Monitoring Strategy of Bio-Colonisation on Mooring Systems based on a Qualifying Sea State: Sensing Network Efficiency using Conditional Entropy Metric

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Sensing Network Efficiency using Conditional Entropy Metric

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Abstract

Bio-colonisation is shown to affect the ageing of materials and the behaviour of offshore structures and consequently their resistance to extreme events or fatigue life time. It was recognized in the 70's that bio-colonisation might change the hydrodynamic loading due mainly to screen and drag effects. Mooring systems and umbilicals belong to a family of components sensitive to bio-colonisation in general: abrasion of ropes by shells, change of dynamic behaviour due to shape and roughness modifications, added mass. However, this stochastic process with time and space is still unknown and knowledge through inspections and monitoring is mandatory. This paper is presenting a first spatial model of bio-colonisation thickness along a mooring line and a method for updating this previous model with sensors.

Our method shows that in calm sea state (with low wave height, with low wind and current velocities), the monitoring of mooring lines tension can help to assess and reduce uncertainty on thickness spatial distribution of bio-colonisation.

This paper deals with a simple assessment of bio-colonisation on a catenary mooring line by accounting for monitoring of tide level, floater's buoyancy and local tension at some points along the mooring line. A first analysis will be performed in order to estimate influence of distance between sensors using conditional entropy metric.

Keywords: mooring lines, bio-colonisation monitoring, sensing efficiency, conditional entropy metric.

1. Introduction

Depending on floater's type, mooring system's main function is to handle relative positioning and/or stability of the floating wind turbine during all its lifetime- 25 years or more. But from commissioning -and even before, to decommissioning, sources and factors of premature failure are numerous. Figure 1 reminds that fatigue and corrosion are the two main degradation mecanisms that affect service life-time of a mooring line.

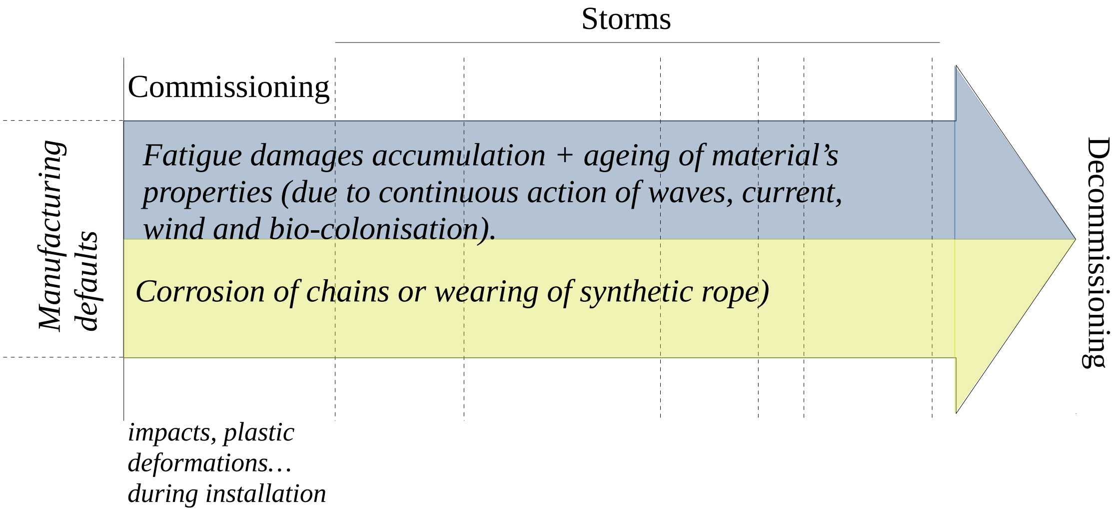


Figure 1. Sources and factors of premature failure of a mooring line during its life-time

The lifetime consumed during limited events in time such as impacts and storms can't be accurately predicted. Therefore the core of scientific and engineering works on mooring lines is to develop methods to reduce uncertainties on the lifetime consumed by everyday action of waves, current, wind and bio-colonisation in order to estimate mooring line's state before a storm for example. But because of latter actions' high variability in time and space, deterministic models fail in accurately predicting their state. Monitoring is therefore a valuable option to update preferred probabilistic models. This paper aims to reduce uncertainties on one of these actions' main parameters: bio-colonisation, through monitoring.

Bio-colonisation is defined as aggregates of marine organisms (seaweed, sponges, mussels, oysters, barnacles, anemones, corals, tubeworms…) on offshore industrial structures [1].

Figure 2. Impacting bio-colonisation macro-parameters (Image from *Biocolmar* structure)

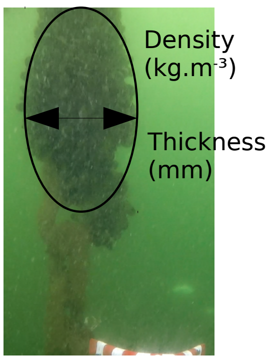


Figure 2 presents a pattern observed after one year of growth on *Biocolmar* structure of University of Nantes during its inspection. Bio-colonisation macro-parameters are its thickness and its density. Both can vary in space and in time along the line. By increasing roughness, external diameter and added mass, bio-colonisation is increasing quasistatic and dynamic loads of waves an current on the line. By increasing line's weight, bio-colonisation is also changing line's buoyancy. Different researches foresee:

- a reduction of mooring line's minimum tension, leading to an increased risk of "slacking event"[2] (fast tensioning of the line).
- a reduction of line's buoyancy, accelerating wearing by rubbing with seabed.
- a shift of natural frequencies towards larger periods at which the floater has larger response amplitudes [3].
- an increase of effective tension's variance [3].

All these effects are leading to a decrease of mooring lines' lifetime [4] and an increase of uncertainties on damages [5].

To quantify the benefit of monitoring and uncertainty reduction, an "a priori" probabilistic model of thickness and density spatial distributions along the line has to be derived from expert knowledge. Thousands of scenarii, constituting an "a priori" set, could then be generated to be used as inputs in a reliability analysis of mooring lines. The first step is therefore to validate an "a priori" model of bio-colonisation thickness spatial distribution along a mooring line.
This "a priori" set has high entropy, which could be understood as a high variability, due to uncertainties on its parameters. Monitoring's interest is then to reduce this entropy by giving indirect information about the real distribution. Thanks to this information an "a posteriori" set of scenarii, included in the "a priori" one, can be retained. The reliability analysis is then based on this "a posteriori" set, making it faster and reducing uncertainties on damages. A natural question comes out: how to compare sensing network efficiency in reducing information entropy of the "a priori" set ?
To address these key issues, the paper is organised as follow: a presentation of the frame of the methodology based on qualification sea state, a presentation of our original bio-colonisation thickness distribution model, a presentation of the assessment of sensing network efficiency using conditional entropy metric, and then results based on a density of sensors are presented and discussed.

2. Methodology based on qualification sea state

Sensing network efficiency study enters into a frame that is hereunder introduced and described.

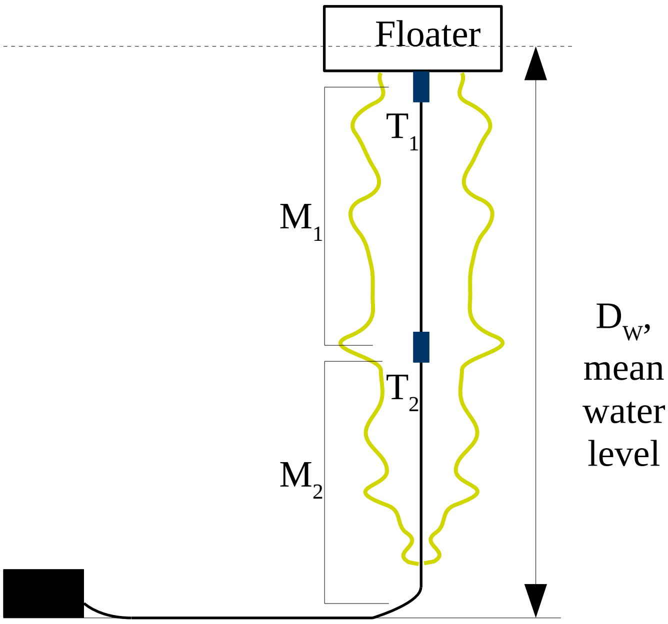


Figure 3. Adopted configuration for sensors' network (schematic draw of *Biocolmar* structure).

Sensors are evenly distributed along the catenary mooring line, considering mean water level D_W on site. Vertical distance between sensors, $I_S = \frac{H}{N_S}$ is introduced, where N_S is the number of sensors. The first sensor is always located at the fairlead - top part of the line connecting with the floater. An example with two sensors is drawn in Figure 3. Each sensor measures local tension. In calm sea state, meaning weak wind, almost no wave and no current, local tension in the catenary mooring line depends only on line's own weight and bio-colonisation weight. Line's weight depends directly on floater's buoyancy and tidal level, which can both be predicted. Therefore some months after commissioning, local tension due to line's weight and pretension could be standardised and bio-colonisation weight could be known by differentiation with the reference state. We define thus sea states as one qualification sea state because the loading is known. An estimation of bio-colonisation mass distribution, for example $[M_{1,} M_2] = \overline{M}$ in Figure 3, could be carried out from local tensions in calm sea state and mean water level D_W. Even if this estimation is riddled with uncertainties, due to unavoidable environmental actions and sensors' accuracy, this is a rough estimation of bio-colonisation distributed mass that can be used to reduce uncertainties on bio-colonisation main parameters such as the thickness.

3. "A priori" model of bio-colonisation thickness distribution

Before introducing the stochastic "a priori" model of bio-colonisation thickness distribution, two essential assumptions are made:

- Bio-colonisation is axisymmetric and its coverage percentage is equal to 100%. It is already known that it is roughly false on field in the first months. This hypothesis is valid after few years. Thus it does not affect the assessment of lifetime of mooring lines.
- Bio-colonisation density (kg/m^3) is homogenous along the line. This assumption is valid if the type of organisms does not vary with depth and it is going to be checked in a near future by experimental measurements on field.

To entirely defined bio-colonisation, a model for bio-colonisation thickness distribution with depth, $th(\vec{z})$ is required.

Bio-colonisation thickness distribution along a mooring line can be described by a combination of an exponential tendency decreasing with depth and a stationary gaussian random field:

$$th(\vec{z}) \sim N\left(\mu, \sigma, \sum\left(Matérn(\nu), lc\right)\right) + A.\exp(-B.\vec{z}) \quad \text{(Eq.1)}$$

It has been checked against experimental data from SEM-REV test site.

Thanks to a non-linear Weighted Least-Squares Method, a decreasing exponential model as introduced in (Eq.1) has been fitted to data. More weights have been given to data in first layer between 0 to 6 meters in depth, which is assumed to be a zone almost always colonised by bio-colonisation and so submitted to less variability in thickness.

Considering both "East" and "West" Moorings (cf. Figure 4), two tendencies have been obtained giving (A_{east}, B_{east}) and (A_{west}, B_{west}). In the followings, A of (Eq.1) is the mean value of A_{east} and A_{west}, same for B. A is then equal to 42.3 mm and B is equal to 0.028.

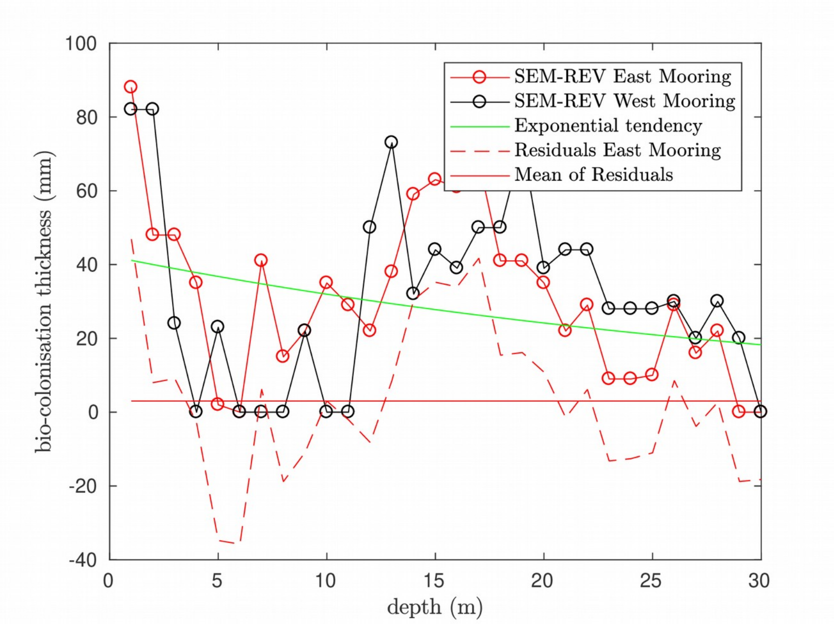


Figure 4. Bio-colonisation distributions from ECN database

Thanks to the protocol in [6], it has been checked that residuals (differences between data and fitted tendency, cf. red broken line in Figure 4) distributions are second order stationary, gaussian with a mean value close to zero and ergodic.
Using a generation algorithm of Gaussian random fields [7] and generating random parameters for (μ, σ, lc), an “a priori” set of N bio-colonisation thickness distributions can be generated.

Table 1. Range of variation of parameters for the “a priori” set

<table>
<tr><td colspan="3">$\forall i \in [\![1;N]\!], th_i(\vec{z'}) \sim N(\mu_i, \sigma_i, \sum(Matérn(\nu); lc_i)) + A.\exp(-B.\vec{z'})$</td></tr>
<tr><td rowspan="2">A = 42.3 mm.

B = 0.028.</td><td>Mean: $\mu \sim U[-3;3]cm$</td><td rowspan="2">Correlation length : $lc \sim U[1;5]m$
Regularity parameter: $\nu = 0,5$</td></tr>
<tr><td>Standard deviation : $\sigma \sim U[1;4]cm$</td></tr>
</table>

Parameters’ range of variation for generating the “a priori” set are based on expert knowledges and databases. Note that ν is constant and has been set to 0.5, meaning that the covariance function modelling Σ is exponential which agrees with experimental covariograms of residuals distributions. This parameter is a parameter leading trajectory’s regularity.
No correlation coefficient between μ and σ has been introduced. One can imagine variability growing with time, and so with μ concluding to a positive correlation. Whereas another can imagine a standardization with time and so concluding to a negative correlation.

4. Sensing Network Efficiency using Conditional Entropy Metric

Having an “a priori” set of bio-colonisation trajectories and information about mass distribution from monitoring, how to quantify sensing network efficiency ? A sensing network is said to be efficient when “a posteriori” information after monitoring has low variability compared to “a priori” information. Because unlike value of information metric, conditional entropy metric is “an information theoretic measure of the uncertainty in a set of random variables, conditioned on available sensor measurements” [9], conditional entropy metric is thus a suitable metric to measure sensing network efficiency. On that basis, sensing network options such as I_S, defined in Section 2, can be compared.

4.1 Conditional entropy metric

In case of continuous random variable, entropy is better called, differential entropy ***h***. Its mathematical definition writes:

If $X:\Omega \rightarrow D \subset R$ *is a random variable on* (Ω, F, P) *then*

$$h(X)=\int_D f(X)\ln[f(x)]dx \quad \text{(Eq.2)}$$

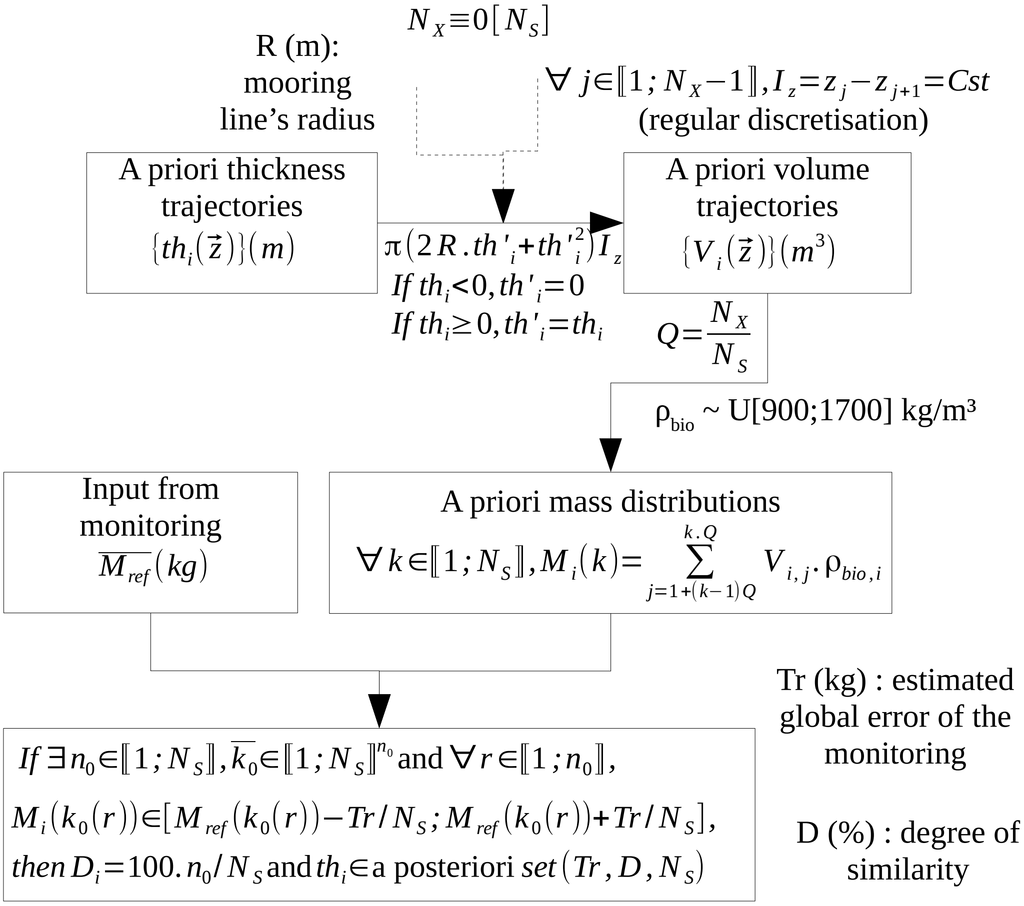
If f is a normal density function with $X \sim N(\mu;\sigma)$ *then,*

$$h(X)=\ln[\sigma\sqrt{2\pi e}] \quad \text{(Eq.3).}$$

Trajectories are discretised in N_X points. At each point, entropy of the “a priori” set $\bar{h}[th(\vec{z})]$ is calculated, the same for the “a posteriori” set, conditional entropy $\bar{h}[th(\vec{z})|\overline{M}]$. Conditional entropy metric is defined as: $\overline{m_{\vec{z}}}(\overline{M}(I_S))=\bar{h}[th(\vec{z})]-\bar{h}[th(\vec{z})|\overline{M}]$.

4.2 Selection of "a posteriori" set using monitoring

Flowchart 1 is explaining how "a priori" trajectories are selected to build "a posteriori" sets. As introduced in *Flowchart 1*, an "a posteriori" set is depending on *Tr*, the estimated global error of the monitoring process to extrapolate mass



Flowchart 1. Selection of "a posteriori" trajectories depending on Tr, D and N_S

distribution from local tension measurements, and on *D*, the imposed degree of similarity, which is intented to be as high as possible. Note that $\frac{Tr}{N_S}$ is representing the distributed error between each sensor. When I_S is decreasing, *Tr* should often be relaxed and increased in order to select enough trajectories from "a priori" set -a minimum of 1000 "a posteriori" trajectories satisfies Monte Carlo's convergence criterion. This is necessary to make "a posteriori" statistics converge without increasing size of "a priori" set. Therefore it is possible to interpret conditional entropy metric moments – such as its spatial mean.

5. Results

Inputs from monitoring have been extrapolated from a random mix of two real bio-colonisation thickness distributions, SEM-REV "East Mooring" and SEM-REV "West Mooring" [3] (cf. Figure 4). Mean water level (D_W=29 m) is also representative of water level on SEM-REV test site. For each I_S case, the best solution has been retained, maximising D and ensuring a sufficient N_2, to be sure that conditional entropy metric moments had converged. Finally it has been tried to minimise $\frac{Tr}{N_S}$ to select most probable scenarii. Note that the size of "a priori" set is N = 10^7.

Table 2. Selection of the highest spatial mean of $\overline{m_{\bar{z}}}$ for each I_S case depending on (Tr, D, N_2)

D_W, mean water level (m)	**Example of an input from monitoring $\overline{M}$ (kg)**	**N_S**	**I_S (m), distance between sensors**	**$\frac{Tr}{N_S}$ (kg)**	**D (%)**	**Spatial mean of $\overline{m_{\bar{z}}}\left(\overline{M}\left(I_S\right)\right)$**	**Number of "a posteriori" trajectories N_2**
29	569	1	29	10	100	0,2153	178226
	[322; 247]	2	14,5	12,5	100	0,3818	27997
	[191; 282; 96]	3	9,67	25	100	0,3453	13060
	[153; 169; 193; 54]	4	7,25	18,75	100	0,4935	2267
	[153; 65; 182; 119; 50]	5	5,8	25	100	0,4879	1931
	[153; 38; 131; 151; 51; 45]	6	4,83	29.17	100	0,4842	1567

Table 2 shows the results for D = 100% and a varying number of sensors.
First comforting result is that $\overline{m_{\bar{z}}}$ seems to be consistent with I_S, which is in fact equivalent to a density of sensors. Indeed between the two highlighted rows, N_S has been doubled so dividing I_S by 2, and D and $\frac{Tr}{N_S}$ between both cases are equal or almost equal. Then, it is noticed that spatial mean of $\overline{m_{\bar{z}}}$, $E\left(\overline{m_{\bar{z}}}\right)$ has been almost doubled. It is therefore strengthening the idea that sensing network should be described in terms of a density of sensors instead of a number of sensors. It is also confirming that information is increasing when I_S decreases and information is always beneficial. Entropy then decreases.

Unfortunately, due to a high threshold $\frac{Tr}{N_S}$ in order to ensure a sufficient N_2 with a high degree of similarity D, both cases N_S = 5 and N_S = 6 suffer from the size of 'a priori' set. However, even if the decrease of entropy is consitent with an increasing density of sensors, there is no proportionality and conditional entropy metric is bounded.

Secondly, a sensitivity analysis has been carried out in order to estimate ($\frac{Tr}{N_S}$, *D*, N_X) influence on $E(\overline{m_{\vec{z}}})$. A "One At a Time" (OAT) sensitivity analysis was choosen. The reference case is N_S= 4, D_W=29m, *Tr* = 75kg, *D* = 50%, N_X = 60, and $\nu=0.5$. OAT Sensitivity Indices presented in Figure 5 are equal to the standard deviation of $E(\overline{m_{\vec{z}}})$ in Figure 5 (respectively $\sigma(\overline{m_{\vec{z}}})$ in Figure 6, the spatial standard deviation of $\overline{m_{\vec{z}}}$), obtained by varying the considered parameter, divided by $E(\overline{m_{\vec{z}}})$ (respectively $\sigma(\overline{m_{\vec{z}}})$) at the reference point. For such a study, it is very important to be sure that $E(\overline{m_{\vec{z}}})$ (respectively $\sigma(\overline{m_{\vec{z}}})$) had converged. Otherwise, a part of indices' magnitude could be attributed to a problem of convergence.

As illustrated in Figure 5, all parameters have a relative influence. But the most influencing parameters is *D*. It is then important to be demanding in terms of similarity as it can be seen in Table 2. $\frac{Tr}{N_S}$ is showed to be less influencing, which is confirming that even if this parameter had been lower, and N_2 had been sufficent to ensure metric's convergence, $E(\overline{m_{\vec{z}}})$ would not have been significantly higher. The conditional entropy metric is bounded. Note that as expected, discretisation is not an influencing parameter.

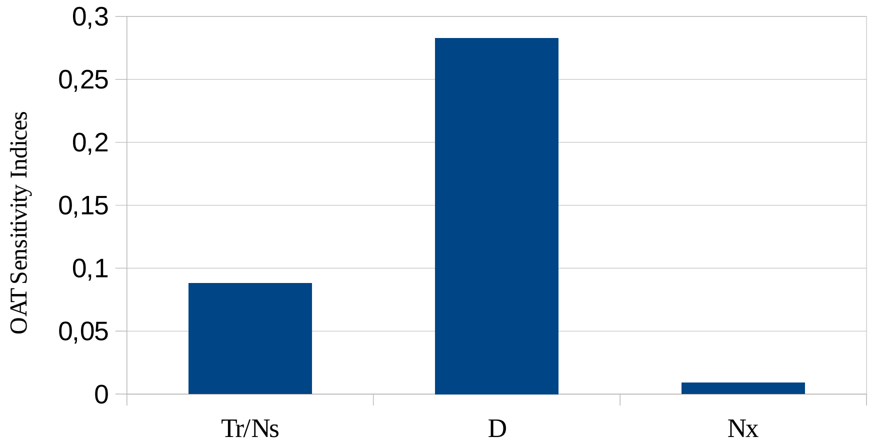


Figure 5. OAT Sensitivity Analysis on Spatial Mean of the metric

A similar sensitivity analysis, with the same reference point, has been carried out in order to estimate ($\frac{Tr}{N_S}$, *D*, N_X) influence on spatial standard deviation of $\overline{m_{\vec{z}}}$, $\sigma(\overline{m_{\vec{z}}})$, confirming that *D* is the most influencing parameters of the metric and should therefore be carefully considered.

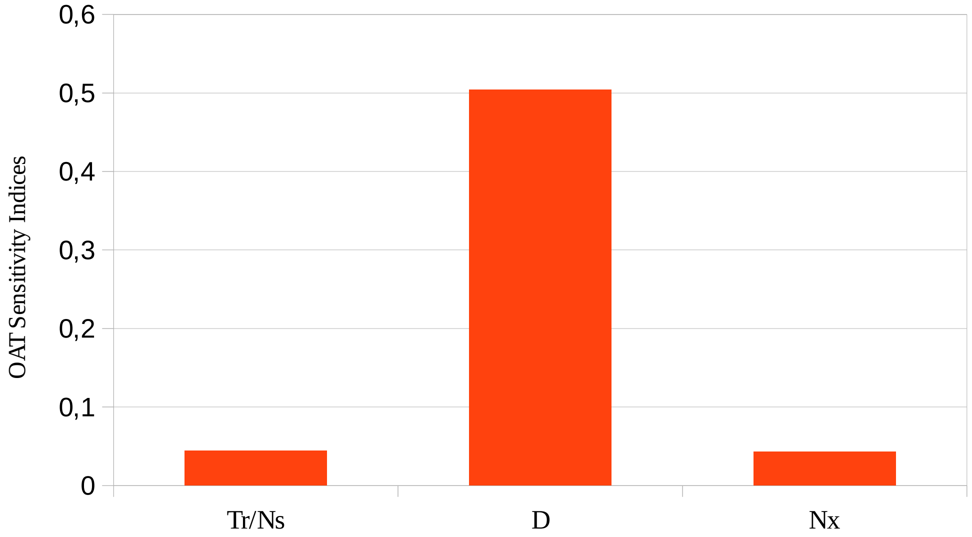


Figure 6. OAT Sensitivity Analysis on Spatial Standard Deviation of the metric

The most interesting result of Table 2 is that because of the non-linear increase of $E(\overline{m_{\bar{z}}})$ with N_S, then when taking into account price P in metric: $\frac{E(\overline{m_{\bar{z}}})}{P(I_S)}$, an optimal density of sensors can be highlighted. Therefore, given a minimum $E(\overline{m_{\bar{z}}})$, a threshold required to significantly reduced the choice of probable and fatigue impacting scenarii of bio-colonisation in “a posteriori” set, a low density of sensors, every fifteen meters for example if threshold is considered around 0.40, is economically more valuable than a high density of sensors. Moreover a high density of sensors also means a higher cost for maintening sensing network. This result is balanced by the fact that financial profit of an increase of $E(\overline{m_{\bar{z}}})$ can’t be estimated yet and that high density of sensors is requiring a higher size of “a priori” set to make $E(\overline{m_{\bar{z}}})$ converging with high *D* and low $\frac{Tr}{N_S}$.

6. Conclusion & Discussion

To the best of our knowledge, it is a first step in modelling probabilistic spatial distribution of bio-colonisation thickness on mooring lines.
Then, a low density of sensors seems enough to significantly and economically reduce “a priori” set entropy. Indeed, lifetime of sensors is often shorter than lifetime of the structure. Therefore too many sensors could turn out to be very expensive in time, without being worth from an uncertainty reduction point of view. But this result should be balanced since financial profit of an increase of $E(\overline{m_{\bar{z}}})$ can’t be estimated yet.

Then some questions still remain. Could density be considered homogenous along the line ? Is density largely varying in a year ? In fact, mooring lines' inspection campaigns, which are the opportunity to calibrate density, are likely to be only done every 4 or 5 years and only thickness would be measured. An academic and experimental campaign is forecasted in 2019 in order to gain data about density's homogeneity and density's variations.

Acknowledgements

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