Artificial Neural Networks for Optimization procedures of Mooring System of Floating Platforms

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Abstract. In recent years, Floating Production Systems (FPS) have been advanced to deep and ultra-deep water subject to both extreme and operational environmental conditions. Under these conditions, mooring systems assume a fundamental role of keeping the FPS on the location and thus ensuring the integrity of other systems. Numerical model of these systems requires rigorous nonlinear static and dynamic analysis in the time domain using Finite Element Method (FEM) which have high computational costs. Therefore, an optimization process that may requires hundreds or thousands of analyses of the candidate solutions can take a long time. Thus, this work aims to optimize a mooring system of a floating production system, changing the evaluation of the objective function and the associated constraints from Finite Element Procedure by an Artificial Neural Network (ANN), in order to reduce the computational costs. Such reduction of time consuming may favor the accomplishment of several studies of the system in question. Case study presents a real-world scenario and the optimization tool employs the Particle Swarm Optimization (PSO) method. From the results we can see that the replacement of the FEM analyses by ANN meta-model has a high level of accuracy and presents low computational cost.

Keywords: Optimization, Artificial Neural Networks, Mooring System

1 Introduction

With the new discoveries and technological advances on offshore activities, its exploration area has increased and became more present in deep and ultra-deep waters over the years. These changes encourage studies about different challenges with deep waters bring to FPS, such as new environmental loadings, weights and new line configurations to be applied. The two main FPS used today in these cases are semi-submersible platforms and moored ships. Both systems are connected to the seabed by mooring lines, which are one of the main options to maintain the floater within a certain limit owing to its simplicity, safety, and economy García and Vásquez [1]. Thus, mooring system design can demand thousands of nonlinear static and dynamic simulations in the time domain consuming high computational costs. This fact indicates that the application of optimization tools can benefit and simplify this key step of offshore system design. In previous works Monteiro et al. [2, 3, 4] have indicated the feasibility of devising a spread mooring optimization procedure based on evolutionary algorithms. Ja'e et al. [5] apply the same methodology, the consideration of integrated design methodology, for a turret-moored FPSO. Here, we will follow the basic guidelines presented in Monteiro et al. [6], however, changing the FEM analysis by a surrogate model based on ANN, in another words, the objective of this work is to optimize a mooring system of an offshore floating unit through evolutionary algorithms replacing FEM simulations by an ANN surrogate model. This kind of application was successful applied by do Prado et al. [7] where they do an optimization of mooring lines considering ANN as substitute the FEM solver, but considering different objective function, constrictions and optimization method. And by Yu et al. [8] where they do an optimization of mooring system taking radial basis function (RBF) as a surrogate model. Moreover, surrogate models have demonstrated accurate results not only in optimization procedures but also in others offshore applications how we can see in references de Pina et al. [9, 10, 11, 12]. Or even by Zhao et al. [13] in which the authors propose a methodology to assess the reliability of mooring lines under given extreme environmental conditions applying an ANN–Bayesian network inference. They consider different ANN types, such as RBF and back propagation to predict the extreme response of mooring lines according to a series of measured environmental data. Moreover, the applications of research in mooring optimization have expanded to include floating production storage and offloading (FPSO) vessels Ja'e et al. [5], J.Lim et al. [14], floating offshore wind turbines Ferri et al. [15], Hall et al. [16], and specialized floating structures Liang et al. [17].

2 Problem modeling

In the following subsections, the main topics considered in the mathematical formulation used in this study will be briefly described. First, presenting the objective function used in the optimization process, followed by a brief description of the ANN employed as a surrogate model to replace the FE analysis. The chapter concludes with an explanation of the PSO, the chosen optimization method.

2.1 Fitness function

In order to keep the platform movement within safe values associated with the operational limits of the risers, the optimization process uses a fitness function (eq. (1)) to find the largest possible platform offset within its constraints. In other words, the objective is to keep the offset as close as possible to the maximum permitted limits considering the safety factors, minimizing the value of this function.

$$f = 100 \times \frac{\sum_{n=1}^{Ndir} e^{\left| \frac{SF \times MaxOff(i) - Offset(i)}{SF \times MaxOff(i)} \right|}}{Ndir} \tag{1}$$

This fitness function, represents the average of the distance percentage from the platform offset (Offset(i)) in each direction (i=1,. . . ,Ndir) in relation to the maximum offset allowed (MaxOff(i)), also called SAFOP (safe operation zone for the risers) considering a safety factor (SF). The exponential function is used to increase the sensitivity of the value for near offset values.

Constraints of this problem are related to: a) maximum offsets, if the value exceed the SAFOP limits; b) maximum tensions in each line should not exceed 60% minimum breaking load (MBL) specified for the materials comprising their segments with dynamic simulation or 50% with static one; c) minimum tensions in each line should be above 5% of the material MBL. Complete description with equations used can be found in Monteiro et al. [6].

2.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are inspired by the human brain. They use layers of connected nodes, called neurons, to process data and learn patterns. By adjusting the weights of connections between neurons, ANNs minimize errors and improving performance. This capability is useful for applications ranging from image recognition to natural language processing. A significant advantage of ANNs is their ability to learn and generalize from examples. During training, they use algorithms like backpropagation to adjust weights based on input-output pairs, enabling accurate predictions even with new data. This generalization is crucial for fields requiring precise modeling of intricate patterns, such as financial forecasting, medical diagnosis, autonomous systems and complex engineering problems. However, ANNs face challenges like requiring substantial computational resources and large datasets for training. Fine-tuning hyperparameters and architectures can be complex, and overfitting remains a common issue. Despite these challenges, ongoing advancements in hardware and algorithms continue to improve ANN robustness and accessibility for various applications. MATLAB© provides several different algorithms for fitting optimization. In this work, parametric studies were carried out among them. They are described in following sections.

2.3 Particle Swarm Optimization

PSO, developed in 1995 by Kennedy and Eberhart [18], consists in a computational method bio-inspired by the social behavior of some animals as flock of birds, where the information acquired by an individual about the search space influences the analysis of the entire population. This method maintains a swarm of candidate solutions, called particles, starting with an initial population randomly generated within the limits of each variable.

Throughout the evolution process, each particle remembers the best position it has found, and the best position found by all particles. This algorithm has a few parameters to be adjusted, population size, inertia coefficient, individual and social terms. Trelea [19] proposes parameters that have been shown to present good results for general applications were used as constants of the problem. Equations and more details about PSO method can be found in Kennedy and Eberhart [18].

3 Case study

3.1 Model description

The FPS used in this study is installed at a water depth of 1800 m and has a mooring system divided on 4 corners, each one with 4 lines in a catenary configuration represented in Fig. 1, with mooring lines represented in green and risers in blue. This model is similar to the ones applied in Brazil's pre-salt fields where the ultra-deep water depths reaches up to 2000 m and has stimulated a variety of studies about new technologies and improvements to overcome the new challenges of new environmental loads and line stresses that have come with the new depth of exploration. Additional information about the model,such as hull description, risers and environmental loading data, is available in Monteiro et al. [6].

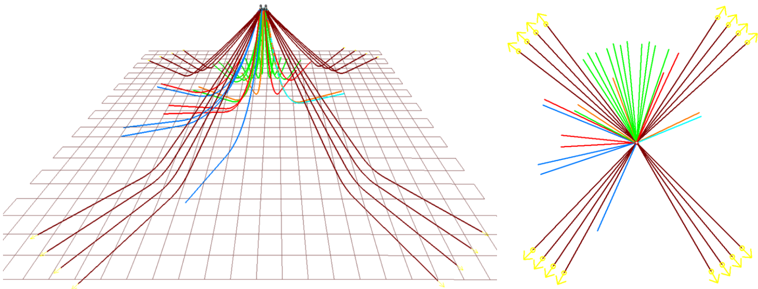

Figure 1. FPS for ultra deep waters, 3D and top views. The mooring lines are represented in brown, and various kinds of risers are represented in different colors.

3.2 Variables

The design variables considered in the optimization process are listed in Table 1 as well as their bounds. The first eight variables, azimuth and radius for each corner, are given from the base model (described above).

Table 1. Bounds for the design variables

Parameter	Description	Lower Bound	Upper Bound
1-4	Azimuth (all corners)	-3º	3º
5-8	Radius (all corners)	-500 m	500 m
9	Pre-tension	1000 kN	5000 kN
10	Material (nominal diameter)	0.122 m	0.262 m

3.3 Parametric studies of the ANN training

The data used to train the ANN was generated from finite element simulations provided by the SITUA-PROSIM software Jacob and Masetti [20]. It returns as output the result of the offsets used to compute fitness function and parameters to compute the constraints, described in subsection 2.1. By using the supervised learning method, the network is trained with both the inputs and the outputs of the FEM analyzes. In order to generate the samples the Latin Hypercube method Kleijnen [21] was applied. Dataset was equal to 3500, i. e., 3500 design variables or 3500 models to be simulated. It was taken eight directions of environmental loadigs with a total of 3500×8=28000 static simulations. For all parametric studies this dataset was divided as follows: 80% for training, 15% for validation and 5% for test. In addition, all parametric study and optimization process was done in a laptop with Intel i7 8th generation processor with 1.8GHz and 16GB of RAM memory.

Previous tests indicate that the hardest parameter to the ANN training was Offset in direction 8 (current and wave aligned to southeast direction), therefore this one was chosen to continue with the parametric analyses. Also, previous tests with ten training functions, two of them, Levenberg Marquardt and Bayesian regularization, presented better results. So, the parametric studies focused on them. Table 2 presents the parametric analyzes for each of these two training functions varying the number of Neurons from 10 to 50 and 2 hidden layers (previous tests indicate that 2 hidden layers are better than 1 for this problem). Values in this table are the best among 10 independent runs. One can note that all of them achieve an error of 10E-4. We consider the best solution the training with Bayesian regularization with 20 neurons in the hidden layers, as it has the better cost benefit, having a good error value with a feasible training time.

Figure 2 shows the regression plot of the trained ANN versus current data.

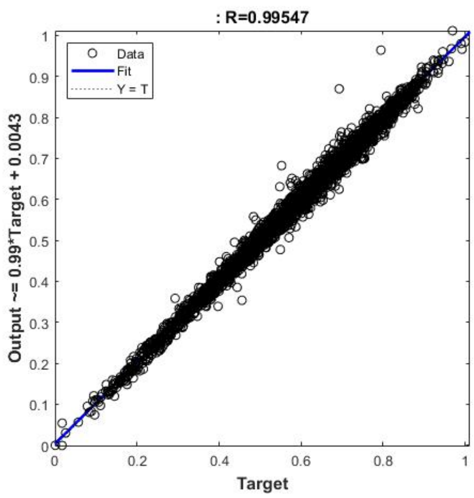

Figure 2. Regression plot of the trained ANN versus current data

Table 2. Parametric study: Levenberg Marquardt and Bayesian regularization with two hidden layers. The best values among 10 runs.

Func	Neurons	Best	Mean	Std	Mean Time(s)
Levenberg Marquardt	10	8.97E-04	9.80E-04	7.10E-05	0.51
Levenberg Marquardt	20	7.34E-04	9.27E-04	1.20E-04	1.39
Levenberg Marquardt	30	7.31E-04	9.02E-04	1.58E-04	3.68
Levenberg Marquardt	40	8.31E-04	1.04E-03	1.80E-04	9.56
Levenberg Marquardt	50	9.19E-04	1.15E-03	1.72E-04	26.05
Bayesian regularization	10	5.77E-04	6.42E-04	7.14E-05	17.76
Bayesian regularization	20	**2.55E-04**	3.42E-04	4.56E-05	110.62
Bayesian regularization	30	1.98E-04	2.90E-04	5.89E-05	424.01
Bayesian regularization	40	1.35E-04	2.63E-04	1.28E-04	1290.28
Bayesian regularization	50	1.56E-04	2.50E-04	5.13E-05	1708.82

Another parametric study was conducted between these two training functions, this time with 3 hidden layers. From Table 3 we can see that there were no significant improvements in results with the same level of errors of 10E-4.

Table 3. Parametric study: Levenberg Marquardt and Bayesian regularization with three hidden layers. The best values among 10 runs.

Func	Neurons	Best	Mean	std	mean time(s)
Levenberg Marquardt	10	8.43E-04	9.17E-04	6.70E-05	0.79
Levenberg Marquardt	20	7.56E-04	9.30E-04	1.37E-04	3.41
Bayesian regularization	10	3.99E-04	4.47E-04	3.21E-05	27.05
Bayesian regularization	20	2.08E-04	3.45E-04	1.33E-04	313.11

In this way, the networks for all parameters necessary to compute the fitness function (subsection 2.1) were trained using Bayesian regularization with 2 hidden layers with 20 neurons. Table 4 shows the results for the best solution among 10 runs. Here, we can see that the biggest error was in Offset 8, what proves that this is the most difficult training parameter as previously stated.

Table 4. Trained ANN to the optimization process using Bayesian regularization

Parameter	Neurons	Best	Mean	std	mean time(s)
Offset 1	20	8.77E-05	9.57E-05	5.88E-06	94.06
Offset 2	20	3.39E-05	4.97E-05	1.29E-05	108.26
Offset 3	20	2.86E-05	3.44E-05	3.29E-06	83.79
Offset 4	20	7.49E-05	8.25E-05	5.87E-06	81.51
Offset 5	20	7.39E-05	8.18E-05	5.37E-06	82.82
Offset 6	20	6.05E-05	9.33E-05	2.45E-05	76.86
Offset 7	20	1.10E-04	1.35E-04	1.74E-05	79.91
Offset 8	20	2.55E-04	3.42E-04	4.56E-05	110.63
Tension	20	1.53E-04	1.82E-04	2.61E-05	92.17

3.4 Optimization process

Optimization process was carried out with 30 independent runs. Each generation had 40 particles. Stop criteria was set as the maximum number of generations equal to 100, or the best fitness value stagnated by 10 consecutive generations. The average time consumed in each run was 5 min 20 s. Figure 3 shows the plot of the best execution, i e, the run that achieve the lowest fitness value. From this plot we can note that all particles converged to the same value, indicating that the number of particles and generations was suitable. Also, it is important to highlight that all optimized solutions are no constrained.

Figure 4 shows 3D and top views of the optimized models.

Finally, Fig. 5 compares the maximum offsets of the optimal solution with the limits of the SAFOP diagram. That solution ensures the integrity of the risers.

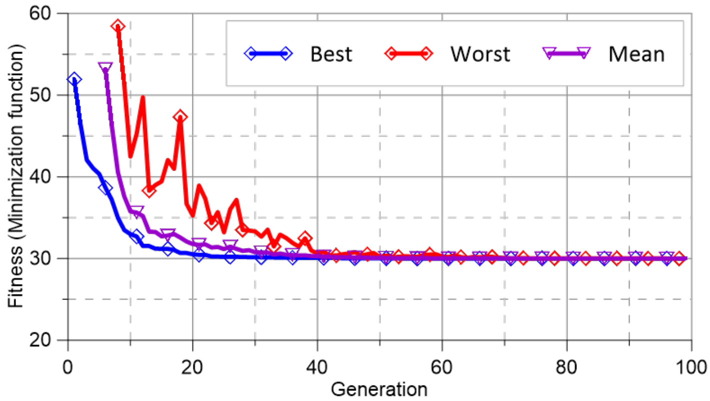

Figure 3. Evolution of the optimization process, the best among 30 runs.

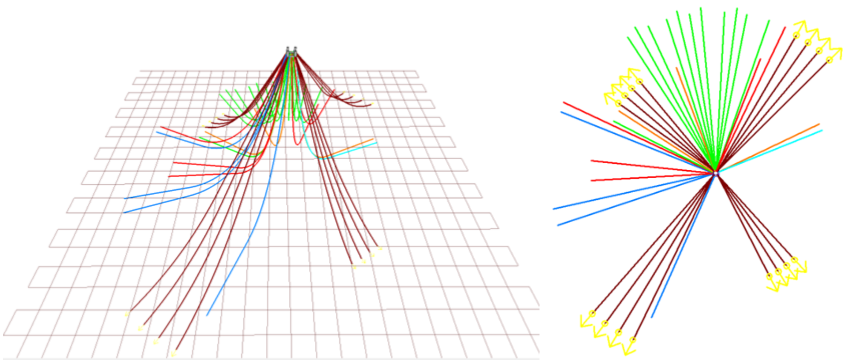

Figure 4. Optimized configuration, 3D and top views.

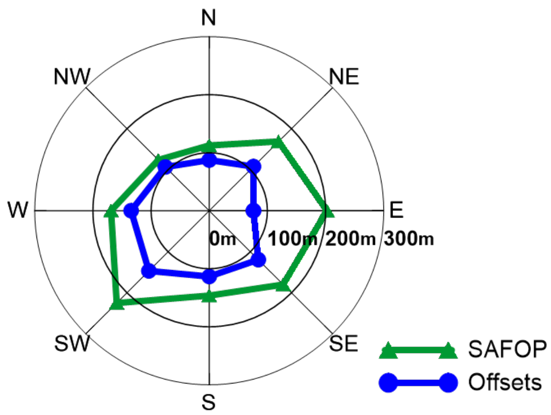

Figure 5. Superposition of SAFOP and Offset diagrams.

4 Conclusions

From the results of this paper, it is clear that for the optimization problem of mooring lines, ANNs comprise an excellent metamodel to replace expensive FEM numerical simulations.

Parametric studies indicate that the ANN training function Bayesian regularization yields superior results compared to Levenberg-Marquardt, despite requiring slightly more time.

The optimization procedure successfully provided feasible solutions that ensure riser integrity with minimal human supervision, completing in an average of only 5 minutes.

Future works can generalize the optimization procedure described here, which focuses on the behavior of the intact system under extreme environmental loadings, to include the evaluation of candidate solutions considering their fatigue behavior and damaged conditions, such as the rupture of a mooring line, by incorporating additional constraints and loading cases for both operational and accidental conditions.

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