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NEW STUDIES ON META-MODELING FOR LAZY-WAVE STEEL CATENARY RISERS

Edivaldo Ramos Delgado[1], Bruno da Fonseca Monteiro[2], Carl Horst Abrecht[2], Breno Pinheiro Jacob[2]

[1]*Polytechnic School, Federal University of Rio de Janeiro*
Athos da Silveira Ramos, 149, CT - Bloco A, Cidade Universitária, Zip-Code 21941-909, Rio de Janeiro, Brazil
edivaldodelgado@poli.ufrj.br
[2]*LAMCSO – Laboratory of Computational Methods and Offshore Systems, Civil Engineering Program, Federal University of Rio de Janeiro. Avenida Pedro Calmon, S/N, Cidade Universitária, Zip-Code 21941-596, Rio de Janeiro, Brazil*
bruno.monteiro@poli.ufrj.br, carl@poli.ufrj.br, breno@lamcso.coppe.ufrj.br

Abstract. Offshore production systems are very complex structures involving safety and economic aspects. For these reasons, several research is done to reduce these costs. At design phase, riser layout and its configuration are a key factor as this is a high-cost component and suffers from the action of environmental loads and dynamic movements of the floating unit where it is connected. This component is mathematically modeled, and calculations are performed using the Finite Element method to assess the structural feasibility and optimization algorithms can be used to determine the viable configuration with the lowest associated cost. The problem with this methodology is that the analysis of different configurations in an optimization process demands a very large computational power, consequently a very high processing time. Previous works have demonstrated that meta-models such as ANN - Artificial Neural Networks can be used to replace the finite element procedure in the evaluation of riser configurations. In this work, novel developments were studied considering two approaches, first the optimization process starts and after a specified number of generations, the training of the meta-model is carried out and from that point the optimization uses the meta-model as a method of evaluation. The second approach has the first part the same as the previous one, however, after the first training, re-trainings are carried out, incorporating new individuals to the knowledge of the meta-model during the optimization process itself.

Keywords: Artificial Neural Networks, Optimization, PSO, Offshore Systems, Riser Lazy-wave.

1 Introduction

The safety and economic aspects of risers in lazy-wave configuration constitute an optimization problem that has already been addressed in previous studies. In this way, this present work is a continuation of several previous works, thus comprising a series of studies on Lazy-Wave catenary risers, which is a very important and complex component in offshore oil and gas production systems [1-5].

The riser design demands a balance between cost and safety factors that result in a formal optimization problem [6]. It is known that the evaluation of a candidate configuration depends on intensive nonlinear dynamic analyses by Finite Elements (FE). As dynamic simulations in time domain are computationally too expensive to be performed during the optimization of the riser configurations, surrogate models (or *meta-models*) may be employed to reduce this cost. In this context, this work studies two different approaches using ANN meta-models for the representation of the riser response, replacing FE analyses. First, starting optimization process and after a certain number of generations the training of the meta-model is carried out and from that point the optimization uses the meta-model as a method of evaluation. The second approach has the first part the same as the previous one, however, after the first training, re-trainings are carried out, incorporating new individuals to the knowledge of the meta-model during the optimization process itself.

2 Problem Modeling

2.1 Lazy-Wave Riser Configuration

In order to evaluate the riser response is needed to know the input of the riser configuration and the material of its components.

Figure 1 shows a schematic model with the parameters that define a lazy-wave riser configuration.

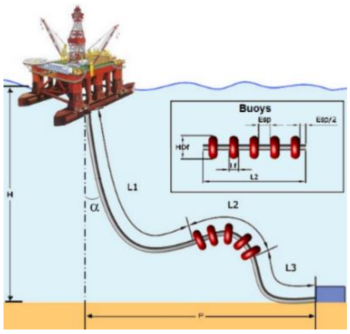


Figure 1. Lazy-Wave Riser Configuration

The water depth is represented by (H) and (P) is the riser horizontal projection. The geometric riser parameters are: (L1) length of top riser segment; (L2), length of segments with distributed floaters; (L3), length of lower segment of the riser and (α) the "top angle", or the angle of the riser axis with the vertical direction at the connection with the platform, measured in the neutral equilibrium configuration. Besides that, there are the parameters related to the buoys, which are (Lf) buoy length, (HDf) buoy diameter, (Esp) spacing between buoys. To evaluate the riser response under certain environmental condition, other parameters such as the specific weight and other mechanical properties of the buoys are considered.

To checking the quality of such configuration, several parameters can be verified, among them we can cite: the maximum equivalent Von Mises stress acting on the riser sections (to assure the structural integrity of the pipe); the maximum angle between the riser axis and the vertical direction at the connection with the platform (dictated by installation requirements); the maximum variation of the "built-in" angle, measured at the top riser axis, between the neutral equilibrium configuration and any configuration acquired by the riser during the application of the environmental loadings and the platform motions (dictated by the design of the flex-joint that provides an articulated connection of the riser with the platform); the maximum tension at the riser top (also dictated by the design of the flex-joint); and the minimum tension at the riser bottom (to avoid buckling and collapse of a riser section).

2.2 Cost function

Cost function used to evaluate the abovementioned Lazy-Wave riser configuration, is described in Eq. 1:

$$C = \frac{C_{min}}{(\sum_{i=1}^{n} CI_i \cdot L_i) + (CI_{buoy} \cdot V_{buoy})} \quad (1)$$

where C_{min} is the lowest possible cost (straight line between the top and bottom connections), used to normalize C in the interval $[0, 1]$; $i = 1..n$ represents the index of the riser segment; CI_i is the cost index associated to each segment; L_i is the segment length; V_{buoy} is the buoy volume and CI_{buoy} is the cost index associated to the buoy volume. By incorporating the constraints, cited in the last paragraph of Section 2.1, of the problem as penalty functions we have the following fitness function:

$$f = 100 \frac{C}{1.0 + \sum P_j} \quad (2)$$

Where, C is the cost function and P_j corresponds to a penalty related to violation of the j^{th} design constraint criterion. More details on the mathematical formulation of this problem can be found in [1-5].

2.3 Artificial Neural Networks

In the offshore industry, ANNs (Artificial Neural Networks) [7] have been widely applied in engineering problems, such as prediction of sea state [8], estimation of platform offsets under environmental loads [9], and numerous other applications [10-13].

ANNs are formed by complex networks of interconnected neurons. Each neuron receives multiple inputs and generates only one output, which can be input to another neuron. In an ANN, the neurons are arranged in layers that can be simple or multilayered.

ANN training consists in a process of weight adjustments. The backpropagation training method is the most common for multilayer Artificial Neural Networks. This method consists of using the errors of the outputs to update all weights, from the end to the beginning of the network [11].

3 Case Study

3.1 PSO

The objective of this work is to assess two methodologies to substitute the finite element procedure by an ANN, keeping a good quality of response and reducing the computational cost. For this assessment the PSO method was used as an optimizer considering its parameters fixed.

More information about this method can been found in [14-16].

3.2 Parametric Studies

Previous parametric studies have been done to choose the best configuration of ANN internal parameters. De Pina [11] found that for this nature problems, the number of hidden layers has little influence on the final result, therefore, only one hidden layer was used in this work. The main parameter to be defined is number of neurons in this hidden layer. For this purpose, ANNs with 6, 10, 15, 30 and 50 neurons in the hidden layer were trained and compared using MSE (Mean Square Error) in the validation set. Which was chosen because it is more accurate than test set since with the increase of neurons the error computed in the training may be masking the generalization of the meta-model, known as overfitting. Sigmoid function was used as activate function.

Furthermore, as the initial weights are randomly initialized, some networks converge faster, and others end up in local minima. For these reasons, one same configuration is trained ten times to choose the trained ANN with the best results. Results of this parametric study can be observed in the Table 1.

Table 1. Results of parametric studies of the number of neurons in the ANN hidden layer

Neurons	Lowest MSE value in the validation set among 10 runs
6	3.79E-03
10	**1.68E-03**
15	3.17E-03
30	3.87E-02
50	4.15E-01

From the results, it was chosen 10 neurons in the hidden layer for the next studies.

3.3 Method 1 – Single ANN Training

In this approach, the optimization process starts using the FEM to calculate the objective function for 50 generations. With the data from these first 50 generations, the ANN training is performed and, from there, the optimization process continues using the trained ANN as a method for evaluating the individuals.

In this method, experiments were performed with different size of training and validation sets. Each experiment is performed with a total of 150 generations in the optimization process, and each generation with a population of 20 individuals. As the objective is to reduce the number of individuals used for training, while still maintaining a good accuracy of the model, several configurations were tested, starting with 30 generations for training, up to the use of 80 generations. Within the training set, individuals were randomly separated so that there is a validation set (20% of individuals), as can be seen in Table 2.

Table 2. Parametric studies considering Method 1

Experiment	Generations before training	Individuals in training set	Individuals in validation set
[a_1]	30	480	120
[b_1]	40	640	160
[c_1]	50	800	200
[d_1]	60	960	240
[e_1]	70	1120	280
[f_1]	80	1280	320

Results of this parametric study can be seen in Table 3.

Table 3. Results of Parametric studies considering Method 1

Experiment	Lowest MSE value among 10 runs in the validation set
[a_1]	5.78E-04
[b_1]	1.10E-03
[c_1]	7.97E-04
[d_1]	5.94E-04
[e_1]	**3.31E-04**
[f_1]	5.46E-04

A visual assessment among the experiments is shown in Figure 2. Here, we can see the scatterplots of the fitness value computed by Finite Elements procedure versus the predicted by ANN in the validation set. The evolution of the optimization process for each experiment is presented in Figure 3. Highlighted area is when the meta-model starts and replaces the fitness calculation previously provided by the FE procedure.

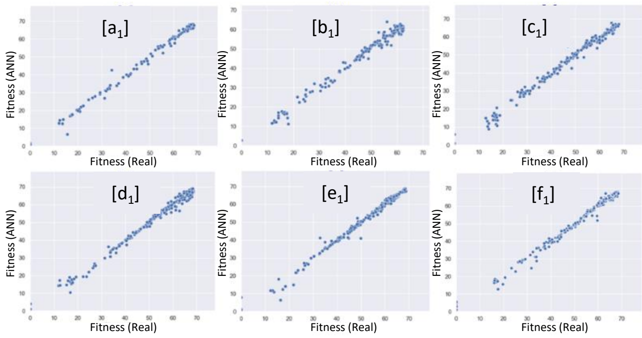


Figure 2. Scatter plot of fitness value predicted by ANN versus Finite Element in the validation set

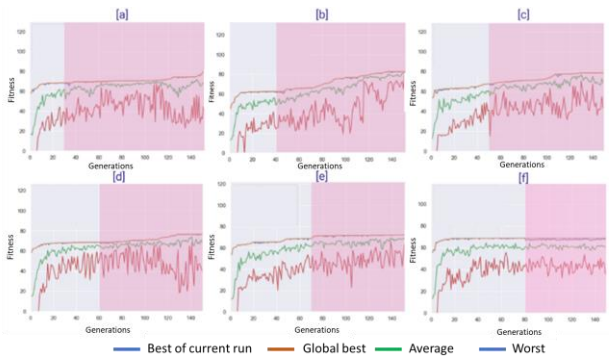


Figure 3. Evolution of the optimization process of each experiment

Figure 4 presents the scatterplots of the fitness value computed by Finite Elements procedure versus the predicted by ANN in all optimization process.

From Figure 4 is evident that in experiments [a_2], [b_2] and [c_2], there are many individuals who have a very large discrepancy between what was the result of the meta-model and what would have been calculated by the finite element method. Which shows that with few generations the network is not able to generalize satisfactorily to follow the optimization process.

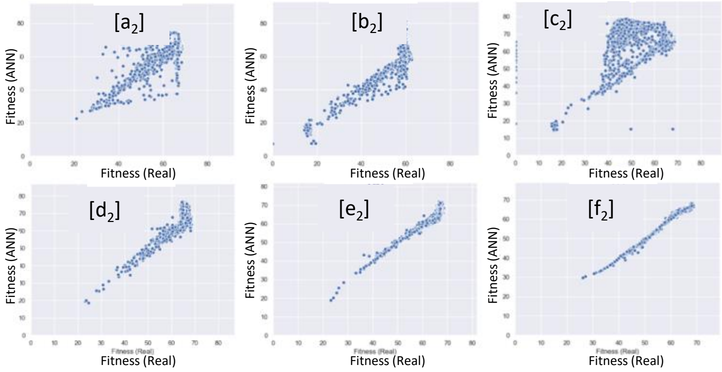


Figure 4. Scatter plot of fitness value predicted by ANN versus Finite Element in the optimization process

3.4 Method 2 – ANN re-trainings throughout the optimization process

Unlike Method 1, this current approach makes after the first substitution of the Fitness calculation for the ANN, next some generations return to the finite element calculation for a few more generations. Thus, we have more data calculated by Finite Elements, which are added to the previous ones and a new ANN training is performed. Repeat this process for a few more times.

The motivation for this approach comes from the fact that in the first generations of an optimization process the search space may not be well represented for an efficient ANN generalization.

From the results of the Method 1, experiments with 30, 40 and 50 initial generations before the ANN training were not performed. Therefore, Method 2 starts ANN training after 60 initial generations of the optimization process with re-training at 10 generation intervals, as can be observed in Figure 5. The same procedure of the Method 1 was applied to Method 2, i.e., 20% of the total individuals was randomly send to validation set in all steps of optimization process, according to Table 4.

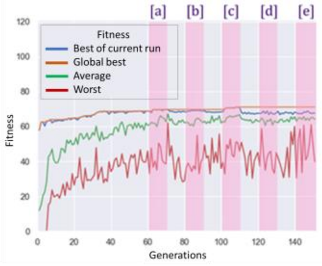
Figure 5. Evolution of the optimization process of each experiment

Table 4. Distribution of individuals in the training and validation subsets in Method 2

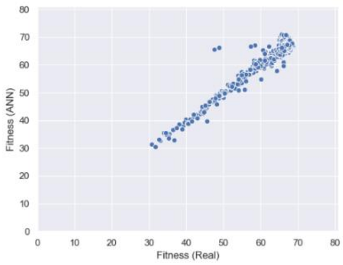
Step	Individuals in training set	Individuals in validation set
[a_2]	960	240
[b_2]	1120	280
[c_2]	1280	320
[d_2]	1440	360
[e_2]	1600	400

It is important to cite that now the stages from [a_2] to [e_2] are no longer independent experiments but are steps of the same experiment.

The evolution of the optimization process is presented in Figure 6(a). Highlighted area is when the meta-model starts and replaces the fitness calculation previously provided by the FE procedure. Results of this approach can be seen in Table 5.



(a)



(b)

Figure 6. (a) Evolution of the optimization process. (b) Scatter plot of fitness value predicted by ANN versus obtained by FE in the optimization process

Table 5. Results of parametric studies considering Method 1

Experiment	Lowest MSE value in the validation set among 10 runs
[a_2]	1.01E-03
[b_2]	8.98E-04
[c_2]	7.67E-04
[d_2]	5.01E-04
[e_2]	**3.10E-04**

The result presented in Table 5 is very consistent, as the smallest MSE occurs in the last step, where the training set has the largest number of elements.

Figure 6(b) presents the scatterplots of the fitness value computed by Finite Elements procedure versus the predicted by ANN in all individuals assessed by metamodel in the optimization process.

3.5 Discussions

After carrying out the experiments, one can compare the results and assess which approach is more effective for the objective of the work. Which is to make as few numbers of evaluations as possible with the finite element software, maintaining the quality of the optimization result. In other words, we want to maintain the quality of the results with the lowest possible computational cost.

For all experiments, the same computer was used, with an Intel i5-7200U processor, with 2 2.5 GHz physical cores, 8 GB of DDR3 memory, 1TB SATA HDD and Windows 10 operating system.

The total time to perform one complete optimization process with 150 generations using only finite elements to compute the fitness function was 8145 s.

Table 6 presents a comparison between the performance of both methods.

Table 6. Comparative between the best results from methods 1 and 2

Method	Best MSE [validation set]	Best MSE [optimization process]	Time saving
1	3.31E-04	1.25E-03	**50.8%**
2	**3.10E-04**	**4.38E-04**	20.4%

The main objective of Method 2 was to be able to incorporate new individuals to the knowledge of the meta-model, so, throughout the optimization, these new individuals would be more representative of the search space. This objective was achieved since this method presents an error with an order of magnitude smaller than the Method 1. On the other hand, the time saving by Method 1 was more than twice that of Method 2.

4 Conclusions

From the results of this work, it is clear that for preliminary analyzes in the study of lazy-wave catenary riser configurations in the optimization process, Artificial Neural Networks are an excellent metamodel to be used in this type of problem. Considering the initial parametric study (Section 3.2) done, it is possible to determine the best configuration regarding number of neurons in the hidden layer of an ANN. In the parametric variation for the Method 1 (Section 3.3) it is possible to determine the minimum number of individuals recommended to perform the meta-model training in this specific problem. Still on Method 1 study, we can see experiments with low MSE and a good visual assessment in scatter plots. About Method 2 (Section 3.4), it is very interesting to observe the decrease in the MSE from each new ANN retraining. Comparing the performance of the Methods, one can see that both present good results with Method 2 being a little better in terms of MSE. But, regarding time savings Method 1 presents the best result. We can conclude that the choice of method depends on the designer's objective, whether a smaller error or greater time saving is preferred.

References

[1] Vieira, I.N., B.S.L.P.d. Lima, and B.P. Jacob, *Bio-inspired algorithms for the optimization of offshore oil production systems.* International Journal for Numerical Methods in Engineering, 2012. **91**(10): p. 1023-1044.
[2] Da Fonseca Monteiro, B., et al., *Studies on meta-modeling for lazy-wave steel catenary risers*, in *OMAE'18 - International Conference on Offshore Mechanics and Arctic Engineering*. 2018.
[3] Benete, A.P., et al., *ARTIFICIAL NEURAL NETWORKS FOR OPTIMIZATION PROCEDURES OF LAZY WAVE FLEXIBLE RISER CONFIGURATION*, in *XL CILAMCE - Ibero-Latin-American Congress on Computational Methods in Engineering*. 2019: Natal, RN-Brazil. p. 11.
[4] Alves, V.Q., B.F. Monteiro, and C.H. Albrecht, *COMPARAÇÃO DE DESEMPENHO DOS ALGORITMOS "PSO" E "DE" NA OTIMIZAÇÃO DE UM RISER EM CONFIGURAÇÃO "LAZY - WAVE"*, in *XXXVIII CILAMCE - Ibero-Latin American Congress on Computational Methods in Engineering*. 2017: Florianopolis - SC, Brazil. p. 20.
[5] de Pina, A.A., et al., *Tailoring the particle swarm optimization algorithm for the design of offshore oil production risers.* Optimization and Engineering, 2011. **12**(1-2): p. 215-235.
[6] Lima, B.S.L.P.d., B.P. Jacob, and N.F.F. Ebecken, *A hybrid fuzzy/genetic algorithm for the design of offshore oil production risers.* International Journal for Numerical Methods in Engineering, 2005. **64**: p. 1459–1482.
[7] McCulloch, W.S. and W. Pitts, *A logical calculus of the ideas immanent in nervous activity.* Bulletin of Mathematical Biophysics, 1943. **5**: p. 19.
[8] Yasseri, S.F., et al., *Prediction of safe sea-state using finite element method and artificial neural networks.* Ocean Engineering, 2010. **37**(2-3): p. 200-207.
[9] Mazaheri, S. and M.J. Downie, *Response-based method for determining the extreme behaviour of floating offshore platforms.* Ocean Engineering, 2005. **32**(3-4): p. 363-393.
[10] Ok, D., Y. Pu, and A. Incecik, *Artificial neural networks and their application to assessment of ultimate strength of plates with pitting corrosion.* Ocean Engineering, 2007. **34**(17-18): p. 2222-2230.
[11] de Pina, A.C., et al., *ANN-based surrogate models for the analysis of mooring lines and risers.* Applied Ocean Research, 2013. **41**: p. 76-86.
[12] de Pina, A.C., et al., *ANN and wavelet network meta-models for the coupled analysis of floating production systems.* Applied Ocean Research, 2014. **48**: p. 21--32.
[13] Pina, A.A.d., et al., *Artificial Neural Networks for the analysis of spread-mooring configurations for floating production systems.* Applied Ocean Research, 2016. **59**: p. 254-264.
[14] Eberhart, R.C. and J. Kennedy. *A new optimizer using particle swarm theory*. in *Sixth Symposium on Micro Machine and Human Science*. 1995. New York, USA.
[15] Eberhardt, R.C. and Y. Shi. *Comparing Inertia Weights and Constriction Factors in Particle Swarm Optimization*. in *IEEE International Conference on Evolutionary Computation*. 2000. San Diego, California, USA.
[16] Hu, X., R.C. Eberhardt, and Y. Shi. *Engineering Optimization with Particle Swarm*. in *IEEE Swarm Intelligence Symposium*. 2003. Indianapolis, USA.