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Reliability Assessment of a Fixed Jacket Platform by Monte Carlo Simulation Using Neural Network

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ABSTRACT

Fixed offshore structures are considered as an important structure in shallow water. Iranian oil and gas offshore structures which have been located in Persian Gulf are mostly fixed jacket. So reliability assessment of these kind of marine structures seems to be very important and is an essential part of offshore structure design. Mont Carlo is a powerful method which is used broadly for prediction of structure failure. The most advantage of this method is simplicity of implementation, the main limitation of this method is about the computational time due to the huge number of structural analyses. Incorporating the artificial neural network for the reduction of the sample size is used to eliminate of MCS‘s time bottleneck. An MCS based method is introduced to take advantage of precision in optimization part. To solve the scaling problem of a large reliability analysis, an artificial neural network is employed. In this paper, an almost new constructed fixed jacket platform in the South Pars is selected and modeled using SACS software. In this regard, the nonlinear static pushover analysis is performed by application of nonlinear soil-pile interaction. Analytical results show that the simultaneous use of these two techniques lead to more accurate and also faster reliability assessment. In MCS method probability of failure calculated using divide the number of failed sample by total samples which is concluded to the value of 9.4e-05 for the test case structure in the current study, and the reliability index is resulted to 3.73.

1. Introduction

Iran is regarded as a developing country, has accomplished many projects with respect to offshore jacket platform. Most of these structures have been installed in Persian Gulf with the aim of extracting oil and gas. The life cycle of these structures is extremely important for the national economy.

Structural reliability assessment methods are useful tools for evaluating the safety of complex structures. These methods have been developed substantially in the last few years by many researchers. Onoufriou and Forbes[1] , Nizamani [2], Zaghloul [3] And Fayazi [4] are researchers which have done the prominent studies on the reliability assessment of offshore structures. Applicable methods for evaluating the reliability assessment can be categorized into two main groups [5]:

- Gradient-based
- Simulation-based Methods or Sampling Methods

First Order Reliability Methods (FORM) and Second Order Reliability Methods (SORM) are considered as gradient based reliability. FORM is based on linear (first order) approximation of the limit state surface tangent to the most probable point of the failure surface to the origin of a reduced coordinate system and SORM estimates the probability of failure by using a nonlinear approximation of the limit state function by a second order representation [6].

Monte Carlo simulation (MCS) method is the origin of sampling techniques. This method gathers a large number of samples to calculate the actual probability of failure using limit state. The approximation is evaluated by means of the number of samples falling into the failure domain.

Here the most important features of MCS are illustrated [7]:

1- This method actually allows use of any probability distribution for random variables used in many practical problems issues.
2- This method is able to calculate the probability of failure with any desired precision.
3- Modeling and implementation is simple.
However, despite the mentioned advantages, using this method is not so pervasive in evaluating the reliability of the complex structures due to its high computational cost.
According to DNV RP 2A [8], standard acceptance criteria for the ultimate strength level is determined based on the ratio of the platform ultimate capacity to the design loading that called Reserve Strength Ratio (RSR). RSR is usually calculated based on a 100-year wave loading.
Reserve Strength Ratio (RSR) which is defined as:

$$RSR = \frac{Ultimate\ Lateral\ Load\ That\ Causes\ Failure}{100\ Year\ Enviromental\ Lateral\ Loading} \quad (1)$$

In the current research, a desired fixed jacket structure is modeled using SACS software. The failure analyses are performed based on the wide range of different parameters. High computational cost is a major problem to structural assessment, especially when complex structures are analyzed based on non-linearity. The computation time can be prohibitively high, especially in the case of performing non-linear full plastic collapse. To eliminate this drawback and in order to reduce the number of samples, the following variance reduction techniques have been proposed:

- Importance Sampling: R.E MELCHERS [9] proposed an application of Importance sampling in structural systems
- Response surface method: Bucher [10] proposed an application of the RSM to structural reliability problems
- Latin Hypercube Sampling method: D. Novak, B. Teply, Z. Kersner [11] proposed an application of the Latin Hypercube Sampling method in reliability engineering
- Subset simulation: S.K. Au, J.L. Beck [12] proposed an application of the subset simulation to Estimation of small failure probabilities in high dimensions
- Using Neural Networks: Shao and Murotsu [13, 14] developed a method to use Artificial Neural Network (ANN) in reliability analysis and Manolis Papadrakakis [15] proposed an application of ANN to reduction of sample test

In this paper, an Artificial Neural Network (ANN) has been suggested to estimate structural response to the predefined load parameters. A well-designed ANN could significantly reduce computational cost of structure response prediction. The simultaneous use of MCS method with ANN gives the desired outcomes including a reduction in computational cost and also desired precision.

This number of 700 samples is obtained which is enough to feed ANN according to number of network input and hidden layer neurons. So mentioned ANN has the ability of predicting RSR factor related to samples with the same accuracy Load Factor Step Size in SACS. Then a feed forward ANN is trained to predict the probability of failure of structure. ANN input parameters are wave height, wave period, drag coefficient and mass coefficient, and the output is RSR.

2. Overview of Reliability Assessment by Monte Carlo Simulation

Parameters such as design parameters, material properties, loading conditions probabilistic nature can affect the structural safety index. An offshore engineer must consider the uncertainties in the structural safety index. Reliability analysis carried out by the following relationship

$$P_f = P[g(X_1, X_2, \dots, X_n) \le 0] = \quad (2)$$

$$\int \int_{g(X_1, X_2, \dots, X_n) \le 0} \dots \int f_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n)\, dx_1 dx_2 \dots dx_n \quad (3)$$

In Eq. (3) $g(x_1, x_2, \dots, x_n)$ is the failure function and $x_1, x_2, \dots, x_n$ are random variables. Limit state function is defined as $g(x_1, x_2, \dots, x_n) \le 0$ and P_f is probability of failure.

If the random variables are correlated or the distribution of these variables is not normal standard or in conditions that limit state function is not clearly explicit, the calculation of this integral is difficult or impossible. Therefore one of the recommended methods to calculate the reliability of this situation is sampling methods such as the Monte Carlo Simulation. Monte Carlo method for reliability analysis and calculation of the probability of failure can be utilized. If the limit state function is expressed as $G(X) < 0$ and $X = (x_1, x_2, \dots, x_n)$ is the vector of random variables, Eq. (2) is written as follows:

$$\boldsymbol{P_f = \int_{G(x) \ge 0} f_x(x) dx} \quad (4)$$

Where $f_x(x)$ for all random variables is the joint probability of failure. Since the MCS method is based on many samples (N_∞) we can accurately estimate the probability of failure as follows:

$$\boldsymbol{P_f = \frac{1}{N_\infty} \sum_{j=1}^{N_\infty} I(x_j)} \quad (5)$$

Where $I(X_j)$ is an indication for an accepted or rejected simulation defined as:

$$\boldsymbol{I(x_j) = \begin{cases} 1 & if\ G(x_j) \ge 0 \\ 0 & if\ G(x_j) < 0 \end{cases}} \quad (6)$$

Based on the number of selected samples, the calculated probability of failure can be obtained with arbitrary precision. By choosing a random number to each variable, in accordance with its distribution function, the function limit state is calculated for each sample. Finally the probability of failure is calculated using Monte Carlo method in accordance with the following formula.

$$\boldsymbol{P_f} \cong \frac{\boldsymbol{N_H}}{\boldsymbol{N}} \qquad (7)$$

Where N_H is the total number of cases where failure has occurred [16].
The corresponding reliability index β is defined as

$$\beta = -\Phi^{-1}(P_f) \qquad (8)$$

Where Φ is the standard normal cumulative distribution function
According to the desired coefficient of variation (COV), the number of samples for Monte Carlo simulation can be determined. COV amount is usually between 2-5% [17].

$$\boldsymbol{\delta_{P_f}} = \sqrt{\frac{\boldsymbol{1-P_f}}{\boldsymbol{N*P_f}}} \qquad (9)$$

$$\boldsymbol{N} = \frac{\boldsymbol{1}}{\boldsymbol{\delta_{P_f}}^{2}} * \frac{\boldsymbol{1-P_f}}{\boldsymbol{P_f}} \qquad (10)$$

Where N is number of Sampling, δ_{P_f} is a coefficient of variation of failure probability and P_f is a failure probability.
The required sample size for Monte Carlo simulations can be calculated due to the favorable coefficient of variation, COV amount is usually between 2% -5% is considered. COV value determines the accuracy of the simulation

3. Neural Network Application in Structural Reliability Assessment

An artificial neural network (ANN) is a mapping mechanism in which one multivariable space could be map to a new space using a special mapping strategy represented by a set of data (Garrett 1994) [18]. An ANN can be constructed to approximate the implicit performance function of a reliability analysis method. An ANN-based reliability analysis can easily consider performance function as the target space [19].
The concept of Artificial Neural Network (ANN) is presented by McCulloch and Pitts [20]. Actually they presented a mathematical model for neural network. ANNs are computing systems made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs. An ANN model can be build based on the artificial neuron.
ANN is an informational system simulating the ability of a biological neuron network by interconnecting many simple neurons. Therefore the advances in biological research promise an initial understanding of the natural thinking mechanism. Complicated information processing in the brain is done based on combination of massive simultaneously simple neurons function. Pattern recognition and learning are two contexts that human and computer ability is more comparable. Sometimes the winner of this comparison is computer because of its complicate mimic of brain. Although the computer can calculate large numbers at high speeds but there is a basic weakness in classification problem, written text, data compression and a learning algorithm. On the contrary, a human easily recognizes and deals with these kind of challenges using humanity nature of brain which is unknown in most of its aspects [21]. The neuron accepts inputs from a single or multiple sources and produces outputs by simple calculations, processing with a predetermined nonlinear function.
This field does not utilize traditional programming but involves the creation of massively parallel networks and the training of those networks to solve specific problems. ANNs have the capability of establishing a functional relationship between two data spaces during a learning process and reproduce generalize these data during a recall process. This method has been widespread usage in different fields of engineering such as structural assessment.
After successful training, an ANN can provide the correlating mathematical relationship between multi-dimensional input/output data
ANN can be classified in to feed forward and feedback or recurrent networks. The basic difference is that in feed forward networks the signal is passed in a forward manner only till the desired output is obtained from the output layer. Whereas in feedback network the output obtained is fed back into the network through the input layer, thus this type of network will have a minimum of single loop in its structure. In this case the error can then be used to change network parameters, which result in an improvement in performance. In unsupervised learning the target output is not presented to the network. It is as if there is no teacher to present the desired patterns and, the system learns of its own by discovering and adapting to structural features in the input patterns. A neuron is a real function of the input vector $X_1, X_2, X_3, \ldots. X_n$ and $W_{k1}, W_{k2}, W_{k3}, \ldots. W_{kn}$ are the weights associated with it.
A multi-layer feed-forward neural network structure is used in this research. In general, an ANN structure consists of several layers and each layer consists of several neurons, which is also called processing elements (PE). Figure (1) shows a typical structure of a feed-forward ANN model, in which the left column is input layer, the right most column is output layer, in between input layer and output layer is a hidden layer.
Generally there could be more than one hidden layer. Each processing element has several inputs and one output.

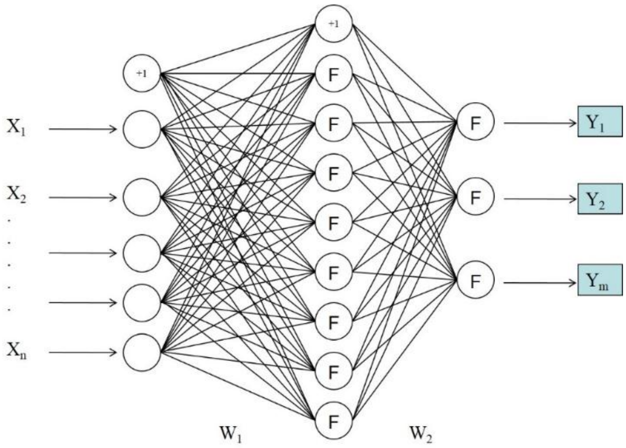

Figure 1. General Structure of an Artificial Neural Network

3.1. ANN Training

To start the training process the initial weights are randomized (typically between 0 and 0.1). Here, feed-forward training algorithm has been used to train all models. During the training of a network the same set of data is processed many times (1000 epoch) as the connection weights are adjusted by back-propagation. The training stops when the model reaches some statistically desired level of accuracy. If a training procedure is not successful, we may repeat the procedure whilst varying the randomized weights, number of neurons in the hidden layer or the activation function. In this research, a set of input and output data is prepared for developing ANN models. A sub-set of data is used for training (over 70 percent), while the other for cross-validation and testing the model.

Figures 2 to 5 show that designed neural network could anticipate RSR factor of test samples. According to figure 5 error ratio in RSR estimation is even smaller than step size in sacs. So it is acceptable to use RSR factor for new samples using ANN instead of simulation these samples using SACS.

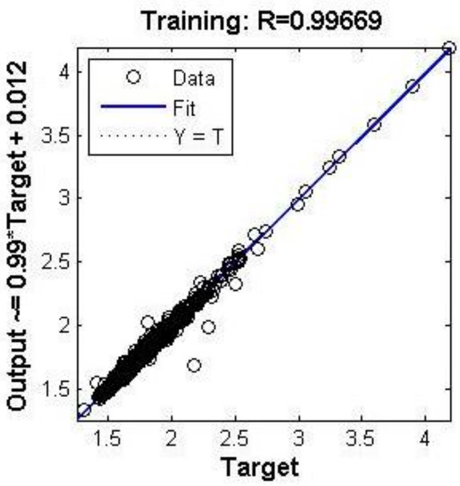

Figure 2. Training Results

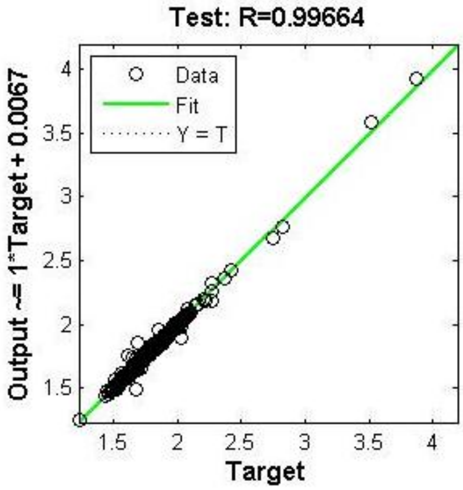

Figure 3. Test Results

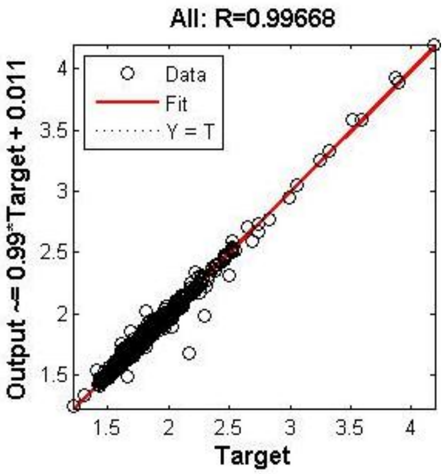

Figure 4. Test and Train Set Results

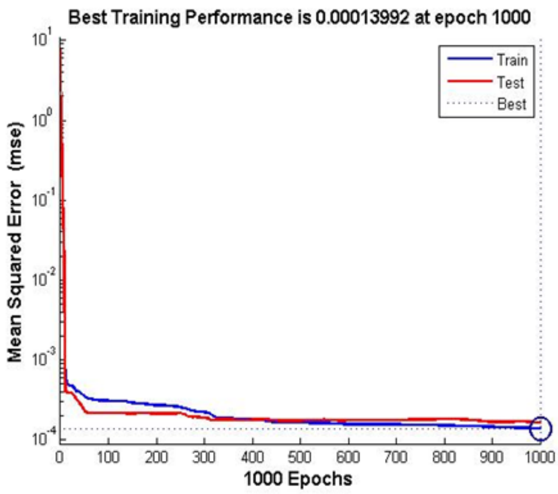

Figure 5. Best Training Performance

3.2. ANN Cross-Validation and Test

The data are divided into three different sub-sets: (a) training, (b) cross validation and (c) test. Corresponding error when the network was presented with the cross-validation sub-set during the training procedure is used as a measure of models accuracy and as a signal to stop the training. Consequently, the ANN model accuracy is verified by introducing the test sub-set. If the error with respect to this sub-set is not acceptable, the training may be repeated. Indeed, this testing is critical to insure that the network has successfully learned the correct functional relationship within the whole set of data. This may be considered as an advantage of using ANN when compared with polynomial-based response surface method. Hence there is not an absolute technique to specify some ANN parameter, the problem of determining the number of hidden layer neurons and finding suitable error function in an ANN, could be solved using trial and test method. Here several efforts have been done to determine mentioned factors. Several error function have been examined to find out minimum obtained error. Trial and error results have been shown in Table 1. Finally "Feed forward" Matlab command with "trainbr" function is used and one hidden layers has been selected. Since there was about 500 samples to train the network minimum of 150 neurons are suitable to determine network weights in an effective way.

Table 1: Trial and error results in an ANN

Hidden layer No.	Neuron No.	Error	function	Matlab command
1	200	0.002	'trainbr'	Fitnet
2	30	0.0037	'trainbr'	Fitnet
2	50	0.002	'trainbr'	Fitnet
1	200	0.0016	'trainbr'	feedforward
1	250	0.0018	'trainbr'	Feedforward
2	50	0.0023	'trainbr'	Feedforward
1	150	0.0018	'trainbr'	Feedforward
1	150	.0067	'trainlm'	Feedforward
1	150	.0032	'trainbfg'	Feedforward
1	150	19.6276	'traingd'	Feedforward
1	150	0.4715	'traingdx'	Feedforward
1	150	.069	'trainscg'	Feedforward
1	150	.063	'traincgb'	Feedforward
1	150	.0878	traincgf'	feedforward

4. Offshore Structure Modeling

The project is modeled based on the platform SPD19B (Figure (6)) which is a 6 legs platform and is located in Persian Gulf. The salient features of the platform SPD19B are given in Table 2.

Table 2: Salient Features of the Platform SPD19B [22]

Geometry	Six legged Jacket with six main piles to support wellhead production facilities (WHP). The dimensions between the legs are 27.5 m × 16.0 m (at W.P. elevation). The overall size of the deck is approximately 32.25 m ×18 m. The topside is composed of upper deck, mezzanine deck, and lower deck.	
Foundation	six grouted main piles	
Piles	54" (1371.6mm) dia.	
Water Depth	72.2 m below LAT	
Jacket Framing Elevations	Level – 1:	EL (+) 6.500
	Level – 2:	EL (-) 10.500
	Level – 3:	EL (-) 28.500
	Level – 4	EL (-) 48.000
	Level – 5	EL (-) 70.000
	Top of Jacket	EL (+) 7.900
	Pile Cut-off level	EL (+)8.800
	Working Point Elevation	EL (+) 9.500

Structural analysis is carried out using the SACS structural software.

Figure 6. SPD19B

The wave and current force are considered at the critical direction. The critical direction is NW.

4.1. Environmental Conditions

4.1.1. Wind

The wind loads are calculated based on the API RP 2A, using following-directional wind speeds for operating and extreme storm conditions. The maximum wind speed 10m above MSL are:

Table 3 : Maximum Wind Speed 10m above MSL [22]

Wind (From) w.r.t PN	Wind Velocity (m/sec)							
	N	NE	E	SE	S	SW	W	NW
Operating (1 yr.)	22.0	21.5	22.2	21.7	20.6	20.4	22.0	22.7
Extreme (100 yr.)	35.6	34.9	36.0	35.2	33.4	33.0	35.6	36.7

In this paper 100-year wind velocity is used as wind loads factor.

4.1.2. Wave

Directional waves are used for the analysis. Wave height with associated period for operating and extreme storm conditions are shows in table 4 and 5.

Table- 1: Wave Height with Associated Period for Operating Conditions[22]

Wave (From) w.r.t PN	1 Year Wave							
	N	NE	E	SE	S	SW	W	NW
Height (m)	5.5	5.1	6.0	6.3	5.6	5.0	6.0	6.7
Period (sec)	7.8	7.5	8.1	8.3	7.9	7.4	8.1	8.6

Table- 2: Wave Height with Associated Period for Extreme Storm Conditions[22]

Wave (From) w.r.t PN	100 Year Wave							
	N	NE	E	SE	S	SW	W	NW
Height (m)	9.7	8.8	10.8	11.6	10.2	8.8	10.8	12.2
Period (sec)	10.0	9.60	10.4	10.8	10.2	9.50	10.4	11.0

To find the reliability index for fixed offshore structures, 100-year loads are used. In this regard, wave height with Weibull distribution function and a lognormal distribution is used for simulation of wave period. Parameters of mentioned distributions are shown in Table 8.

4.1.3 Current

The following currents are considered for the design of the platform. Table 6 shows Current Stretching Profile above Storm Mean Water Level.

Table- 3: Current Stretching Profile above Storm Mean Water Level [22]

Current	Current Velocity m/sec (1 year storm)	Current Velocity m/sec (100 year storm)
Surface current	0.90	1.28
Mid-depth current	0.90	1.28
1.0m above seabed	0.68	0.78
0.5m above seabed	0.62	0.71

A 100-year current velocity is used as the current load value.

4.1.4 Drag and inertia coefficients

Table- 4: Mass & Drag coefficient For Original model[22]

Member Description	C_{dn}	C_{mn}
Flat members(Clean an Fouled)	1.60	1.60
Tubular member smooth	0.65	1.60
Tubular member rough	1.05	1.20

Mass & Drag coefficient in original model have been shown in table 7 but in this paper, inertia coefficient and drag coefficient are in accordance with Table 8 and are considered to be log-normal distribution. Jacket sections considered to be in a rough tubular member.
The depth of scour is considered as 1.5m below the mudline. The scour depth is considered by removing the top 1.5m from the soil curves in the psi-input file.

In this study, appropriate parameters of wave force are regarded as a random variable. Failure probability of structures is calculated by non-deterministic parameters. In the following table, probability distribution function related to each parameter has been given.

Table -5: Random Variables of Wave Loading Condition

Random Variable	PDF	Mean	(C.O.V)	reference
Wave height (H)	Weibull	6.86	2.65	[2, 22]
Wave period(T)	wave period conditional on Wave height*			[23]
Drag coefficient (CDN)	Log-Normal	1.05	0.2	[4]
Mass coefficient (CMN)	Log-Normal	1.2	0.1	[4]

*According to API-RP-2A the wave period conditional on Wave height is modeled by a lognormal distribution where the distribution parameters μ and σ are functions of the wave height

5. Results of the Reliability Analysis

In this research, wave height, wave period, drag coefficient and mass coefficient parameters are intended as uncertainty variables. We've chosen 700 samples of the parameters in accordance with the standard normal distribution which is named Sample Set1. By analyzing the platform using SACS software, the RSR value for each sample is obtained. They considered as test data and also train set for neural network. Nearly a 70% of these data is used as the ANN train data and the rest is considered as test set.
In similar studies almost a collection of 10e6 samples are used for reliability assessment of such a complex structure. While in our method 2×10e7 samples produced using ANN. Then limit state function values for these samples has been calculated (named sample set2).
Breaking point limits the height of wave. Based on the small-amplitude wave theory, the wave celerity and the wave height are independent quantities. So, the wave will break as the wave height increases and subsequently the crest particle velocity will eventually equal the wave celerity [24]. According to DNV standard, there is no possibility of occurrence for some special set of parameter values in natural environment, which is due to wave breaking phenomenon. In shallow water the limit of the wave height can be taken as 0.78 times the local water depth and breaking wave height dependent on wave period [25].So this kind of samples was removed from the original set (Table 9).

Table- 6: The number of broken waves

Total number of samples	In this number of samples wave breaks	Samples will not be break
2×10^7	4677839	15322161

Analyzing the result of sample set1, shows that increasing the uncertainty variable leads to RSR reduction. However, since increasing the value of different parameters lead to increase forces on structure. It could be claimed that RSR reduction due to increasing the parameter value is predictable.

Therefore, Based on this assumption, we should refine sample set 1, and then analyses the value of limit state function for remaining samples (sample set 2) the result off this analysis see in Table 10. The applied reduction leads to smaller test set feed ANN and also more accuracy in the term of network error reduction. Calculated RSRs using ANN on this sample are shown in Table 11. The sample set1 is used to train ANN and also evaluate it. According to the routine procedure for the division existing data into test and train sets, up to 70 percent of available data is used as train set and the rest (less than 30 percent) considered as test data.

According to Eq.9, when there are 15322161 samples and probability of failure is 9.4e-5, calculated deviation is 2.6%. The results are shown in Table 12.

Table -7: Compare the samples set2 with sample set1

Compare the samples set2 with sample set1	A number of samples with RSR>1.6	15293110	The rest of the samples are determined by the neural network. The total number is 28846 sample
	A number of samples with RSR<1.6	205	

Table- 8: Results of Artificial Neural Network

The total number of samples that have been tested with neural network is 28846	A number of samples with RSR>1.6	27618
	A number of samples with RSR<1.6	1228

Table -9: The Results of Reliability Assessment

Total Samples will not be break	A number of samples with RSR>1.6	A number of samples with RSR<1.6	Probability of Failure	Reliability index
15322161	15320728	1433	9.4e-05	3.73

6. CONCLUSIONS

Reliability assessment is a modern method to evaluate the structural performance. Due to the complexity and importance of offshore structures, implementing an efficient method for reliability analysis is an opening challenge. Iran country has many platforms in the Persian Gulf's which is a strategic area. The development of these platforms is a milestone to develop of oil industries. The environment loads related to these structures are completely random, so reliability assessment of these structures is a valuable task. In this research, a new constructed fixed jacket platform of the South Pars is modeled, and reliability of this platform is determined using Monte Carlo Simulation (MCS) method by application of an Artificial Neural Network. The results show that probability of failure for this new constructed fixed jacket platform is 9.4e-05, and the reliability index is resulted to 3.73

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