On building physics-based AI models for the design and SHM of mooring systems

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ABSTRACT: Expert systems in industrial processes are modelled using physics-based approaches, data-driven models or hybrid approaches in which however the underlying physical models generally constitute a separate block with respect to the Artificial Intelligence (AI) technique(s).
This work applies the novel concept of "imbrication" -a physics-based AI approach- to the mooring system of offshore renewable energy devices to achieve a complete integration of both perspectives. This approach can reduce the size of the training dataset and computational time while delivering algorithms with higher generalization capability and explicability. We first undertake the design of the mooring system by developing a surrogate model coupled with a Bayesian optimiser. Then, we analyse the structural health monitoring of the mooring system by designing a supervised Deep Neural Network architecture.
Herein, we describe the characteristics of the imbrication process, analyse preliminary results of our investigation and provide considerations for orienting further research work and sector applicability.

1 INTRODUCTION

Digitalisation is foreseen as one of the strongest drivers in order to achieve decarbonization goals of society and more specifically of energy (IEA, 2017). A pivotal role in decarbonising the power is carried out by offshore renewable energies, in particular offshore wind. A cumulative installed capacity of offshore wind greater than 380 GW can be deployed by 2030 and more than 2 000 GW by 2050 globally, according to (IRENA, 2021).

(Ciuriuc et al., 2022) have identified some of the opportunities that digitalization can offer to the development of the floating offshore wind sector. Indeed, the market of floating offshore wind is supposed to achieve a market stage in the short-medium term, decreasing the cost of energy and narrowing the gap against fixed offshore wind (Wiser et al., 2021). For this reason, (Ciuriuc et al., 2022) have identified that the developments in three research area -namely, the optmisation of sensoring, development of digital twins and Building Information Models (BIMs)- can enhance cost reductions in the floating offshore wind, supporting the decision making process of the optimal maintenance strategy. Optimisation of maintenance is crucial to boost the reduction of costs in the operations of offshore wind farms (Peinado Gonzalo et al., 2022). **Preventive** and condition-based approaches for **maintenance** are particularly important for reducing the number of more costly maintenance actions based on replacement of components, minimising system downtime as well as the risk of unexpected failures (Lu et al., 2018). The reliable and robust early fault detection in offshore wind turbines is therefore particularly relevant for guaranteeing the functionality, operability, maintainability and survivability (in case of critical failures) of the offshore wind turbine (Liu et al., 2020; Pliego Marugán and García Márquez, 2019). Several studies exists for the fault detection of subsystems in (mostly onshore) wind turbine using Artificial Intelligence AI techniques, see for example (García Márquez and Peinado Gonzalo, 2021) for an extensive review. In most cases, the data-based algorithms for the detection of failures in gearbox are combined with Supervisory Control and Data Acquisition (SCADA) systems, and make use of Artificial Neural Networks (ANN) (Bangalore and Bertling Tjernberg, 2015) or fuzzy logic (Cross and Ma, 2015).

However, digitalization can influence positively the development of offshore wind sector not only in the detection of failures during operation of the plant (Clifton et al., 2022). The authors point out how the full lifecycle of a floating offshore wind farm can highly benefit from an appropriate use of the data. Heuristics of data, indeed, can solve or at least support the different phases in an offshore wind project, from resource characterisation to turbine design, plant layout, construction, commissioning, and maintenance and operations.

However, the major criticisms in the adoption of Artificial Intelligence (AI) **data-driven methods** in the offshore wind sector consist in the lack of transparency in the models (typical of any data-driven approach), as well as the lack of real in-situ data in operational and damaged conditions, which is a problem specific to offshore wind sector. The infancy of the industry and the lack of a common framework for sharing the data represent, indeed, a huge obstacle in the development of data-driven approaches for offshore renewable energy. For this reason, traditional approaches based on **physics-based modelling** or empirical and practical experience represent the standard way for design and operate offshore wind platforms. Transferrable skills from other sectors, mainly oil and gas, are the greatest source of information at the time of designing and planning operations for subsea power cables, mooring systems, and the support structure for floating offshore wind platform, pending the establishment of recommended practice and standards specific for the sector. The Offshore Standards of DNV (DNV GL, 2015), for example, is commonly adopted for the design of **mooring systems** in floating offshore wind turbines, even if it often makes explicit reference to the oil and gas sector.

Most of the physics-based approaches used in the offshore wind sector are based on differential equations, or analytical and semi-analytical derivations of physical principles. Generally, complex phenomena can be described -when possible- by complex physics-based models, requiring huge computational efforts especially when high accuracy is required. This can be particularly cumbersome during the initial design stage, when the cost of decisions should account for the computational cost of each simulation, design optimisation (requiring many iterations) and design validation (requiring various load cases and simulations to account for random wind & wave excitations). In contrast, empirical and engineering approaches are generally faster, but subjected to greater uncertainty.

Currently, the scientific community is focusing attention on problems related to explicability of AI systems (Barredo Arrieta et al., 2020) (Qin and Chiang, 2019). In the field of process industries, for example, the basic principles of physics have been encapsulated into data-driven approaches to improve their transparency, explicability and deployment of the solutions. In ocean engineering, only few example of such interlinking between these two perspective exists, as in (Ibarra-Berastegi et al., 2015) for resource forecasting. In this case, however, the physics-based model for wave prediction is coupled but not merged with a machine learning algorithm (random forest). A stronger integration of AI with physics-informed models, i.e. "**physics-based AI**" consists in a full **imbrication** of data-driven models with the fundamental principles of physics (JiaXiaowei et al., 2021; Willard et al., 2020). To the best of the authors' knowledge, there are no cases of imbrication of AI techniques with domain knowledge in the field of floating offshore wind in the literature. The imbrication process as shown in Figure 1 will try to combine both approaches to:

Reduce the amount of data to train and validate the AI models,

1. improve the explicability and interpretability of the results, and,
2. provide higher accuracy or exploring wider solution spaces.

In this work, we present the development of physics-based AI algorithms to two cases of study relevant for the offshore wind sector. We have focused on the mooring system of a floating offshore wind turbine, and we are proposing two different AI approaches for solving two different problems. The first question we answer is:

"Can we build a physics-based AI approach for supporting the designers' decisions by accelerating, and reducing the number of simulations while investigating in a wider domain of technical solutions?"

The second question we answer is:

"Can we build a Neural Network architecture fed by a set of physical "features" derived from expert's knowledge in order to identify the health status of the mooring system?"

In this work, the case studies are described in Section 2. Section 3 proposes our adopted methodologies and Section 4 reports some initial results of our investigation. Conclusions of this work are wrapped up in Section 5.

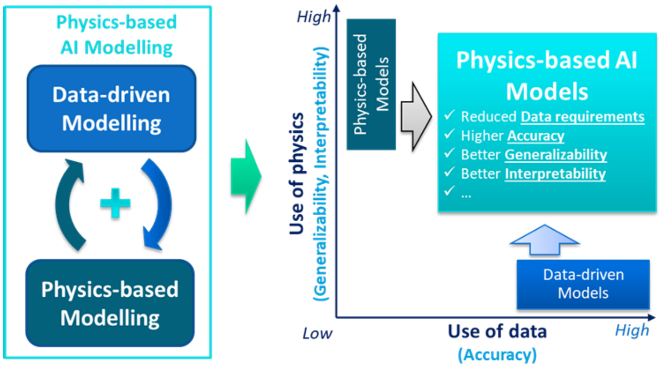


Figure 1. Physic Based AI Models as a combination of domain knowledge and Artificial Intelligence techniques

2 CASE STUDIES

(Clifton et al., 2022) identified some areas in which AI could support the development of the offshore wind sector towards the cost reduction. During the lifecycle of an offshore wind project (see Figure 2), physical simulations are generally adopted at the initial stages of the project, i.e., before the installation of the asset, to conceptualise the design, carry out the engineering design, simulate the operation of the plant and plan the installation and maintenance activities. Data generally become available during and after the installation of the plant, from SCADA systems or other sensors at higher sampling frequency, used for increasing the redundancy in the measurements and condition monitoring purposes. In this work, we focus on a critical subsystem (the mooring system) and on two problems, corresponding to two different stages in an offshore renewable energy project (see Figure 2, in bold):

1. The **design** of the mooring system of the floating offshore platform. Design is a very complex task, in which several design options must be analysed under a predefined number of design load cases (DLCs) based on environmental and operational conditions, and several simulations must be run to account statistically for the randomness of the excitations. The experience can drive towards the selection of some designs to be analysed instead of others, while the physical and constitutive laws rule the behaviour of the structural components.
2. The **identification of failures** in a structural component in an operational floating offshore device (structural health monitoring, SHM). While direct measurements can continuously evaluate deformation, tensions and other quantities representative of the condition status of structural components, the cost of sensors, communication and their reliability can constitute a limit in practice. Virtual sensors can make up for the lack of an adequate number of sensors. However, they require a high-fidelity numerical model to represent the structural components as built and installed, as well as a deep knowledge of the boundary conditions. Civil engineering is focusing on Deep Learning approaches to detect failures in structures as bridges. However, algorithms may lack of transparency and physical interpretation.

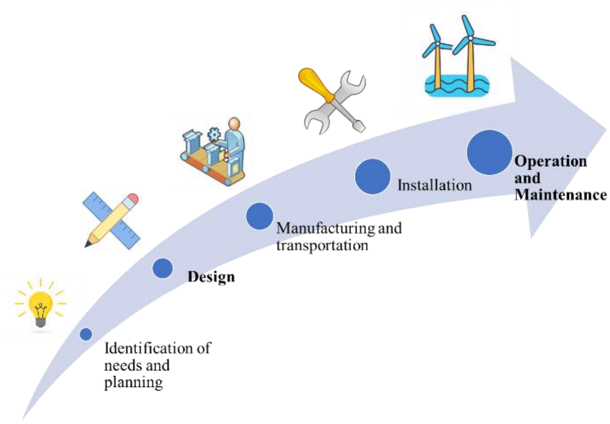


Figure 2. Main lifecycle phases in an offshore renewable energy project.

In both cases, we investigate solutions for the same structural component, i.e., the mooring system of a floating offshore device. We consider simplified models, as the conclusions can be easily generalised for more realistic cases.
We focus our research on the mooring system for two reasons:

a. The *costs* (both inversion and operational ones) in mooring systems impact considerably the Levelised cost of Energy (LCOE) whatever the floating offshore wind concept is (Myhr et al., 2014). Physics-based AI may help in investigating a wider space of more economically viable solutions during the design of the system (first case of study), Similarly, physics-based AI can serve for the detection of failures and/or lower severity damages at earlier stages in order to improve operational costs (second case of study).
b. It is one of the subsystems in which the experience of the oil and gas -especially in terms of design methodology- has been transposed almost directly to the offshore wind sector. *The sector lacks its own methodologies*, accounting for the different final functional requirements of the mooring systems.
c. Especially at concept stage, the sector may need new tools for achieving *quicker design convergence* of the mooring systems, as the traditional design approach requires several lengthy simulations.
d. Mooring system is a *critical subsystem* for the survivability of the entire offshore turbine. Direct measurement of mooring system tension can become not reliable especially when the

mooring line load is not very high and because of external conditions (temperature, salinity, etc.…) as well as friction, ageing of the transmission cables and other phenomena related to degradation (COREWIND, 2020).

2.1 *Design of mooring systems for floating offshore renewable energy devices*

The design of mooring system in an offshore facility is a complex and iterative task that must satisfy various requirements:

- different external sources of excitations: wave, current and wind forces. The site of installation of the mooring system must be characterised with appropriate parameters describing the metoceanic conditions of the site;
- the coupling between the dynamics of the platform and the dynamics of the mooring system. In case of energy production systems (wave, wind, etc.…), the effect of the power take-off must also be included in the coupled system dynamic analysis;
- a set of physical constraints (water depth, type of soil, etc.);
- a set of design load cases DLCs must be defined or assigned by general standards, official rules or recommended practice as a function of the type of structure to be studied;
- a set of minimum safety and functional requirements to be respected under all the DLCs.

The iterative task involves a set of characteristics of the mooring systems:

- configuration: the number of mooring lines and their layout;
- materials: rigid inextensible chain or materials as synthetic ropes; in some cases, mixed lines (i.e., a combination of both) can be adopted; moreover, chains are grouped into classes based on the resistance;
- the working principle: from taut to catenary systems, including semi taut intermediate conditions;
- the anchoring to the seabed and the position of the fairleads (connection to a point in the device).

The number of combinations of design parameters grows up exponentially. Furthermore, for the fulfilment of functional and safety requirements as well as because of the randomness of the excitation, a burdensome number of simulations for several DLCs, with a sufficient length in the time domain (up to 30 hours per DLC) must be simulated to extract meaningful statistics.

The final decision on the mooring configuration to be chosen is therefore taken based on the optimisation of a proper multi-objective function, minimising costs (economic criteria) and/or increasing the reliability.

The process is generally simplified by expert domain knowledge, based on knowledge of the dynamics of moored bodies and previous experience:

(1) by reducing the layouts configuration to be considered
(2) by reducing the selection of materials
(3) by choosing and positioning anchor systems based on the soil types in the lease area.

The scope of the traditional approach is huge, and it is practically impossible to explore the full domain of potential solutions, if only a solution exists. This is worsened by the computational cost of each time domain simulation, using either commercial or in-house software, which can be cumbersome even if based on quasi-static approaches.

2.2 *Structural Health Monitoring of mooring systems for floating offshore renewable energy devices*

Traditional condition monitoring techniques based on vibration analysis based on (Lifshitz and Rotem, 1969) were developed in several sectors, as aeronautics and civil engineering (Doebling et al., 1998). They have been used in oil and gas sector as well (Chang et al., 2003; Prislin and Maroju, 2017). Still, in the oil and gas sector, some studies have been carried out exploiting ANNs for detecting line breakage from motion sensors, as in (Siréta and Zhang, 2018). Operational Modal Analysis has been used in (Ruzzo et al., 2016) for the detection of anomalies in floating offshore spar wind turbine.

However, more generally, fault detection of the mooring system in floating offshore wind turbines has been studied by (Bae et al., 2017; Ma et al., 2019), with the focus on the behaviour of the platform in case of broken lines. (Arockia Dhanraj et al., 2019; Martinez-Luengo et al., 2016) have investigated approaches based on thermal imaging and acoustic emission monitoring for detecting anomalous conditions in the offshore wind platforms.

At authors' knowledge, apart from the simplified model developed by (Gorostidi and Nava, 2021), which has been extended in this work, there is no example in literature in which the most conventional techniques for condition monitoring based on vibration and modal analysis are merged into AI algorithms for early detection of failures in the mooring systems of offshore wind turbine.

3 METHODS

The methodology adopted for the two cases of study differ significantly one another, due to the different nature of the problems. In the design of mooring systems, indeed, we propose a Bayesian optimizer coupled with a solver for the time-domain dynamics of the mooring systems. Due to the computational burden of the solver, then a surrogate model is also trained. In the problem of early detection of failures, we are training a Deep Learning algorithm for solving the classification problem.

3.1 *Design of mooring systems for floating offshore renewable energy devices*

The procedure of the imbrication of AI with expert knowledge and physical laws in the case of study for the design of mooring systems is shown in Figure 3.

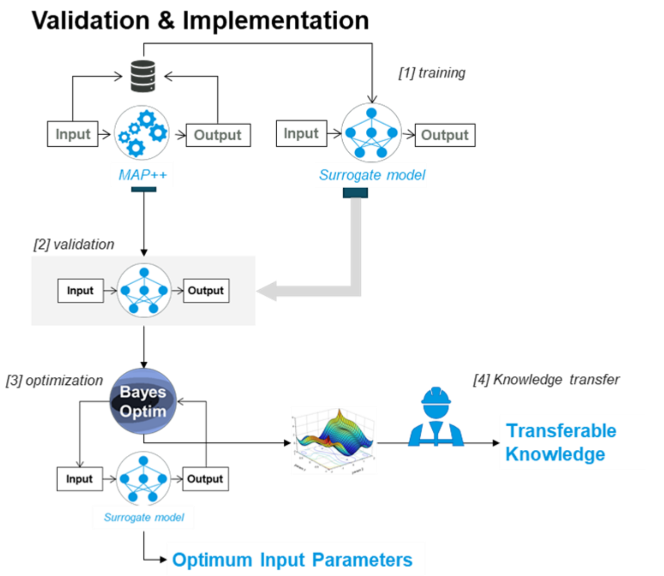


Figure 3. Physic Based AI Models as a combination of domain knowledge and Artificial Intelligence techniques

The following stages can be distinguished:

1) **Training**: this phase consists in building a surrogate model of the coupled dynamics of the floating body with the mooring systems. For that purpose, the hydrodynamic solver HydroDyn ("OpenFAST," 2022) has been used coupled to MAP++ ("OpenFAST," 2022), which is a quasi-static mooring solver. Both solvers are open-source, and the coupling between both has been carried out using OpenFAST("OpenFAST," 2022) with a zero-mass wind turbine. The idea behind the use of a quasi-static mooring solver instead of a dynamic solver is to reduce the computational cost of the simulation at the first stages.

Experimental Design methods can guide the creation of this dataset to minimize its size and maximize the accuracy of the surrogate model. The surrogate model is trained on the generated data and is updated as more simulations become available

2) **Validation of the surrogate model**: the validation phase is performed code-to-code, comparing the results in MAP ++ with the ones obtained by the surrogate models.

3) **Optimisation**: A sampling strategy based in Bayesian Optimisation is used together with the surrogated model to find the set of input parameters that minimizes a given cost function within the given constrains.

4) **Knowledge transfer**: The solution space is explored to detect insights that might be transferable to other context scenarios. Further, the exploitation of the surrogate model allows the user to explore new scenarios, being the model able to interpolate results. In this case, the user does not need to run a new simulation, contrary to what happens when using MAP++. This usage of the surrogate model is complementary (and not subsequent) to step 3.

In order to reduce the massive solution space, several assumptions have been adopted for building the surrogate model. We have analysed a simple moored buoy, instead of considering an offshore wind turbine. The buoy shape is cylindrical, moored with regularly spaced simple catenary mooring lines, at a fixed water depth. The metocean conditions considered are based on the inverse first order model (IFORM) contour line at return period of 50 years in the test site BiMEP. Each sea state is characterised by a significant wave height Hs and a peak period Tp, with the implicit assumption of JONSWAP spectrum. The effect of the current is also included, considering the current speed of 50-year return period. As a conservative assumption, waves and current are assumed to be collinear. All the mooring lines are equal, organised in a regular pattern, angularly equidistant one another. The first mooring line is oriented downstream and aligned with the direction of the wave propagation when waves propagate in the 0 deg direction. The objective function corresponds to the economic criterion, i.e. the cost of the materials for the mooring lines.

The design problem therefore can be summarised in the calculation of the linear mass LinMass and the total length of the each mooring line (equal to maximum suspended length max(Ls[i](t)])) so to minimise the cost function:

$$Cost = NLines * LinMass * \max(Ls[i](t)])$$

The optimisation problem is constrained. Some constraints are "strong", i.e. a solution that does not satisfy the constraint is not technically acceptable:

- $Characteristic\ Load \leq C_s * TBL$, , C_s is a security coefficient equal to 0.95 and TBL is the breaking load for the mooring lines, calculated with the empirical formula extracted from Orcina manual ("Orcina Ltd - the home of OrcaFlex," 2022). As defined in DNVGL-ST-0119 (DNV GL, 2018), the characteristic load of the mooring lines is determined as follows:

$$Characteristic\ load = 1.3 \cdot T_{MPM} + 1.75 \cdot T_{MEAN}$$

Where $T_{MPM} = \mu - 0.45\sigma$ with μ and σ the mean and the standard deviation of the tension process.

Some other constraints are “soft”, i.e. the selection of some variables lead to solution technically acceptable but not preferable. In this case, solutions leading to very large offsets and long chains are penalised in the evaluation of the technical solution and optimisation but not excluded.

The creation of the surrogate model involves domain knowledge in the definition of the assumptions, constraints, and limitation of the search space.

3.2 *Structural Health Monitoring of mooring systems for floating offshore renewable energy devices*

In this case study, the imbrication process consists in exploiting the domain knowledge -obtained from the most traditional techniques based on vibration analysis- as initial step for definition of features in a conventional supervised classification problem based on Deep Learning (Deep Neural Networks, DNNs), and it builds upon (Gorostidi and Nava, 2021). The method used in this section is described in (Gorostidi et al., 2022) and herein summarised. The imbrication process in this case of study is regulated by using a set of parameters derived from the displacements of the support structure of the floater of an offshore wind turbine in the frequency domain. Because of the lack of real data, synthetic data have been simulated. We are using a supervised approach to not only identify an anomalous behaviour but also to identify the damage and potentially its severity. To address this last point, we set a minimum threshold in the damage severity.

In this project, the procedure consists of two steps:

1. **Dataset generation**: This is a necessary step for training and validation purposes, as no real data are available. The motions in six degrees of freedom (dofs) of a floating offshore wind platform have been simulated under a wide range of metoceanic conditions and structural conditions. Then, after extracting the power spectral densities (PSDs) of the signals, meaningful quantities, such as standard deviation, peak frequencies, have been extracted. The dataset is built with those statistics and the appropriate label based on the damage condition and severity. Simulations have been carried out in OpenFAST considering the OC4-DeepCwind platform (Robertson et al., 2014). In this case, as in (Gorostidi et al., 2022), two health conditions have been considered: undamaged conditions and biofouling increase of mass, adding up to 10% of the total mass of the mooring systems. A total of 3140 three-hour-long simulations were carried out in a range of significant wave height from 4m to 10m, peak period varying from 5 s to 15s and wind speed from 2 m/s to 15 m/s. A total of 24 features were considered (mean, standard deviation, peak frequency and zero momentum o the response for each degree of freedom). Metoceanic parameters are disregarded in the dataset.

2. **Network design, training and validation**: we have designed a four-layer simple feedforward, fully connected deep neural network (see for example Figure 4). At the time of writing, the model is being extended and improved from (Gorostidi et al., 2022). In that work, we considered 24 inputs and 2 outputs (binary, expressing if the sample is in undamaged condition or in presence of biofouling). The hyperparameters for training are shown in Table 1. We have used 75% of the dataset for training and 25% for validation purposes.

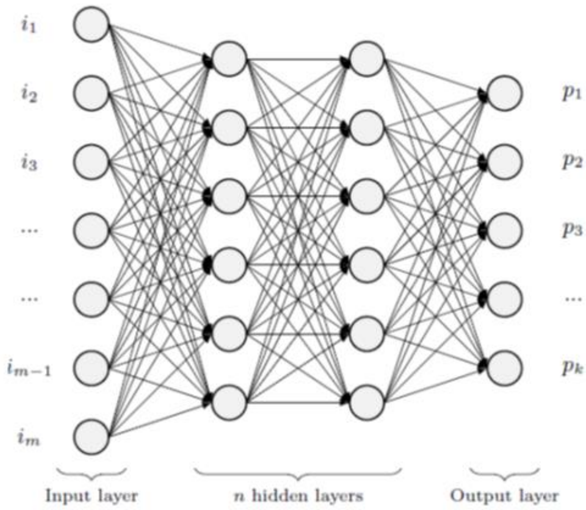


Figure 4. Example of the adopted topology of Neural Network (figure from (Gorostidi et al., 2022)

Table 1. Hyperpameters used in the training stage.

Parameter	Description
Neurons per layer	24, 16, 12, 2
Activation functions	RLU, Softmax
Layer connection	All dense layers
Optimiser and learning rate	Adam, 0.0001
Cost function	Binary cross-entropy
Early-stop criterion and patience	Validation loss, 500 epochs
Training epochs	10000

4 RESULTS

For both cases of study, the models are still under development and/or improvement, and thus the results herein presented are to be intended to be preliminary, partial and/or to be further investigated.

4.1 *Design of mooring systems for floating offshore renewable energy devices*

The first analyses we have carried out show that the surrogate model reduces computational time of more than 90% for the full stack of simulations of one design of mooring system. Indeed, the training of the surrogate model we are developing guides the simulations towards the sea states leading to more extreme conditions in terms of response for the mooring lines, reducing the number of sea states in the IFORM contour line to be analysed. This is particularly encouraging as in a notably shorter time, the Bayesian optimiser will explore a larger number of different solutions to optimise against the independent variables of the design, i.e. the number of mooring lines, their linear weight and length.

4.2 *Structural Health Monitoring of mooring systems for floating offshore renewable energy devices*

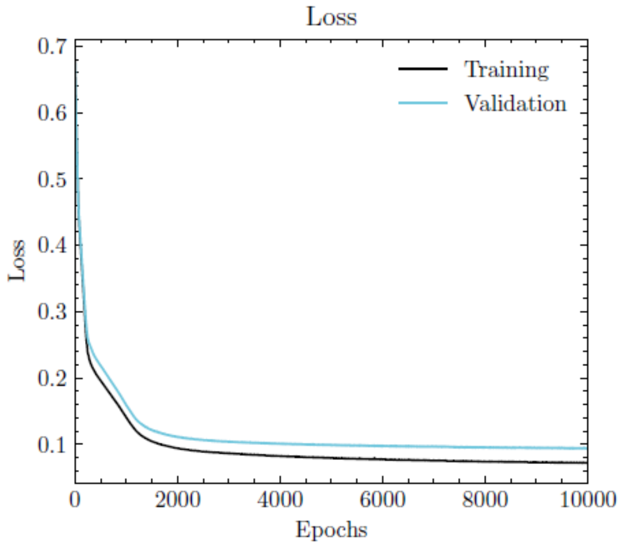
As in (Gorostidi et al., 2022) the authors have pointed out that (see Figure 5):

- No major overfitting issues were affecting the performance of the algorithm;
- The accuracy reached 95.7% after around 6000 epochs.

Results were obtained and a relatively small dataset, with only two conditions examined and with 3-hour-long simulations. However, as the first results are encouraging, the model will be further expanded, including further failure modes, sensitivity analyses on the duration of the samples and severity of the damage.

5 CONCLUSIONS

We investigated the "imbrication" process of AI techniques with physics-based models for the design and the early detection of failures in mooring systems in offshore wind systems. While the models are still under development as part of a longer project, the initial results are encouraging:



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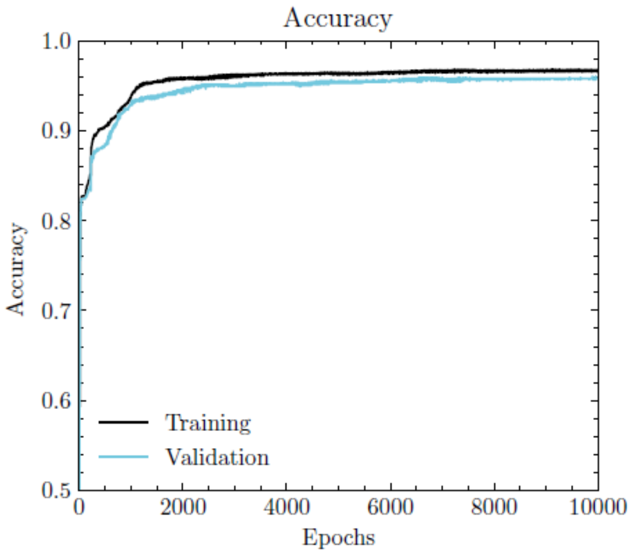

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Figure 5. Evolution of training and validation (a) loss and (b) accuracy as training progresses. (figure from (Gorostidi et al., 2022)

1) In the case of the design of mooring systems, the Bayesian optimisation coupled with a surrogate model for the analysis of mooring systems seems to notably reduce the computational time; this allows the investigation of a much larger design solution space in a shorter time. The "expert" knowledge is encapsulated while constructing the surrogate model, accounting for domain practice and physical constraints.
2) In the case of SHM of mooring systems, the DNN architecture fed with spectral characteristics of the response provides a reliable solution to the identification and classification of the failures in the mooring systems. The selection of the input variables, preprocessed from the data, is based on expert knowledge.

Both the models attack the reduction of costs, providing solutions aimed at reducing the capital expenditure (cheaper mooring systems) as well as the operational expenditure (detection of failures and degradation at early stages opening the way to implement more effective preventive maintenance strategies).

The developed approaches are affected by limitations. In the first case of study, we have applied several simplifications at the time of building the surrogate model. In the second case of study, the solution is based on synthetic data, and it is not provided online at real time. Nevertheless, the initial results are encouraging. In the design problem, the selection of a mooring layout is achieved in a much shorter time; in the SHM problem, such a DNN is able to identify a damaged condition with a good accuracy.

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