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Putting fish in the tank: An Agent Based Model with flow interaction

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***Abstract*— An Agent Based Model (ABM) coded in Matlab is described in which fish (or other marine creatures) are introduced into the 3D underwater flow domain modelled by TELEMAC. The released fish individuals are preassigned a set of physiological characteristics and behavioural traits and are then free to swim and interact with each other in the flow field environment. The model is particularly designed to model potential impacts on marine organisms due to anthropogenic induced stresses, such as caused by underwater noise and/or interaction with power station intakes or hydro-power turbines. A description of the algorithms is given followed by an example of how the ABM can be used to assess the potential stress exerted on fish populations due to underwater noise generated from pile driving during construction of a hypothetical offshore windfarm. Future developments of the model will also be described.**

I. INTRODUCTION

Since the 1970's, the growth of micro-processing power has led to the development of ecological models that consider a population from the point of view of the individuals instead of the more classical top-down empirical models based on demographics [7]. Such models are known as Agent Based Models (ABM) or Individual Based Models (IBM).

A well-known example of an ABM is called *Boids*, which was developed in 1987 by Reynolds [13] to simulate the flocking behaviour of birds. This model demonstrated how a few simple rules (refer to Section II.A) could produce realistic emergent patterns of flock-like behaviour. The qualitative realism of this approach meant it has been used in Hollywood movies such as Tim Burton's film Batman Returns (1992).

Whereas the classical top-down modelling approach is useful for assessing observed trends in populations, the ABM approach, whereby a set of individuals each with its own set of prescribed behaviours and responses with no overarching rules on the population, has potential to make predictions into the future [7]. Combined with an increase in the requirement for ecological assessments as part of Environmental Impact Assessments (EIA), ABM models like *Boids* offer potential in simulating impacts on species populations in response to shocks to the environment, be they anthropogenic or natural in origin.

Recent research at HR Wallingford has investigated how the ABM approach could be used to assist in the assessment of the impacts of underwater sound on fish in the marine environment [15]. In the marine industry, regulators and decision makers have become more aware of the importance of underwater sound and its potential impact on animals. For example, underwater sound has been shown to have detrimental impacts on fish physiology by increasing blood cortisol (stress hormone) levels [21], increase heart rate [6] and inducing temporary hearing loss [18] [2] [20]. On a behavioural level, sound exposure in fishes can reduce anti-predator responses [3] [19], change swimming patterns [8] [9] and alter group behaviour [4]. Additionally, the impacts of sound exposure can be more severe in individuals of low body condition [12].

Guidelines now outline how much sound emitted during marine construction works is acceptable, what the potential effects are and how it can be monitored and mitigated [1] [14]. This has resulted in the requirement for studies of the impact of underwater sound on organisms that can be used for EIAs as regulators require better data on the impacts in order to properly assess potential effects.

This paper describes an ABM model developed at HR Wallingford called *HydroBoids*. The model algorithms will be described followed by a description of case study where data on fish behavioural in response to pile driving noise were collected and used to parameterise the model. Initial results from the model will also be presented.

II. MODEL DESCRIPTION

In *HydroBoids*, numerous fish individuals (or other mobile marine creatures) are represented as moving Lagrangian points in a three dimensional underwater space which are carried (advected) by the Eulerian hydrodynamic flows calculated by the TELEMAC modelling system [10]. A flow result file must first be generated using TELEMAC which can be either time varying or steady state and either 2- or 3-dimensional.

The fish are placed into the model domain defined by the TELEMAC geometry file within defined polygon regions and with a given initial horizontal and vertical separation, thus defining the total number of fish in the calculation. Each placed fish is assigned characteristics or traits that are both *physiological* (e.g. swim speed) and also *behavioural* (e.g. schooling).

The fishes physiological characteristics are applied across the population as normally distributed values about a mean with a specified standard deviation. The ability to model this type of inter-population variability is an important reason why the ABM approach is useful for modelling ecological impacts since not all the individuals will respond in the same way or be affected to the same degree [1].

A. Swimming and flow interaction

The main physiological characteristic is the fish swim speed which is assigned to each individual in the population from a normal distribution of speeds (i.e. some fish can swim faster than others as would be the case in reality). Each modelled species is also assigned a maximum acceleration to prevent an individual from changing speed and direction too abruptly given its mass and momentum.

If the swim speed for a particular species is set to zero, these individuals are effectively Lagrangian drifters that are advected purely by the flow. Turbulence can also be applied using a random walk model with constant viscosity in the horizontal direction and a mixing length formula in the vertical direction, which effectively turns the simulation into a classical Lagrangian dispersion model.

The fish move in 3D underwater space, therefore in general those individuals near to the bed will be subjected to slower flows than those near the surface. If a 2D model result is used then the vertical flow profile is assumed to be logarithmic and hence the fish near the bed will be advected less than those in the surface waters. If a 3D hydrodynamic file is used then the flows are interpolated directly at the fishes 3D location.

As shown in Figure 1, fish that are assigned a swim speed in the model move under their own propulsion in addition to the flow advection according to a *correlated random walk* (CRW) algorithm [5] [22]. A CRW is a pattern of movement where the direction of the fish at the current time step is dependent on the direction at the previous time step. A directional error term, or *directedness*, is added at each time interval chosen randomly from a normal distribution with a predefined standard deviation. Assuming no other influences on movement, if the directedness term is zero, the correlated random walk is simply a straight line and if the directedness term is maximum (180°) then the correlated random walk is a conventional uncorrelated random walk [22]. The directness parameter has both a horizontal (azimuth) and a vertical (elevation) value, the latter usually being smaller since fish tend to move in the horizontal plane more frequently.

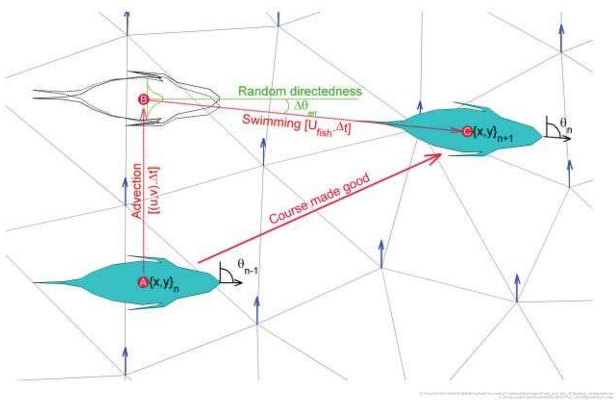

Figure 1: Schematic of 2D fish movement using a correlated random walk and advection by hydrodynamic flows (indicated as blue vectors on at triangular mesh nodes)

Thus to define a new fish position at each step in a correlated random walk one only needs 1) the present fish position, 2) its previous direction, 3) the angular error in the present direction (directedness), and 4) the swim speed, or distance travelled, during each step [22].

Correlated random walks are a good analogy to animal movements because the angular error at each step can represent a variety of unknown external influences on the ability of an animal to continue a course on a particular bearing. Examples of such influences are rough terrain, complex and chaotic small scale water movements, inaccuracy of any navigation method being used, or any other dispersion or displacement made at a smaller scale than explicitly modelled.

After the new position of each fish has been calculated the model checks that this position is valid (i.e. within the model domain and not on dry land). If not, the fish maintains its position from the previous time step and rotates its direction 90 degrees to the left or right (chosen randomly).

B. Behavioural traits

Behavioural traits are also assigned to the fish depending on particular characteristics of that species, which may include the following:

- Schooling
- Migration
- Predator-prey interaction and scavenging
- Response to external stimuli

Each of these behavioural traits is described below.

1) Schooling

HydroBoids uses the *Boids* method of Reynolds [13] to simulate schooling behaviour. Three simple rules are prescribed to all the individuals in the model to control schooling behaviour as shown diagrammatically in Figure 2. These rules are:

1. *Collision avoidance* (or *separation):* Avoid contact with neighbours and obstacles
2. *Velocity matching* (or *alignment):* Match the general speed and direction of neighbours
3. *Flock centring* (or *cohesion*): Steer towards the centre of surrounding neighbours

A modification of the original method is to include a *probability of schooling* (refer also to Section C) which introduces some randomness into the schooling behaviour to take into account unknown causes of variability that are not modelled, effectively allowing the school to become less rigid in pattern. Setting the probability of schooling to a value of one returns the schooling algorithm to the classical *Boids* approach, whereas a value of zero effectively turns of schooling behaviour.

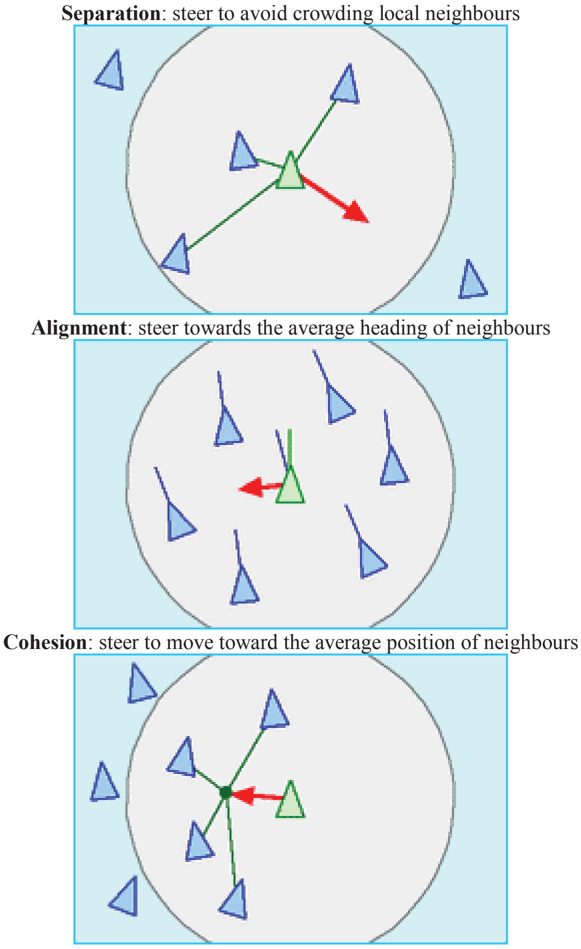

Figure 2: The three rules of the *Boids* method of schooling behaviour (adapted from http://www.red3d.com/cwr/boids)

2) *Migration*

The instinctive behaviour of a some fish species to travel from their current location to a predetermined distant location, such as annual spawning grounds, is included in a simplistic way by defining one or more waypoints which the individuals are explicitly programmed to head towards. The justification for using such a heuristic method is that, for many species or situations, the exact method or behavioural cue that the individuals use to find their way along a migration path is not known to science. All that is known is that the animals somehow find their way to the same location year after year. Therefore the migration path is explicitly defined as shown in Figure 3 which shows migration of fish up the Mersey Estuary, with the tidal flow modelled using TELEMAC-2D. Of course if a behavioural cue is identified for any given species then this can be readily modified in the code.

As with schooling, a *probability of navigation* is applied which means each fish species has a user specified probability (between 0 and 1) which is tested for each fish at each model time interval to decide whether it steers towards the next waypoint or not. A probability of navigation value of one means that the probability will always be met and hence the fish will immediately change their heading for the next waypoint. A probability of zero completely turns off migration behaviour. Fractional values between zero and one mean that some of the fish population will be chosen at random to change direction towards the next waypoint. For example, a probability of 0.25 means that, on average, 25% of the fish population will be chosen to navigate. When selected, the fish also have their speeds returned to normal (if not already so) which means that any other previous fleeing response to a stimulus or predator is reset. The fish that are not chosen carry on with their correlated random walk or may be selected to perform another behavioural activity (e.g. schooling).

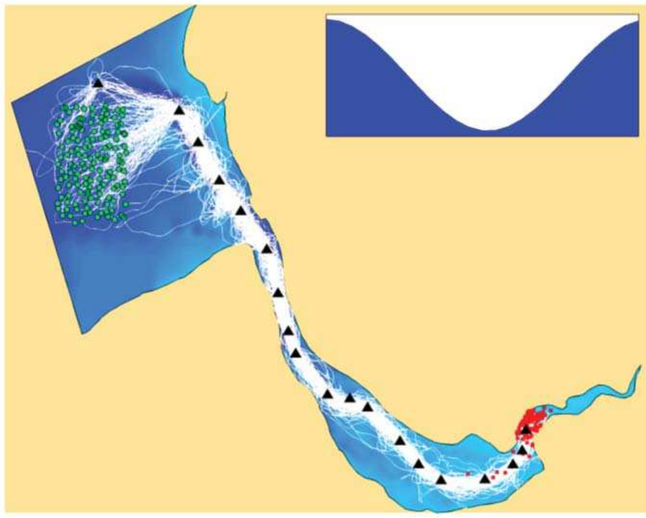

Figure 3: Example of modelled tracks (white lines) of fish navigating up the River Mersey (UK) using the waypoint method during a single tide modelled by TELEMAC2D. The fish start and end positions are represented by green circles and red squares respectively.

3) *Predator-prey interaction and scavenging*

If more than one species is introduced into the model flow domain simultaneously, it is possible to assign predator-prey interactions between them. For each species, a list of prey species is prescribed, with the list empty for those that do not predate. If the predator species comes into a specified target range of one or more of its prey (synonymous with the sensitivity of the eyesight of the predator) then it swims towards the closest individual at a defined *chase speed*. This is shown schematically in Figure 4. If the predator then reaches a distance closer than a second threshold range it is assumed that it cannot see the prey anymore and so carries on moving according to a correlated random walk. Similarly, the prey are assigned a range at which they can detect predators. If a predator is within that range they swim directly away from the predator at their own predefined chase speed. Once a chase has finished, i.e. when the prey has either been eaten or escaped, the individuals carry on at chase speed until they are selected to navigate when their speed is reset to normal.

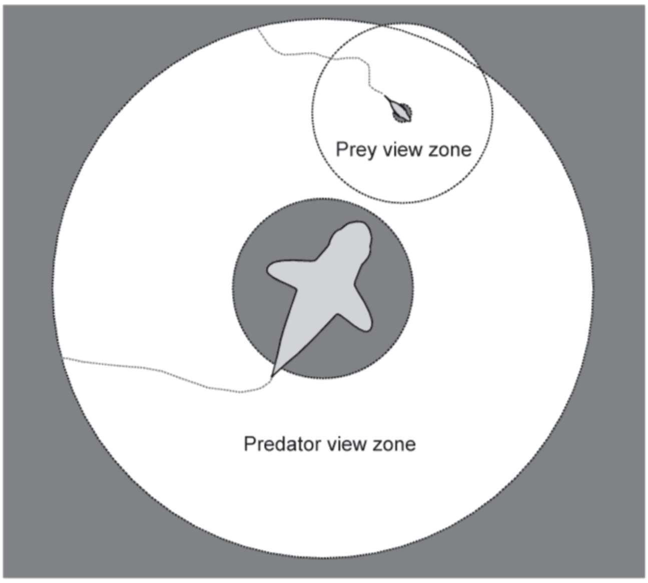

Figure 4: Predator-prey zones of detection. Dark grey zones are out of view. In this example the predator shark in the centre has detected its prey, but the prey is unaware of the danger.

Feeding of fish that do not predate on other modelled fish species (for example those that feed on phytoplankton) can be parameterised using a *probability of feeding*. In this case, the selected fish change speed randomly to a fraction of their average swim speed (chosen randomly) to simulate scavenging behaviour.

4) Response to external stimuli

The individuals within the model can be programed to respond to a stimulus such as underwater sound or a pollutant tracer. The stimulus field is input directly from the TELEMAC hydrodynamic file as a variable and can be a time varying field or constant.

Upon exposure to a stimulus above a specified certain threshold, the swim direction of the fish is changed to be either directly towards or away from the source (e.g. a pile driver emitting noise) or, alternatively, up or down the gradient of the stimulus field (e.g. a pollutant tracer). For example a fish may respond to a sound level above 140 decibels and swim directly away from the noise source. Another example is shown in Figure 5 where fish have been assigned a thermophilic response to a thermal plume modelled in TELEMAC-3D. The fish therefore swim up the temperature gradient towards the plume discharge and against the flow. The direction of each fish is further modified as they move due to the correlated random walk.

As well as changing direction, each fish affected by a particular stimulus is assigned a new swimming speed selected randomly from a normal distribution of fleeing speeds as a multiple of its usual speed. Swimming speed reverts to the fish's usual swimming speed the next time it is selected to navigate, which again is decided each time interval based on the *probability of navigation* (see Section 2).

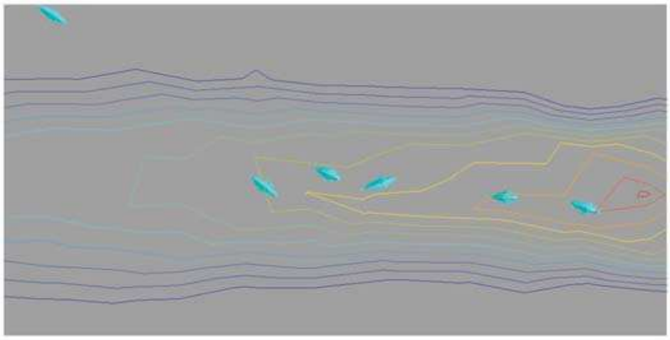

Figure 5: Fish parameterised with a thermophilic response to a modelled thermal plume discharge in TELEMAC-3D (indicated with coloured contours).

C. Probability and decision making

A fundamental problem with any ABM is how to implement and validate a numerical method for decision making in animals. For example, will a fish decide to navigate towards a spawning ground in preference to staying with the school? The basis of such choices will ultimately depend on which is the best in terms of increasing the *fitness* of the individual animal in question [1]. Data on this problem is both difficult to obtain and the number of decisions that require parameterising can be many. Keeping the number of decisions to a minimum is therefore important, although too few will make the simulation unrealistic.

In *HydroBoids*, decisions are parameterised heuristically using weighted probabilities. Probabilities (i.e. fractional values between zero and one) are set by the user for each of the behavioural traits, i.e. navigation, schooling, feeding and responding to a stimulus. These probabilities are specified in such a way so that they add up to less than or equal to one. At the beginning of each time step, an imaginary dice (i.e. a random number generator) is rolled for each fish to determine which activity it will perform during the time step. If none of the activities are chosen, then the fish carries on with a correlated random walk.

This process is modified if the fish individual finds itself in a situation involving high risk such as a dangerously high stimulus above a specified threshold (e.g. a loud underwater noise level) or in the presence of a predator that is within a specified range. In such instances the fish is assumed to be in *panic mode* and the probability is ignored and the individual responds regardless.

III. Model Application

The model has been developed as part of ongoing research at HR Wallingford in collaboration with the University of Exeter. Calibration of fish behavioural characteristics and stimulus thresholds is an important area in which data are currently lacking. To address this, experiments have been carried out in a former ship building dock (dimensions 90 x 18 x ~2m deep) in which electronically tagged fish were subjected to intermittent pile driving noise over a six day period (Bruintjes et al, in prep.). A brief summary of the experiment is given here.

Trials were performed over 6 days, during which pile driving was carried out twice daily for two hours, with a one hour pause between the two periods. A ~1.6 kJ pile driver hammer was used to strike a 7.5 m long 0.17 m diameter pile at a strike rate of 10 strikes per minute. Equal numbers of tests were performed with the pile located at each end of the dock (see Figure 6). The southwest end of the dock was shallower, with a depth of approximately 1.7 m as opposed to 2.6 m at the opposite end. At the deeper end there was also a deeper area near the original entrance to the dock which was cordoned off with a net so fish could not enter it. In each trial the movements of between 14 to 24 (~18 on average) acoustically tagged cod were measured. The batches of cod were reused for 3 piling periods, to give a total of 71 cod tested.

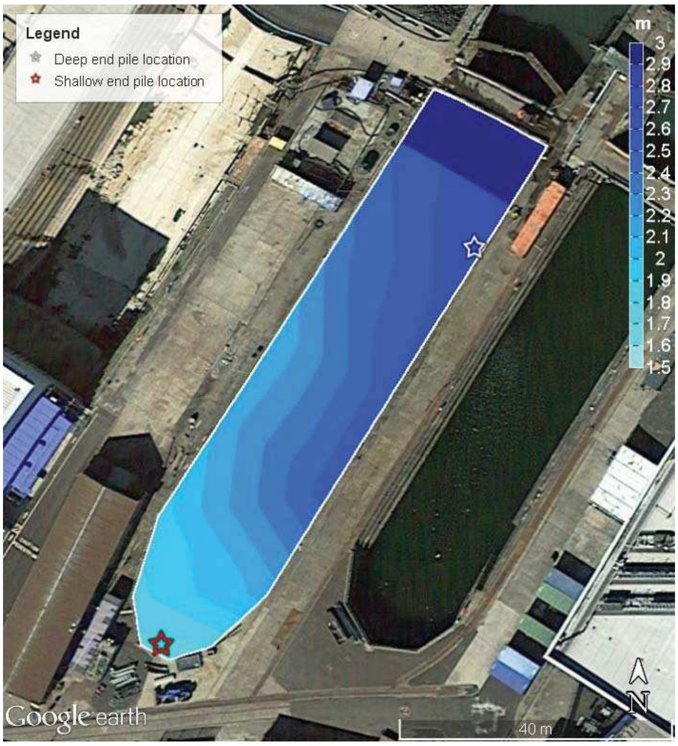

Figure 6: The ship building dock in which fish tag measurements were made (Blyth, UK) with water depth contours drawn. The pile driving was carried out at the two marked locations.

During the experiments to sound field was also measured throughout the dock at 27 locations using a hydrophone. The RMS sound pressure fields for the deep and shallow end pile locations are shown in Figure 7.

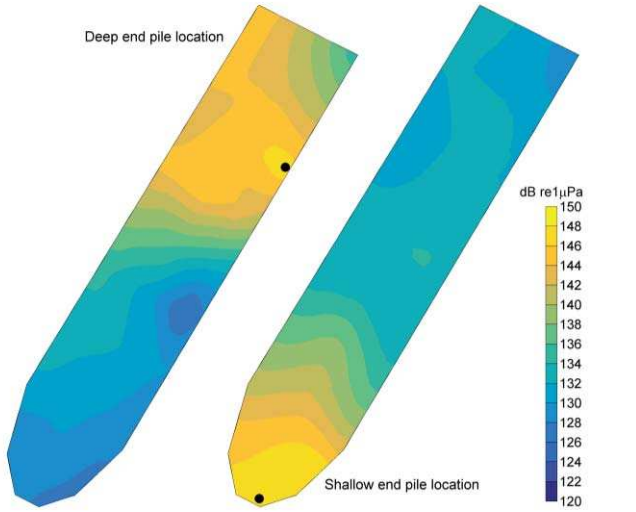

Figure 7: RMS sound pressure measured during pile driving at the deep and shallow end pile locations

The average fish positions for each of the experiments are shown in Figure 8 and Figure 9 for the deep and shallow end pile driver location scenarios respectively. Also plotted on these graphs (in grey) are the results from the *HydroBoids* model. The model was run ten times for each pile location scenario and the standard deviation of all the results are plotted as error bars. Parameters for the model setup are summarised in Table 1. As can be seen, the measured distances of the fish from the piles are largely contained within the standard error of the modelled distances which suggests that the model is capturing the variability in the data.

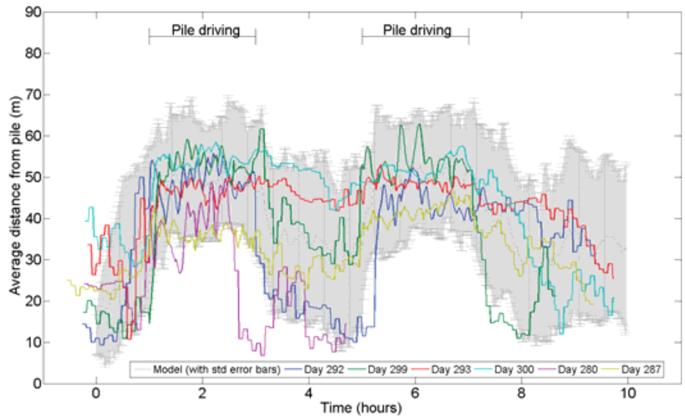

Figure 8: Measured (coloured lines) and modelled (grey error bars) distances of fish from the pile during piling at the deep end of the dock. Periods of pile driving are indicated.

Figure 9: Measured (coloured lines) and modelled (grey error bars) distances of fish from pile during piling at the shallow end of the dock. Periods of pile driving are indicated.

Interestingly, the model appears to give better comparison for the deep end pile location. It appears that the fish prefer to stay in deeper water after they have experienced the piling sound and therefore do not return as quickly as in the model. This possibly indicates that they have a memory of the previous piling event. Another finding was that the model fit improves if a low *probability of responding* to the stimulus of just 5% is used. So it appears that the fish take time to decide whether to move away from the noise. These are both interesting findings and will be investigated further in a future paper.

Parameter	*Value*
Swim speed range (normal)	0.2 to 0.3 m/s
Maximum acceleration	0.5 m/s^2
Fish time step	2.5 s
Number of fish per run	24
Directedness (horizontal and vertical)	3° & 0.1°
Probability of navigation	5%
Probability of schooling	50%
School separation (min/max)	0.2 - 0.5m
Probability of feeding	5%
Sound threshold of potential response	135 dB re1μPa (+/-3dB)
Probability of responding to stimulus	5%
Swim speed multiplier during stimulus	2.5
Stimulus response action	Flee directly from source

Table 1 – Summary of *HydroBoids* model parameters

IV. FUTURE WORK

HydroBoids is an ABM that has been around for several years but has recently undergone significant development. Recently the model has been used in a collaboration between HR Wallingford and the Zoological Society of London to locate the spawning grounds for Smelt in the Thames estuary [17]. Currently, another collaboration with Nottingham and Southampton Universities is underway to use the *HydroBoids* model to investigate the interaction of eels with hydro-power turbines and fish passes on an EPSRC funded project titled *Vaccinating the Nexus* [16]. New algorithms associated with avoidance behaviour of eels and other species will be incorporated into the model code during this collaboration.

The model is presently coded in Matlab. This enables changes to be made to the software relatively easily and results can be visualised *on-the-fly* which allows for rapid development with good quality control. In the future when the software has become less developmental, the code could be translated in Fortran and incorporated in the TELEMAC suite. This would be preferential since the code would be more computationally efficient and would potentially enable two way coupling of interactions between fish and the hydrodynamics and/or tracers such as to simulate the depletion of algal food supply.

V. CONCLUSIONS

Here an Agent Based Model has been described which has potential to assist in the EIA process for marine construction works to assess potential impacts on fish populations (or other marine wildlife). Early results show that the model can offer useful insights into population dynamics and is easily adapted to a wide range of scenarios. The coupling of the flows with TELEMAC is a novel improvement to standard ABM models which generally do not consider the flow field.

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