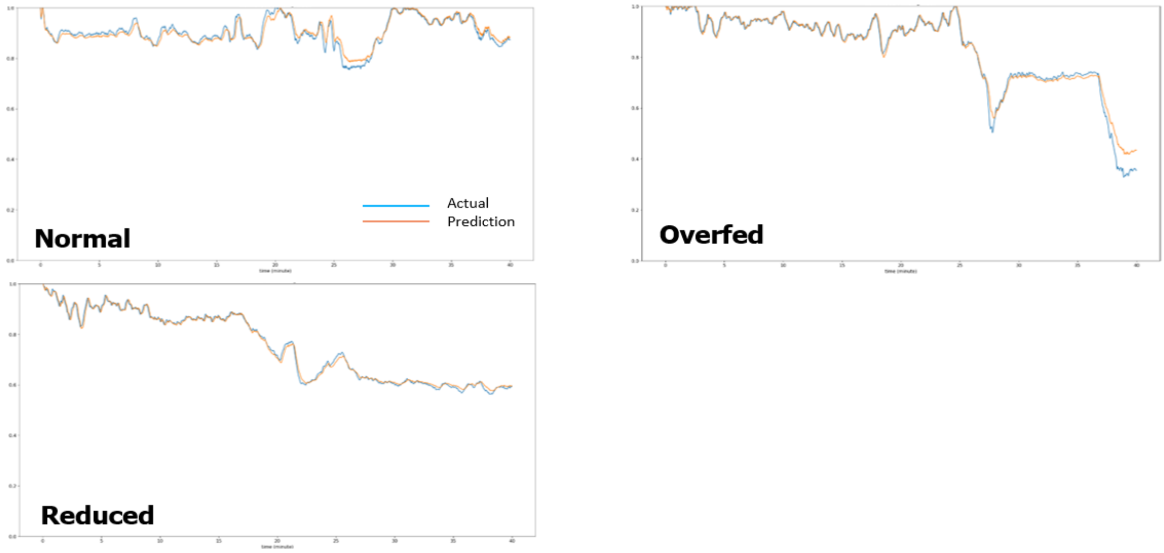

Figure 17. Actual (blue) and predicted feeding behavior index for the normal, reduced and overfeeding scenarios.

Results presented above, indicate that fish behaviour is sensitive to changes in the feeding plan. Several behavioural variables were tested here, group polarization, fish turns, group speed and the feeding behaviour index. The polarization and the fish turns did not show significant changes before and after feeding and further analysis is needed to ensure that these parameters cannot be considered as useful for studying feeding behaviour. In contrast, the group speed and the feeding behaviour index showed a high sensitivity in the different feeding scenarios and can be further considered as possible indicators for the state of the group in terms of their satiation levels. Below the possible ways that these variables could be used are discussed in order to define satiation thresholds and control the feeding in the cage.

2.3.2.3 Towards control feeding

Feeding control represents the main objective of the work performed in this demonstration. This ought to be achieved utilizing a wide group of parameters that, in this particular case, includes environmental and behavioural data. Hence, feeding control can be applied in two levels. The first is the real time control that allows the stop of feeding in case some parameter value exceeds predefined limits. The second is based in evaluation of a feeding event and its adjustment at a later stage.

Specific algorithms have been developed in the iBOSS platform that are able to control a feeder according to the parameters collected. Hence, based on the main environmental parameters (T and DO) threshold values were set to decide whether or not feeding could be performed or not. These values for the DO were 50% of saturation while for the temperature the lower limit for feeding was set to 12°C and the upper limit at 28°C. The limits are user-defined and in this case, respected the biological requirements of the E. seabass. Therefore, either during a feeding event or before it, when oxygen concentration drops below 50% saturation the operation of the feeder is forced to stop. The same occurs when the temperature value is outside the defined interval.

The same, real-time control may be applied using behavioural threshold values such as the duration of the excitation observed together with the value of the speed setting a relevant threshold as it seems that if speed exceeds 0.6bd/sec the fish are in an excited state and have higher hunger levels. Also, the value of the feeding index is based on the predictive model in order to decide when satiation levels are reached and therefore stop the feed delivery.

For a second level of control, parameters such as the symmetry of the motion and the clustering comparison may be used for the evaluation of the feeding event and subsequent adjustment. The symmetry index (i.e., comparison between the daily signal to the reference signals as shown in Figure 12) showing the increased activity observed prior to feeding in reduced feeding events compared to the increased activity after feeding associated to overfeeding behaviour, can provide insight on the level of feeding and create an alarm for the farmer accordingly. The same approach may be followed with the cluster comparison of the feeding index. By studying the duration and the time of the appearance of the different feeding clusters, information could be gained on the satiation levels of the fish during the day, and the feeding schedule could be adapted accordingly. Finally, the duration of the excitation can be also used as longer excitation times could be indicators of the satiation levels of fish in the day, so that feeding is adapted accordingly.

Although the behavioural parameters are not ready to be used in pilot/commercial set up the results obtained are promising. To achieve the goal for automatic control of feeding, the presented results need to be complemented with new results, after running long-term trials for all the different feeding scenarios. This will help increase the sample size and decrease the uncertainty of the behaviour of the parameters, as shown in the high standard deviation. Thus, additional data from long term trials and analysis of larger datasets may result in more robust threshold of these sensitive new parameters.

2.4 Conclusions, recommendation for application of the results in the industry

The information and results gathered from the demonstration, even though not directly applicable in an industrial setup shed light on the feeding behaviour of E. seabass. For the first time, a methodology has been created (a camera set up and the relevant algorithms) for the detection and monitoring of European sea bass in cages. It is worth noticing that the same setup and algorithm has been successfully tested for Atlantic salmon.

With the analysis performed it is now possible for the automatic detection of feeding events (start/end) while the newly introduced metric, the "Feeding index" can be used for automatic detection of satiation levels. A first estimation of satiation levels/thresholds using the mean speed and the "Feeding index" has been achieved.

Furthermore, the behavioural parameters' values have been correlated with environmental data deriving interesting results that support the validity of the method.

Finally, it has been demonstrated in operation for long time periods the integration of fish behaviour and environmental parameters through cameras, hydroacoustic, water quality sensors on a common platform (iBOSS) for an unprecedented interpretation of fish status and prediction of their needs. Thus, defragmentation and digitization of this information has been achieved in a single system that, to the knowledge of the authors, is the first that integrates data from cameras, sonar and environmental sensors to leverage predictions of the fish status in an open aquaculture cage.

2.5 Dissemination of the demonstration

Part of the results presented here have been already published in scientific journals (3 articles and 1 in preparation) while on various occasions has been presented in a scientific audience (5 presentations in EAS conferences) and as part of classes for Master in Biology students at the University of Crete (twice for the ACES Master course).

Some specific events were organized in order to present the results to the industry. In particular an online event was organized for the Technical Committee of the Hellenic Producers Organization, which represents the majority of Greek farmers in May 2023. In addition to this HCMR group was invited to present the results (including the ones presented here) in the farm managers of the Greek company PhilosoFish following the EAS 2022 event.

An invited talk was given during the iFishIENCi organized "Fish Farmers Training" in Hungary in January 2023 while the results were presented during the common event "Horizon for Aquaculture" in June 2021. Finally at a technical webinar "Promoting Aquaculture 4.0 at farm level" organized by the NewTechAqua project in June 2023.

Finally, the results of this demonstration trial were presented during the final public event of the iFishIENCi in Bergen Norway in June 2023. There were some requests from the industry following the event but are still at a discussion level.

Part of the results and in particular the algorithms for recognizing feeding behaviour are subject to copyright.

3 NORCE – Open Cage

3.1 Key Performance Indicators

In salmon aquaculture, open cage systems are by far the most extensively used and represent more than 90% of the production in Norway. in recent years, a wide range of emerging technologies have filled the market to provide an increased understanding and management control over the production through management systems, sensors, cameras, hydroacoustics, big data, and AI. However, these products often do not interact with other products which is essential for a robust decision support, for example efficient feeding requires the knowledge of water quality, fish behaviour and feed control. iFishINCi´s iBOSS is such a system (see public deliverables 2.5). In addition, iBOSS is designed to adapt to the available data inputs from sensors a site has available, gathering into one cloud-based system that can then optimise management and control features to maximise feeding efficiency. In addition, the Fish-Talk-To-Me feeding behaviour algorithms developed for seabass (above) has been tested in salmon to allow the behaviour of the fish to regulate how and when to feed. In this demonstration, we are testing if a standard feeding camera can be used with the algorithm.

The key performance indicators (KPIs) for this demonstration were as follow:

- Integration of standard water quality data sensors into iBOSS.
- Adapt Fish-Talk-To-Me feeding behaviour algorithms for salmon standard feeding camera.

3.2 Demonstration Methodology

The open cage site for the Norway salmon demonstration took place at Ovum´s grow-out sea cages located at 62,6275° N, 7,192817° Ø, Gjermundnes 13852. Sea locality in Vestnes, Møre and Romsdal, Romsdalsfjorden, Norway. The cage is equipped with a pneumatic feeding system and lice skirt. The cage (circumference 125m, diameter 40m, depth 30m) contained 150 000 Atlantic salmon at an average weight of 2,05 kg and fed 3800 kg per day.

Figure 18. NORCE Open cage Atlantic salmon demonstration site in Norway.

3.2.1 Connection to iBOSS

As most salmon production systems, the demonstration site is remote and communication to the cloud can be variable and relies on stable G4 or G5 network. In this demonstration, the Imenco camera and sensors from the open cage were connected to Egget´s control system from Guard through Bluetooth to a dedicated subnet. Guard together with iTeam setup a VPN so that Oxyguard through Cobália could relay sensor data to iBOSS for real-time monitoring.

3.2.2 Camera and installation in open cage

Figure 19. Imenco Gemini feeding and inspection camera.

In this demonstration, the Imenco Gemini standard feeding and inspection camera was installed. The camera is fitted with double IP colour cameras, 360 degree viewing angle, one on top and one on bottom. The camera installed in the open cage was fitted also with oxygen and temperature sensors and placed 5m under the feeder. This camera was chosen as it is a standard feeding camera used in the industry and the same feeding camera used in the semi-closed system demonstration in Egget (public deliverable 3.3), allowing direct comparisons between the open cage and Egget without additional modification of machine vision algorithms.

3.2.3 Video collection and testing Fish-Talk-To-Me feeding algorithm

In this demonstration, the Imenco camera video stream from the open cage as connected to Egget´s Guard network through Bluetooth to a dedicated subnet together with the sensor data. In the case of the Fish-Talk-To-Me demonstration, the video data is not streaming to iBOSS for monitoring, but rather videos were collected to test the smart feeding algorithms developed by HCMR. For this, Guard together with iTeam setup a VPN so that NORCE could access the video stream and record specific test periods to verify the adaptation of the algorithm to salmon in sea cages.

The camera was installed July 15 and remain until Oct 15, 2023. The camera was placed 5m under the feeder with one camera facing upwards and the bottom camera facing horizontally. Videos before, during and after feeding were tested to demonstrate the application of the feeding behaviour algorithm in salmon open cage systems.

3.3 Demonstration Results

The results of this demonstration are ongoing and will be completed in September 2023.

3.3.1 Integration of standard water quality data sensors into iBOSS

It was demonstrated that real-time water quality data can be streamed to iBOSS dashboard from the open cage site, through Guard, to Cobália and then to iBOSS cloud.

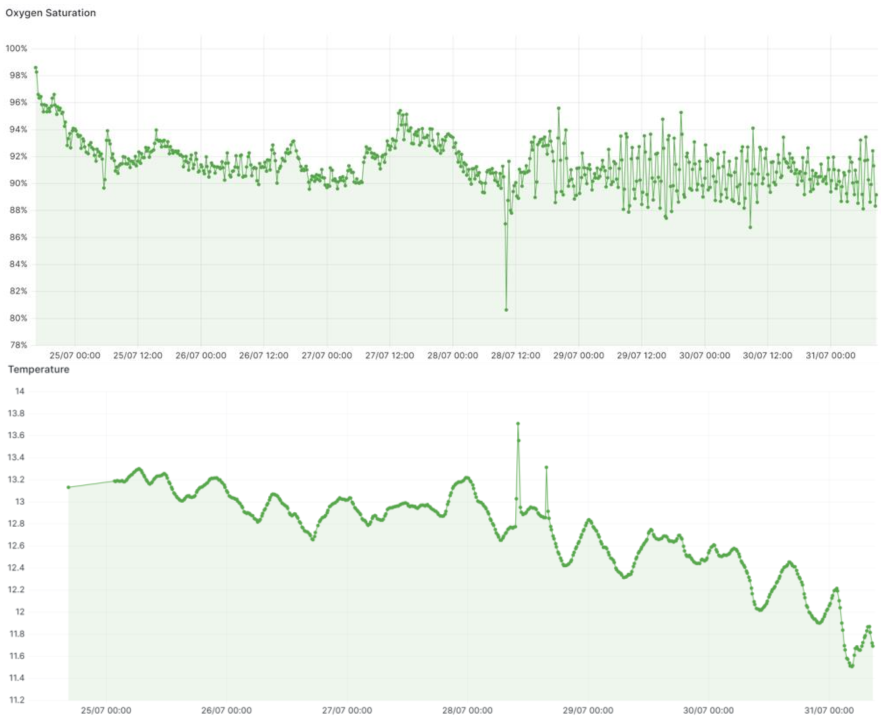

Figure 20. Screenshot from sensor data (O2 and temperature) streaming to iBOSS.

3.3.2 Video stream, collection and algorithm adaptation

Here it was demonstrated that the video could be streamed and stored for future analysis. Videos were captured before, during and after feeding (see Figure 21) to test the feeding behaviour algorithm developed in European seabass.

Figure 21. Screenshot of video streaming of salmon from open cage, before, during and end of feeding.

Employing the fish behavior algorithm developed for E. Seabass, salmon show significantly higher speeds before feeding, and the speed value per se, and could be used as an indicator for hunger and possible threshold values could be potentially defined (Figure 22).

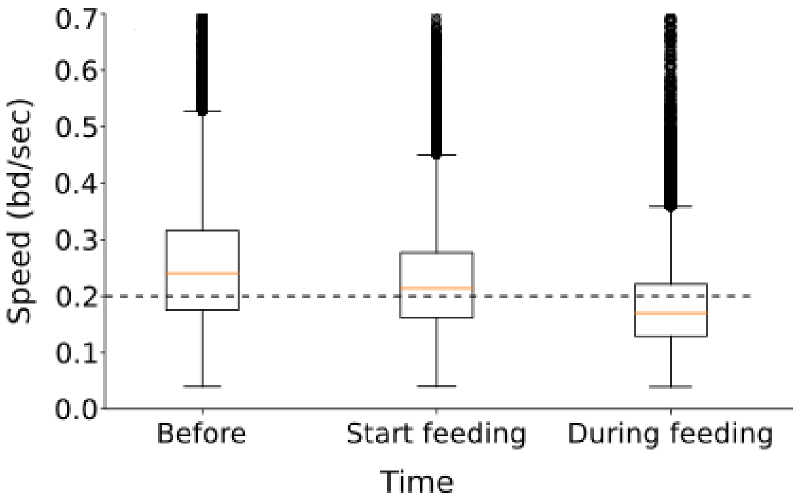

Figure 22. Fish speeds before, at start and during feeding analysed by Fish-Talk-To-Me algorithm

3.4 Conclusions, recommendation for application of the results in the industry

Here it was shown that iBOSS is able to incorporate sensor data from different suppliers demonstrating the flexibility of the system to adapt to the existing systems that the fish farmer has. This will give an important tool for farmers that presently get data from a set of suppliers individually but not a system where this can be integrated and used together to make more robust decisions on for example how to optimally regulate feeding.

Regarding the cameras in the sea cage, there is considerable fouling of the top camera in the sea cage so it might be important to either design an algorithm that is not based on a facing up camera, or alternatively have a simple robotic feature that can easily access the camera for cleaning or periodically removal from the sea to maintain a clean lens. It is also clear from this and other demonstrations that the machine vision must occur at the edge to ensure rapid responses to changes in behaviour and to avoid communication constraints for continuous video feed.

The adaptation of the fish behaviour algorithm developed for E. seabass was successfully used in salmon to detect speed differences surrounding feeding events that suggest that this together with additional adaptation to fish density and polarization in the school near feeder would allow for a robust tool for more efficient feeding applications in salmon production.

4 Dissemination of the demonstration

- Hungarian (MATE) event: The adaptation of iBOSS and Fish-Talk-To-Me in relation to salmon open cage production in Norway were presented at the Fisheries and Angler Specialists Meeting in Gödöllő, Hungary on 26th. Of January 2023. Over 200 participants from aquaculture companies attended the event. The lecture covered the potential uses of these products in salmon production, but also how they could be adapted to different types of fish production systems.
- 23rd Annual Embedded Vision Workshop in Vancouver, Canada June 19, 2023. Over 70 participants attended the event. The iBOSS and Fish-Talk-To-Me was presented and in particular the machine vision challenges and needs associated with behavioural analysis in different salmon production systems to enable robust edge control systems.