Monitoring Loads Severity and its Consequences from a ML Perspective

MARINE 2023

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ABSTRACT

In this paper, the outline of a smart system capable of detecting critical load conditions and consequently triggering the interrogation of sensors to verify the occurrence of damage onboard ships is considered. The target ship for is a ro-ro fast vessel, which suffers relevant slamming phenomena. The slamming detection can be obtained in a robust way by training Machine Learning (ML) algorithms according to physics-based criteria on data from a scaled model of the same ship. The on-board sensors measure rigid-body motion, global dynamic stress due to transient vibrations and relative wave elevation. If classification of these events is properly carried out, information on slamming type drives the identification of damage by using data-driven hybrid methods. The type of damage experimentally analysed consists of a local variation of stiffness in hull panels. The choice of relevant and robust features for damage assessment is based on modal strain energy through the definition of a damage index. They require setting up a reference (intact) configuration which the damaged structure is compared with. The process requires preliminary the identification of structural modes, which are obtained from the accelerometers installed on the hull panels. Pattern Recognition methods based on the use of Machine Learning algorithms are developed and trained on numerical simulations including a variety of damage scenarios. The combination of information about slamming and direct damage detection shows the idea behind the development of such expert systems to assess the structural integrity of the ship.

Keywords: Structural health monitoring; Machine learning; Pattern Recognition; Slamming identification; Damage Detection; Fast ship.

1. INTRODUCTION

In ship engineering, safety concerns have required in past decades an increasing level of technology from design to production, being compliant with the revised rules issued by international organization and classification societies as well as considering potential issues related to climate change. Focusing on structural aspects, extensive use of finite element method and computational tools for the prediction of environmental loads has allowed for considering with higher confidence the statistical occurrence of extreme loads, due to slamming, water-on-deck and sloshing, as well as whipping and springing dynamical responses. More recently, attention has also shifted to the possibility of systematically acquiring information on the ship behaviour from full-scale on-board measurements. In particular, full-scale measurements are indeed considered important to achieve thorough understanding of complex phenomena as those mentioned above, but also cover other aspects such as comfort, continuous wave loading and fatigue. The Structural Health Monitoring (SHM) systems come into play by providing a robust, resilient, and reliable data-informed foundation. A guideline (DNV-GL, 2018) presents the standard components to receive a Hull Monitoring System Notation (HMON) for different vessel types. Although developing a hull monitoring system according to the classification guidelines for such vessels is broadly acceptable, the data processing requirements can be as sophisticated to implement as the system components themselves. Thus, structural integrity is nowadays a goal that is not only a matter of a reliable design, but increasingly depends on intelligent management of the ship asset throughout its life. Reliably assessing the vessel design under the actual conditions that operates is an important concern for shipyards. Condition based maintenance to properly schedule ship docking as well as targeted inspections on critical zones, need to be based on an extended sensor network and automated data processing. Assessing the actual structural health status of the vessel after extreme events is a task to be part of decision support systems, requiring close to real time analysis. Nonetheless, growing trend for digitalization in the marine sector (ISSC 2022) offers new perspectives regarding the use of monitoring data and pushes the adoption of new technologies such as artificial intelligence (AI) and digital twin in achieving objectives (Shabani et al., 2021).

Therefore, the SHM system involves a combination of sensing technologies (both active and/or passive) and analysis tools (data and/or physics driven) to allow the loading and damage conditions of a structure to be identified, recorded, analysed and eventually predicted throughout the whole operational life of the vessel. In this paper, the objective is to present a concept design of an expert system for damage identification based on a two-stage approach:

i. Identification of the load event(s) which might have caused possible damage,

ii. Application of a damage identification procedure to verify if damage exists, and where is located.

Both tasks are here sequential but independent modules, processing different sets of data from the monitoring systems. The module for identification of slamming events processes global information about the ship response such as accelerations, relative ship motion, strains. Exploiting Machine Learning (ML) algorithms (Decision Trees and Supporting Vector Machine, plus some extensions), it is capable to distinguish between different type of slamming events such as bottom slams satisfying or not Ochi's threshold on vertical impact velocity, as well as bow-flare slamming events. The module for damage detection is instead based on local measurement of the accelerations on hull panels likely to be exposed to the slamming events highlighted by the first module. It uses different approaches, namely Pattern Recognition methods based on the use of Machine Learning algorithms, for the first two levels of Rytter's paradigm for damage detection, i.e., existence and localization of damage (Rytter 1993). A description of the pipeline of such two-stage Decision Supporting System for damage detection is shown in Fig. 1. The target ship is a fast vessel built, the MDV3000, built by FINCATIERI, which has interesting features because of its V-shaped hull and lightweight aluminium construction. It is worth to underline that it is matter of current research effort not only developing new AI methods for dealing with such problems, but also demonstrating that AI predictions are more or at least as reliable as physics-based methods. This paper does not intend to propose any crucial achievement in terms of accuracy. However, our intention is to settle the fundamental motivation for developing such expert systems. While general framework, basic concepts and problem-oriented methodology are globally set herein, the development of data science approaches arises from the possibility of partially removing the independence of these two modules, and commonly picking the same data streams to identify events of interest at different levels for structural health monitoring.

2. SLAMMING IDENTIFICATION: CONDITION BASED APPROACH VS ML APPROACH

2.1 Detection of Slamming Based on Kinematic and Response Conditions

When a ship sails in rough sea, the violent impact between the water and the hull, that is, slamming, may determine relevant local and global effects on the ship's structure. Among global effects, the impulsive characteristic of the slamming load induces ship's vibrations at hull girder natural frequencies, commonly denoted as whipping. Wave-induced stresses arise as a consequence of both external fluid loading - continuous waves and random impacts - and induced, transient loads - hull vibrations excited by slamming impacts. In the framework of a fatigue life analysis of the ship's structure, not only the amplitude, but also the number of stress cycles has to be considered. Bow slamming for monohulls has been extensively studied by many authors who have further developed and extended the original concepts of von Karman and Wagner relative to a rigid body impacting the water. The attention has been devoted to modelling of slamming loads first via analytical models and then with numerical approaches dealing with more complex hull forms. For the

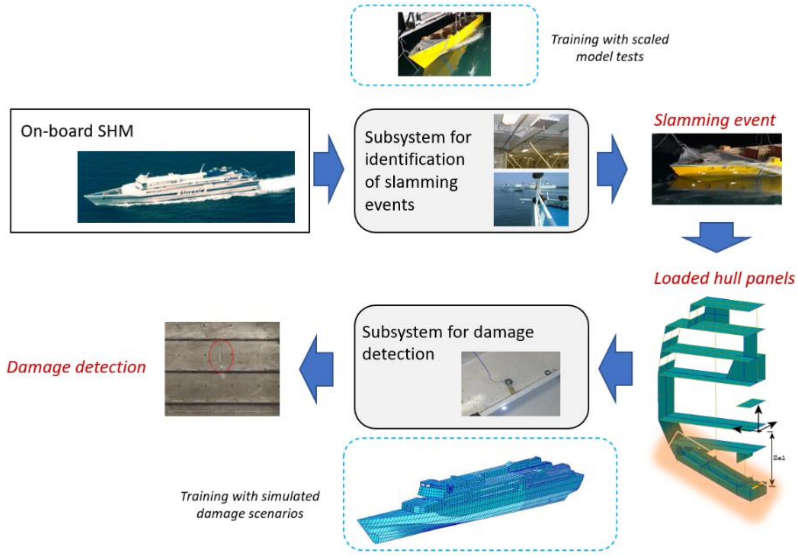


Figure 1. Outline of the two-stage approach for the damage identification following slamming events.

monohull under consideration in this paper (see Fig. 2), the wedge-shaped bow allows for pointing out that relative velocity and acceleration, which are measurable variables from which sectional loads depend in 2D theories (Dessi and Mariani, 2008), are of concern for accurate slamming identification.

The different criteria developed for slamming identification in last decades are then a consequence of descriptive models featuring this violent flow phenomenon. Ochi (1964) stated two clear conditions based on kinematics: (i) relative motion must exceed the sectional draft; (ii) relative velocity at the instant of re-entry must exceed a certain magnitude. According to Ochi, bow-flare slamming does not fall into the set of identified water-entry events because it cannot provide any damage to hull plating in the ship's bottom, which was initially one of the main concerns. However, bow-flare slamming might also produce relevant whipping, if the bow dives rapidly into the water. If the focus is on the global response, the existence of sequences of consecutive impacts, denoted as 'clusters', implies that the analysis of a single slam may not be sufficient in establishing its severity. The above consideration motivated a change in the point of view of slamming identification, and the introduction of a new criterion to evaluate global effects, more related to the induced ship response. Dessi and Ciappi (2013) observed that there exists an imperfect correlation between impact velocity and the peak magnitude of high-frequency vibratory response after the slam. The high-frequency response is then isolated using two different numerical approaches: wavelet analysis and envelope extraction of the filtered Vertical Bending Moment (VBM) response. Particular attention is dedicated to the choice of the high frequency VBM threshold value which discriminates the presence or not of a previous slam event. With a focus on catamarans, a similar approach was carried out by Thomas et al. (2005), who identified slamming on the basis of maximum time derivative of stress at a certain location. The development of alternative methods based on ML needs to take into account past approaches to slamming modeling and identification.

Figure 2. MDV3000 fast monohull: full-scale and bow hull sections.

2.2 Detection of Slamming Based on Data-Driven Techniques

Machine Learning models are powerful for their capability to learn from data without being explicitly programmed. In this manner, ML techniques facilitate data-driven models aimed at modeling the underlying data. To summarize the uses of ML, it is worth noting that, fundamentally, there are two aspects of a given problem that may require the use of programs capable of learning and improving on the basis of ‘experience’, namely, the problem complexity and the need for adaptation. Regarding complexity, building of descriptive models for a physical system sometimes cannot be easily developed on the basis of ‘first principles’; the number of features involved in the target process or phenomenon could be very large, and the actual knowledge of the underlining relations may not be sufficient for a proper description. Moreover, the continuous changes in the system itself and in the environment around it motivate the use of adaptable models. The problem of slamming identification, in its generality, is complex, it often evades the fulfillment of prescribed criteria, and is strictly dependent on the type of ship and loading conditions. There is a large variety of ML techniques suitable to be implemented for the slamming problem. In the present work, considered ML algorithms fall under categories of Supervised and Unsupervised learning approaches. In supervised learning techniques, algorithms learn from data and associated target responses which may consist of numerical values (regression problem) or string labels (classification problem), such as class or tag, in order to later predict the correct answer when posed with new examples. In the case of unsupervised learning, algorithms learn from datasets with no associated answer, leaving the algorithm ‘free’ to determine the data models alone. This type of ML techniques tends to recast given data into something else, adding new characteristics to the data that can represent a class or some new values useful for additional analysis. Generally speaking, the key point for enabling the use of ML algorithms is to switch from a continuous signal to discrete data. Thus, the approach is based on dividing the signals in a meaningful way, and then calculating properties from each time segment. This technique is called segmentation in the following. For short, the following main steps of the data preparation pipeline can be identified: (*i*) selection of the signal which will be used to trigger the signal ‘segmentation’; (*ii*) extraction of time synchronous portions of each signal (segments); (*iii*) min/max analysis of each segment; (*iv*) collection of properties from different signal segments to form a vector of features.

3. MODEL-SCALE TRAINING OF SUPERVISED ML FOR FAST MONOHULL

3.1 Scaled-Model Experimental Set-Up

To make available a large set of measurements for ML analysis, data collected in several seakeeping tests at CNR-INM on a scaled (1:30) monohull are merged. The physical model is a segmented one, representing the fast ferry MDV3000 (Fig. 3), and was designed according to the elastic backbone technique (refer to Dessi and Mariani (2008) for more details). Sea states following the JONSWAP spectrum included significant wave heights spanning from 2m to 5m in head sea and forward speeds varying from 10kts to 4kts, for total 1734s equal to 2.6 hours navigation at full-scale. The vertical bending behavior was reproduced by shaping properly the aluminum elastic beam that formed the backbone of the segmented model (see Fig. 3 for a schematic view). To shape the beam sections of the backbone, bending stiffness and shear area distributions at full-scale were used as reference data. The experimental wet-mode frequency f_(wet,1) at model scale is 7.4Hz, a value that will be chosen as reference to extract whipping vibrations. As a rigid-body, the physical model was free to heave, to pitch and, partially, to surge. The ‘physical’ sensor layer, including a wave probe, an optical system to record motions, and strain-gauges along the beam, provided respectively the following physical quantities: (i) absolute wave height, (ii) displacements and rotations at cener of gravity, (iii) vertical bending moment on several beam sections. The incoming, absolute wave height was measured by using a Kenek finger probe placed at fixed position (FP) with respect to the towing tank. The optical system (Krypton Rodymm DMM) consists of cameras placed on the carriage and LEDs glued on a plate carried onboard the model, depicted as a triangular frame in Fig. 3. The bending moment acting upon the beam was measured at 12 points by using strain gauges glued to the top face of the beam. The acquisition system was based on a National Instruments SCXI module at a 500 Hz sampling rate.

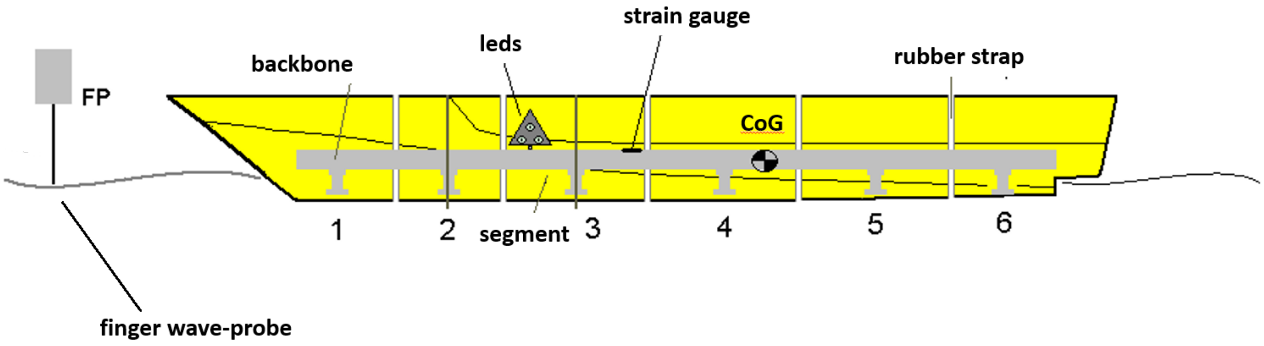


Figure 3. Scaled elastic segmented model tested in the towing-tank.

3.2 Supervised ML Techniques

In supervised learning, the objective is training ML algorithms to be able to recognize and classify data according to given examples. Thus, the application of supervised learning techniques is divided into main three steps: (*i*) labeling of a consistent amount of data samples according to chosen classes; (*ii*) training iteratively the classifier to reach acceptable scores in classifying the data of a smaller dataset, known as validation dataset; (*iii*) after training is over, verifying the capability of tuned ML models to correctly classify samples belonging to a remaining dataset, known as testing dataset, not employed in the previous steps. For this reason, each time segment or its discrete counterparts, i.e., associated features, constitute an event, which needs to be labelled as no slamming (NS), Ochi's slamming (OC), bow-flare slamming (BF), and low-velocity slamming (LV), according to conditions defined in Sec. 2. Table 1 shows features extracted for each time segment. In the data preparation phase, data cleaning excluded inconsistent data relative to the absence of bow-entry motion in the time-segments as well as outliers from the dataset, based on thresholds defined for each variable α_i as $\breve{\alpha}_i = \bar{\alpha}_i + 2.5\,\sigma_i$, where α_i is its arithmetic average and σ_i its standard deviation (all variables are considered in absolute value). Features were scaled to have a mean value of zero and a standard deviation of 1. It is worth noting that the standardization, using the function $\hat{\alpha}_i = (\alpha_i - \bar{\alpha}_i)/\,\sigma_i$, was conducted after the features listed in Table 1 were calculated from all the 55 towing-tank runs. Normalization is necessary since data is heterogeneous, with different units and scales, and is required to avoid the data analysis being biased towards any particular feature. As MATLAB 2020a ML package was used for the calculation, different ML techniques were initially chosen from those provided by the software. With a few negative exceptions, the calculated accuracy relative to the slamming detection and slamming classification problems was similar for many of them. Therefore, it was decided to focus just on some of them that were best suited for the present problem. Decision Tree (DT) is a supervised machine learning technique that can be used for classification problems. A decision tree can be 'learned' by splitting the source set into subsets based on an attribute test value. Every internal node corresponds to a variable and every edge to a child, representing possible values of that variable. Each leaf represents a value of the target variable as a consequence of the tree topology and input variables from the root to the leaf. The idea behind Support Vector Machine (SVM) is to map data attributes onto a high dimensional feature space via a kernel function. The SVM then uses that space to find the hyperplane that separates the classes with the lowest error margin. The separating hyperplane is the classifier, attributing data samples to a 'positive' class if it is on one side of the hyperplane, or to a 'negative' class if it is on the other side. It can be extended to the resolution of multi-class problems combining different partial classifiers into a unique model, using the so-called Error Correcting Output Code (ECOC model). The Adaptive Boosting is a technique used as an Ensemble Method, which is in general a machine learning technique that combines several base models (in the present case, Decision Tree) to identify the optimal predictive model. The word 'adaptive' depends on weights that are assigned to each instance, with higher values given to incorrectly classified instances, and recursively updated based on a cost function.

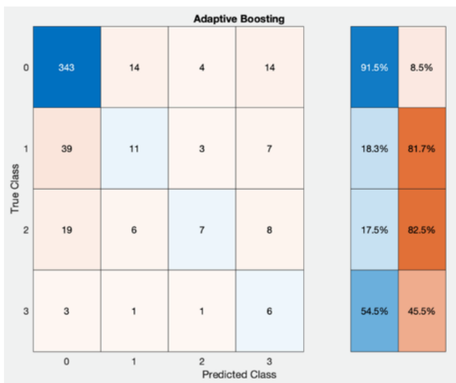
Table 1. Scaled elastic segmented model tested in the towing-tank.

No.	Variable	Selected feature
#1	Relative vertical bow displacement	Minimum value for each segment
#2	Relative vertical bow velocity	Minimum value for each segment
#3	RB vertical acceleration	Maximum value for each segment
#4	Structural acceleration	Maximum value for each segment
#5	Upper Envelope of pass-band VBM	Maximum value for each segment

3.3 Results

The original dataset to which ML is applied has 2921 samples, each one corresponding to a time segment characterized by the five features in Table 1, which after data cleaning reduces to 2430 records. According to labeling of data, 1875 records are not associated with slamming (77.2%), and the remaining 555 records are related to slamming events of different types. Data splitting is the operation by which, in supervised learning, the cleaned dataset (CD) is divided into two main groups, named Training & Validation (80% of CD) and Test (20% of CD). Using a proper random sampling, slamming statistics can be mirrored into Training & Validation and Test groups. However, in this way, there is a poor representation of slamming classes OC and LV, especially after further splitting into Validation and Test subsets. For this reason, the Training & Validation (TV) dataset can be recast into a statistically balanced dataset. Data sampling balances the class distribution in the training data by either adding examples to the minority class (Random Over Sampling, ROS) or removing examples from the majority class (Random Under Sampling, RUS). Classification of slamming events requires adapting the plain DT and SVM models to address better multi-class problems. For this reason, Adaptive Boosting embedding DT and SVM-ECOC, extending SVM capability to multi-class problems, are here considered. SVM-ECOC model is first applied to data splitting shown to the 'cleaned' dataset, preserving original statistics. The confusion matrix (Fig. 4a) shows quite a low accuracy, equal to 45.3%. Classification is repeated using balanced datasets via ROS and RUS. Results show an increased accuracy in both cases, reaching 62.3% and 71.8%, respectively. The use of AdaBoost-DT (Fig. 4b) is less dependent on better balancing of classes in the training phase. Its application to original data gives an accuracy of 75.5%, which lowers in the case of RUS-AdaBoost-DT to 71.8%, and for ROS-AdaBoost-DT to 71.6%. In general, it is worth noting that there is a decrease in accuracy passing from detection to classification as expected because of the higher complexity of the problem. Statistical balance of sampling appears more relevant with SVM-ECOC than with AdaBoost, where a slight decrease in performance is recorded.

(a) SVM-ECOC.



(b) AdaBoost.

Figure 4. Confusion matrix for slamming classification.

4. DAMAGE IDENTIFICATION ON A HULL PANEL

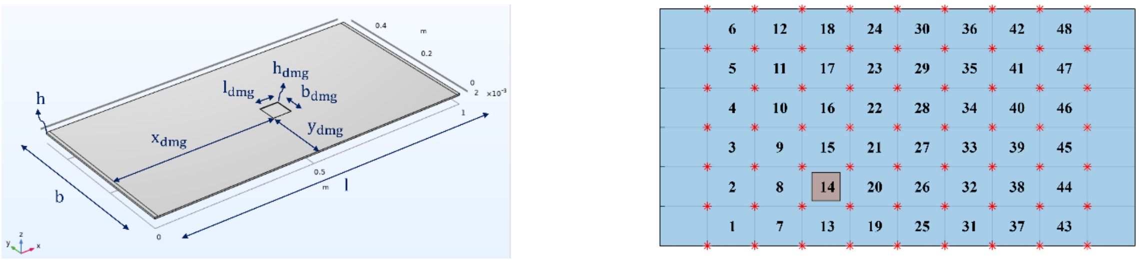
4.1 Hybrid Approach and Virtual Test-Bed

Once the hull portions subjected to higher loads have been identified with the help of the methods described in previous sections, it is necessary to assess whether or not damage has occurred in the hull plates exposed to impulsive pressure loading. Ideally, the underlying idea for developing an expert system would be to interrogate only the sensors where damage is likely to be present. This should reduce the amount of data processed by the central unit in order to get answers in real-time, while routinary analysis on all the instrumented panels can be performed with prescribed timing.

As stated in the Introduction, one of the main differences between the slamming identification and the damage detection with ML algorithms is due to the need of performing learning and validation on numerical data in the latter. Indeed, it is not conceivable to generate experimentally enough damage scenarios (position and severity) for training. Moreover, to validate the present approach, also data for testing will be generated numerically. The geometry and properties of the ship structural component under monitoring must then be known in advance. As a preliminary study, the structure considered in this paper is an aluminum plate described in Table 2 and schematically shown in Fig. 5a. The plate is supposed clamped at its shortest edges and free at the other two. For this panel, experimental data was also available from previous experimental campaigns (Dessi and Passacantilli, 2022). Though not specifically suited for the present application, they will be used for testing as well.

Table 2. Plate properties.

Quantity	Symbol	Unit of measure	Value
Young Modulus	Y	[Pa]	$74.98 \cdot 10^9$
Poisson Ratio	ν	-	0.33
Plate length	l	[m]	1
Plate width	b	[m]	0.5
Plate height	h	[m]	0.005
Damage length	l_{dmg}	[m]	0.06
Damage width	b_{dmg}	[m]	0.06
Damage height reduction	h_{dmg}	[m]	0.002
Damage X coordinate	x_{dmg}	[m]	-
Damage Y coordinate	y_{dmg}	[m]	-
Clamp stiffness x=0	k_1	[N/m^2]	$363 \cdot 10^9$
Clamp stiffness x=l	k_2	[N/m^2]	$107 \cdot 10^9$
Clamp width	b_{cl}	[m]	0.05



(a) (b)

Figure 5. Plate geometry (a) and measurement grid with subdivision of the plate into cells/panels (an example damage is set on panel 14).

In view of the preliminary application to experimental data, it is necessary to have a reliable numerical model of the reference (intact) structure. The model updating was done enhancing the numerical and experimental correspondence on a modal basis using an optimization approach, that is, resonance frequencies and the mode shapes. The optimization was carried out assuming as design variables the stiffness of the clamps and the actual Young modulus of the aluminium plate. The objective function J was defined as the product of the relative frequency variation and the MAC value between the set of numerical and experimental modes, respectively:

$$J = \sum_{k}^{M} \left(\frac{f_k - f_{exp,k}}{f_{exp,k}} \right)^2 \cdot \left(1 - MAC_{k,k}\right)^2 , \tag{1}$$

where M is the total number of modes considered, f_k and $f_{exp,k}$ are the resonance frequency of the *k-th* mode obtained respectively from simulation and experiments, and $MAC_{k,k}$ is the value of the Modal Assurance Criterion (MAC) on the mode shape of the *k-th* mode between the simulation and the experiment. Only the first four experimental modes (Fig. 6) were considered for the updating procedure (and later for the damage analysis) because their frequencies were sufficiently separated.

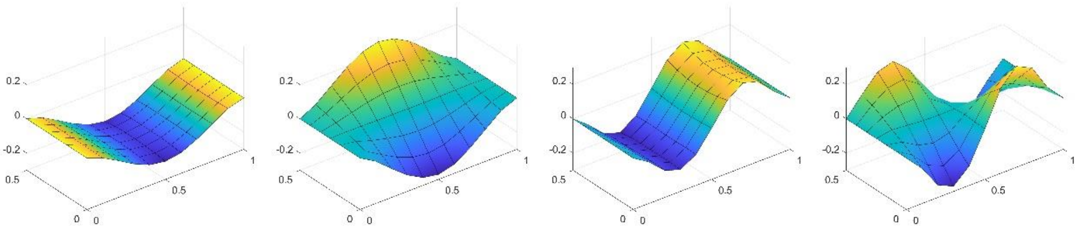


Figure 6. Experimental mean mode shapes ($k = 1, \dots 4$).

For the purpose of this paper, damage is supposed to manifest as a localized reduction of the panel stiffness, as it may occur in case of corrosion or advanced fatigue damage.

In Data Driven approaches, physical world data obtained from sensors must be preliminary processed to obtain a set of meaningful features. A possible family of approaches is provided by Statistical Pattern Recognition methods, which analyse these features to highlight the phenomena of concern. Therefore, the choice of the features is fundamental because they must contain the information about the phenomena involved and, at the same time, they should be as insensible as possible to other effects. In damage assessment problems from ambient vibration measurements, the modal parameters that are most used in literature are natural frequencies. Nonetheless, resonance frequencies suffer a strong dependency to any external factor, such as temperature and even loading conditions, and they become less reliable with the increase of structural complexity. Other methods consider the variation of mode shapes due to damage presence. These approaches require a rather dense sensor network and a sensitivity only to macroscopic damage (Dessi and Camerlengo, 2015). Thus, in order to have features insensible to the variation of external factors and robust to the presence of damage, Damage Indices based on modal strain energy were chosen. Between all the possible indices, the Cornwell index β_{ij} was chosen because of it relates directly to the damage as (Cornwell et al., 1999):

$$\beta_{i,j} = \frac{\bar{D}^*_{ij}}{\bar{D}_{ij}}\ , \tag{2}$$

where i,j indicate a particular rectangular panel into which the plate has been divided, $\bar{D}_{ij}$ is the average and uniform stiffness of the intact panel and $\bar{D}^*_{ij}$ is the average stiffness of the same panel after potential damage has occurred. It follows that β_{ij} is less than unity if there is damage on the panel, because of stiffness reduction. The actual evaluation of β_{ij} involves the calculation of integrals on the panels and on the entire plate which are functions of the square of modal curvatures in the coordinate and mixed directions, which in turn are obtained from second-order finite differences on the (virtual) sensor positions for both intact and damaged panels. In this way, the index depends in principle on the considered mode, and should be indicated with $\beta^{(k)}_{i,j}$. This dependence is not present in the Cornwell's definition because summation over all the modes is performed, but it is kept in the present formulation. An additional change was introduced in this paper. Defined $\beta^{(k)}_{i,j}$ as the index value in the panel i,j for the k-th mode, as said before, the theory states that its value should be 1 if the panel is undamaged, and less than 1 if the panel is damaged. Since measurement noise are involved, $\beta^{(k)}_{i,j}$ may assume values much greater than 1, especially in nodal points for each mode shape. Since there is in principle no upper bound for non-damaged panels, to limit the value of $\beta^{(k)}_{i,j}$ in the range [0,1], the modified index $\tilde{\beta}^{(k)}_{i,j}$ is defined as:

$$\tilde{\beta}^{(k)}_{i,j} = \begin{cases} \beta^{(k)}_{i,j} & if\ \beta^{(k)}_{i,j} \leq 1 \\ 2 - \dfrac{1}{\beta^{(k)}_{i,j}} & if\ \beta^{(k)}_{i,j} > 1 \end{cases} \tag{3}$$

To obtain the curvature measurements for the evaluation of such modes, a sensor array based on a grid of accelerometers was placed in the virtual model. From the acceleration measurement it is possible to calculate approximately the value of the modal curvatures that, for thin plates, are directly related to modal strains. With respect to strain gages, the accelerometers offer the advantage of being more robust and less affected by noise, though introducing numerical errors due to finite differencing. The measurement point grid is shown in Fig. 5b. In any case, the presence of noise must be taken into account in the training phase to enhance a correct correlation between simulations (numerically computed modes) and target real case, otherwise any real data would not be recognized as anything seen in the training phase. Particular attention was then given to describe the nature of random measurement noise. Based on the results of the experimental campaign conducted in the Structural Dynamics and Diagnostics Laboratory (LabSDD) of CNR-INM, the authors were able to reconstruct the measurement noise probability distribution assuming that in each measurement point *i,j* for the *k-th* mode, The noise contribution to the mode shape value $\phi^{(k)}_{i,j}$ is assumed to be given by the sum of a stochastic parameter η_1 and a term proportional to the mode value through the stochastic parameter η_2:

$$\tilde{\phi}^{(k)}_{i,j} = \eta^{(k)}_1 + \left(1 + \eta^{(k)}_2\right) \phi^{(k)}_{i,j}, \tag{4}$$

The statistical distribution relative to the parameters $\eta^{(k)}_r$ is Gaussian with zero mean. By calculating the variances of each term in Eq. 4, the following linear set of equations is obtained,

$$\sigma^{2\,(k)}_{i,j,exp} = \sigma^{2\,(k)}_1 + \sigma^{2\,(k)}_2 \bar{\phi}^{2\,(k)}_{i,j}, \tag{5}$$

which is solved in the unknowns $\sigma_1^{2\,(k)}$ and $\sigma_2^{2\,(k)}$ through a Least Square method and the l.h.s. $\sigma^{2\,(k)}_{i,j,exp}$ and $\bar{\phi}^{2\,(k)}_{i,j}$ are input parameters experimentally obtained. The results are shown in Table 3.

Table 3. Noise variance parameters reconstructed.

Mode	σ_1	σ_2
1	0.0011	0.0088
2	0.0023	0.0069
3	0.0015	0.0024
4	0.0068	0.0722

With this information, a population of sample displacement modes is obtained through a Monte Carlo approach for each damage considered damage scenario, including also the undamaged case. More in detail, for each configuration (damaged or intact, for a total of 151), numerical noiseless modes are obtained from the FEM model. These modes are then contaminated with noise, obtaining N noisy samples for each $\boldsymbol{k}$-th mode, according to the probability distribution described before. As a compromise between computational cost and generality to the trained ML algorithms, a sensitivity analysis suggested as best value $\boldsymbol{N}$=1000. For the index evaluation, for both numerical and experimental cases, an undamaged noiseless simulated configuration is used.

4.2 Employed Algorithm(s)

One may argue that built features are themselves able to allow for damage detection and location. However, it is known in literature that experimental noise on measurements may propagate to the damage indexes making the identification of weak damage a rather difficult task, with possible false positives and negatives. According to the well-known Rytter's paradigm of damage assessment, the present methodology aims at separately (i) identifying and (ii) locating the damage. This distinction corresponds to the adoption of different techniques for each level:

- For the Identification problem, a Novelty Detection (ND) approach was implemented, exploiting its one-class classifier capabilities. In this way, the algorithm is trained only on the undamaged case data, and any damaged case is considered something "distant" in some sense from the training class.

- For the Location problem, a Regression approach was implemented. Since the data is simulated, the approach was implemented using a Supervised Machine Learning algorithm.

It is worth to underline that this separation reflects the fact that it is easier to distinguish between two different damaged cases than between an undamaged and a damaged one, based on data distributions. In the next subsections a brief description of the methods adopted is provided.

4.2.1 Novelty Detection for Damage Assessment

Novelty Detection (ND) strategies aim to identify if the provided data is deviating from its normal condition. These approaches are extremely interesting in SHM problems because they require training the algorithm only on reference data (i.e., undamaged). The problem is extremely challenging, and the performance of a ND method depends both on the type of method used and the statistical properties of the data (Markou and Singh, 2003). In their paper Markou and Singh identified several fundamental principles that must be satisfied in order to build a precise ND method.

Since the data in the feature space is extremely clustered around the value of 1 both for damaged and undamaged scenarios, only Probabilistic-based, and Reconstruction-based methods were implemented for this paper among the five categories identified by Pimentel et al (2014) for ND approaches. In particular, the following approaches have been investigated:

1. Histogram Scores (HS).

2. Autoencoders, also known as Auto-Associative Neural Networks (AANN), with score based on Mahalanobis distance between input and output.

All these methods are accompanied by the definition of a threshold value that distinguishes between normal (intact) and novel (damaged) cases. Usually, the definition of this parameter is arbitrary, therefore an optimization based on some performance descriptor needs to be implemented. One of the most used performance representations for these algorithms are the ROC (Relative Operating Characteristics) curves, that illustrate, for different values of the threshold value, which True Positive rate (TP) and False Positive (FP) rate one obtains, where positive stands for damaged. On these curves the cut-off for high performing model is represented by the point farther from the no-discrimination line (the straight line corresponding to TP = FP and accuracy 50%, which represents the case where the algorithm is randomly assigning normal or novel tag to any data).

4.2.2 Supervised Regression for Damage Location

Another way to search for the damage location in an automated way is through regression. Since the structure is 2D, a Multivariate Multiple Regression approach was implemented on a single NN trained to obtain X and Y coordinates of the damage.

For the training purposes, damages positions were randomly chosen following a Design of Experiments approach: a uniform distribution is assumed for the generation of X and Y coordinates, with the attention of not having two equal coordinates among different simulations. This was granted by the use of a Sobol distribution for the generation of damage (position) coordinates. Sobol sequences are categorized as a quasi-random sequence, in which the test sequences generated are randomly planned in the design boundary utilizing the primitive polynomials over a Galois Field and gray code encoding. Sobol sequences generate test sequences in a high degree of scattering while avoiding overlapping of previous test sequences (Katsidimas 2023). The so generated random positions are shown in Fig. 7.

Damage dimensions instead, for this preliminary case, were kept fixed. A 70%-15%-15% division was used for training-validation-testing with NNs, granting that each folder contained the same amount of samples for each possible damage position.

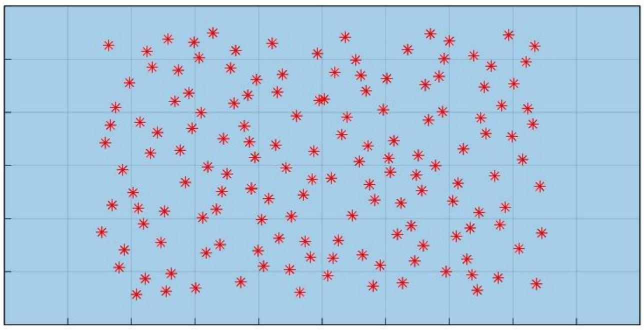


Figure 7. Random generated positions for the damage centers with the Sobol sequence.

4.3 Results

Novelty detection was performed on the same numerically obtained database as for the regression approach. Figs. 8a and 8b show respectively the ROC curves of the Histogram Score (HS) approach and the Autoencoder (AANN) approach. For both curves the maximum accuracy point is indicated, namely 66% for the HS and 65% for the AANN.

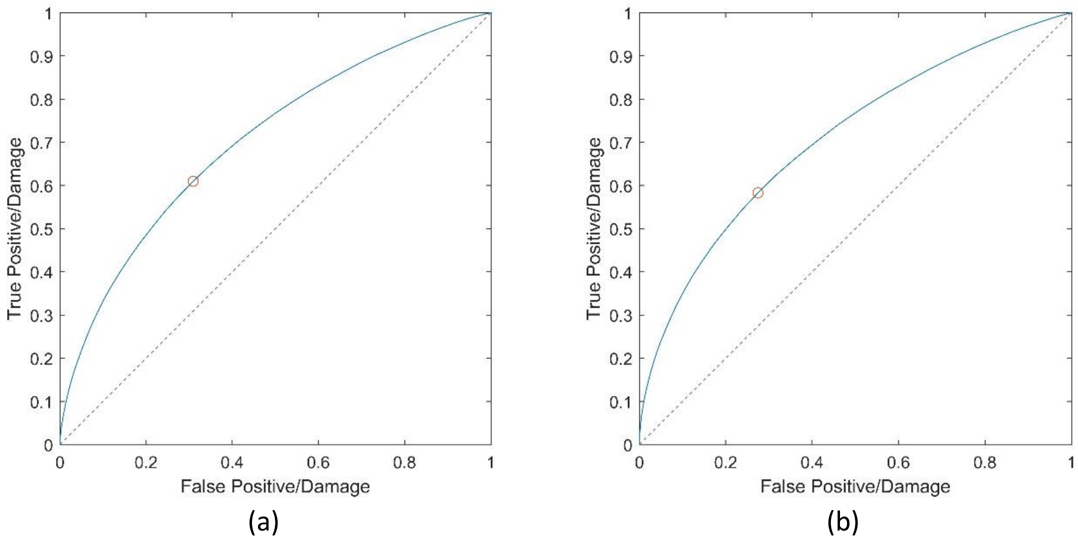


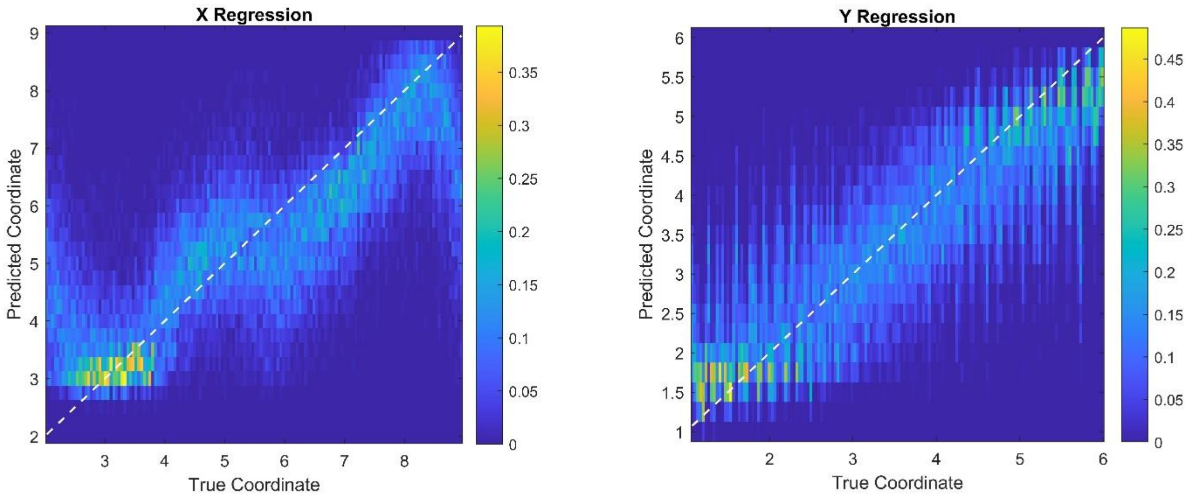
Figure 8. ROC curves for a) Histogram Score approach, b) AANN approach.

Though preliminary results are shown, it seems that the presence of noise prevents from obtaining a sufficiently clear damage identification in both approaches. A further analysis over the features by which the algorithms are trained will be considered in the future Once the experimental data is presented to the trained algorithms, however, all 20 cases are properly recognised as damaged by both ML algorithms.

Results relative to damage location based on supervised regression are illustrated in Figs. 9a and 9b, where the distribution of the predicted coordinate over the true coordinate in the testing phase is shown in terms of panel on which the damage is supposed to be. The panel or cell numbers range from 2 to 9 in the x direction, and from 1 to 6 in the y direction, whereas the color bar indicates the probability distribution value. Correct predictions lie on the diagonal line shown in white. As can be seen, predictions fall mostly very near to the diagonal line of exact correspondence between predict and true panels. Less accurate predictions occur for external, and to a less extent, for mid panels. This result is related to the fact that these panels are close to nodal points for the modes considered, and measurement noise error becomes predominant over the actual modal displacement. Regression performances are usually measured with the Root Mean Square Error (RMSE) of the overall predictions. RMSEs were separately evaluated for the x and y coordinates of the predicted damage position center:

$$RMSE_x = \sqrt{\frac{\sum_{j=1}^{N_{test}} \left(\tilde{x}_j - x_j\right)^2}{N_{test}}},$$
$$RMSE_y = \sqrt{\frac{\sum_{j=1}^{N_{test}} \left(\tilde{y}_j - y_j\right)^2}{N_{test}}}, \qquad (6)$$

obtaining respectively a value of 1.23 and 0.86. In Eq. 6 terms with and without the tilde represent the predicted and exact values, N_{test} is the number of test cases considered. Finally, in Fig. 10 two examples of damage identification relative at damage positions (centroid of the panels) not considered in the training phase (Sobol sequence) are shown. The blue and red circles represent the true position, identified by panel indexes (4,2) and (8,5), while the purple and yellow stars are the respectively predictions. Their distribution follows exactly the trends plotted in Figs. 9a and 9b: for example, the first scenario (blue circle) is characterized by a slight overestimation of the x coordinate for the blue damage (True Coordinate equal to 4 in Fig. 9a) and an uncertainty on the y direction of ± 1 panel (True Coordinate equal to 2 in Fig. 9b).



(a) (b)

Figure 9. Testing error distribution for a) x coordinate regression and b) y coordinate regression.

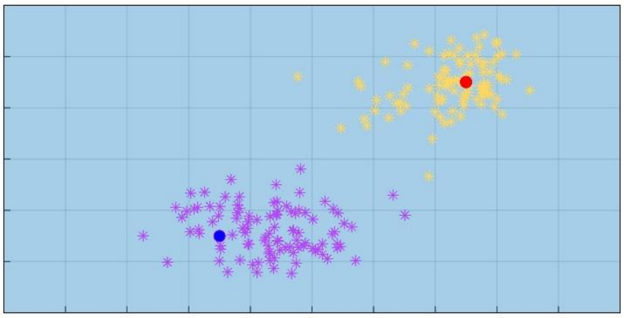


Figure 10. Predicted locations for 2 numerical examples. The actual damage center is shown by a full circle, the predicted positions are shown by stars.

The results on simulated data appear to be sufficiently satisfactory. If the experimental data is provided to the trained algorithms, the predictions are promising as well; the x damage coordinate is identified with acceptable precision, while a strong indeterminacy in the y direction is present, as one can see in Fig. 11.

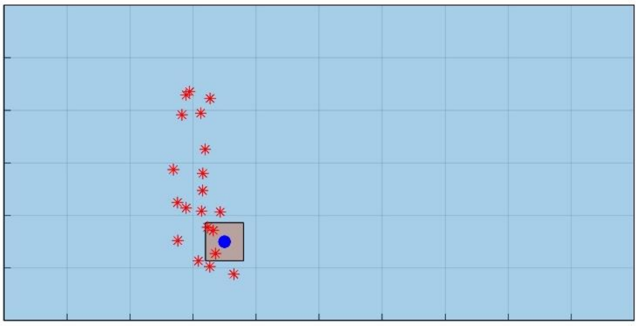


Figure 11. Predicted locations for experimental cases. The actual damage center is shown by a blue circle, its shape is represented in the figure. The predicted positions are shown by red stars.

5. CONCLUSIONS

This paper outlines an analysis pipeline of a smart SHM system focused on damage assessment on ship hull panels subjected to impulsive loading due to slamming. The techniques and applications reported herein allows for an explanatory and preliminary introduction to the design of a real expert system. The test case should include portions of the real structure, with stiffened and not uniform panels. At the present stage, slamming identification only discriminates between bottom and bow-flare slamming, providing only vertical indication of the most loaded panels; in a future upgrade, also the longitudinal position of the impact area will be considered. Moreover, algorithm performances in the different identification and detection levels should be further explored to provide reliable and useful indications.

Nevertheless, Machine Learning algorithms seem promising in doing the job in place of approaches based on physical interpretation of the different phenomena. There are several advantages in using a ML approach to slamming identification with respect to condition-based or physics-based approaches. The extraction of features from the analyzed dataset is provided by a minmax analysis of time series, separately carried out, which is a much more robust procedure than setting a sequence of linked conditions on several signals, implying strict synchronization. In case of degradation of sensor performances, due to poor Signal-to-Noise Ratio or hardware failure, or even in case of new sensor insertion, classical algorithms for slamming identification must be reformulated to address the new layout, that is not the case of the present ML approaches. Regarding damage assessment, Novelty Detection strategies allow for training only on undamaged data, which can be obtained also experimentally instead of damage cases. This advantage could lead to more "instructive" hybrid datasets based on both simulated and measured data. Regression approach for Damage Localization shows promising results as well. Moreover, regression approaches allow to localize the damage even if it is situated between panels, something that simple physics-based approaches based on the same indices have a problem obtaining.

One of the main aspects is the inclusion of measurement noise to improve the learning phase and be prepared to deal with damage identification in real cases. Even if less accurate than identification on numerically generated data, the present application to measured data on the uniform panel seems promising.

ACKNOWLEDGEMENTS

The present paper has been partially supported by the Sustainable Mobility Center (Centro Nazionale per la Mobilità Sostenibile – CNMS - CN00000023), granted by NextGenerationEU, and in particular within Spoke 3 Waterways.

REFERENCES

Cornwell, P., Doebling S. W. and Farrar C. R. (1999). Application of the Strain Energy Damage Detection Method to Plate-like Structures. *Journal of Sound and Vibrations*, 224 (2), 359-374.

Dessi, D. and Mariani, R. (2008). Analysis and prediction of slamming induced loads of an high-speed monohull in regular waves. *Journal of Ship Research* 52 (1), 71-86.

Dessi, D. and Ciappi. E. (2013) Slamming clustering on fast ships: From impact dynamics to global response analysis. *Ocean Engineering* 62 (1), 110-122.

Dessi, D. and Camerlengo, G. (2015). Damage identification techniques via modal curvature analysis: Overview and comparison. *Mechanical Systems and Signal Processing*, 52-53 (1) 181-205.

Dessi, D. and Passacantilli F. (2022). Application of modal strain energy analysis to damage identification in marine structures. *PRADS 2022 15th International Symposium on Practical Design of Ship and Other Floating Structures*. 9-13 October 2022 Dubrovnik, Croatia.

DNV-GL (2018). Rules for classification: Ships - Hull monitoring systems - HMON: DNVGL.

ISSC 2022. Storhaug G. et al, Committee II.2 “Dynamical Response” Report, in Proceedings of the 21st International Ship and Offshore Structures Congress (ISSC 2022) – Xiaozhi Wang and Neil Pegg (Eds.).

Katsidimas, I., Kostopoulos V., Kotzakolios T., Nikoletseas S.E., Panagiotou S.H. and Tsakonas C. (2023). An Impact Localization Solution Using Embedded Intelligence-Methodology and Experimental Verification via a Resource-Constrained IoT Device. *Sensors.* 23 (2), 896.

Markou, M. and Singh S. (2003). Novelty Detection: a Review - Part 1: Statistical Approaches. *Signal Processing.* 83, 2481-2497.

Ochi, M. (1964). Prediction of the occurrence and severity of ship slamming at sea. *Proceedings of the 5th Symposium on Naval Hydrodynamics.*

Rytter, A. (1993). Vibration Based Inspection of Civil Engineering Structures. PhD Thesis, University of Aalborg, Denmark, Department of Building Technology.

Pimentel, M. A. F., Clifton D. A. Clifton L. and Tarassenko L. (2014). A Review of Novelty Detection. *Signal Processing.* 99, 215-249.

Thomas, G., Davis, M., Holloway, D. and Roberts, T. (2005). The influence of slamming and whipping on the fatigue life of a high-speed catamaran. *Proceeding of the International Conference on Fast Sea Transportation,* 27-30 June 2005, St Petersburg, Russia.

Shabani, B., Ali-Lavroff, J., Holloway, D.S., Penev, S., Dessi, D. and Thomas, G. (2021). Using remote monitoring and machine learning to classify slam events of wave piercing catamarans. *International Journal of Maritime Engineering,* 163 (3).