SEISMIC VULNERABILITY ASSESSMENT OF LARGE-SCALE GEOSTRUCTURES

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ABSTRACT :

Seismic vulnerability analysis of structural and infrastructural systems is commonly performed by means of fragility curves. There are two approaches for developing fragility curves, either based on the assumption that the structural response follows the lognormal distribution or using reliability analysis techniques for calculating the probability of exceedance for various damage states and seismic hazard intensity levels. The Monte Carlo Simulation (MCS) technique is considered as the most consistent reliability analysis method having no limitations regarding its applicability range. Nevertheless, the only limitation imposed is the required computational effort, which increases substantially when implemented for calculating lower probabilities. Incorporating artificial neural networks (ANN) into the vulnerability analysis framework enhances the computational efficiency of MCS, since ANN require a fraction of time compared to the conventional procedure. Thus, ANN offer a precise and efficient way to determine a geostructure's seismic vulnerability for multiple hazard levels and multiple limit states.

KEYWORDS: slope stability, fragility curves, neural networks, Monte Carlo simulation

1. INTRODUCTION

Earthquake engineering applications, including the geotechnical ones, are characterized by inherent uncertainties related to the material properties, the loading conditions, the numerical modelling, and others. Nevertheless, in geotechnical engineering practice deterministic simplifications are employed due to the complexity and the computational cost required by the probabilistic methods. However, probabilistic methods are gaining popularity nowadays due to the advances in both computational resources and numerical methods. In the early nineties new non-conventional data processing and simulation methods have been developed designated as Soft Computing (SC). These methods are widely applied lately in various time-consuming structural and geotechnical engineering problems. In a recent edited book by Lagaros and Tsompanakis (2006) a survey of the application of SC methods in earthquake engineering problems is presented. Among SC methods, Artificial Neural Networks (ANN) are considered as one of the most eminent approaches (Lagaros and Tsompanakis 2006, Tsompanakis et al. 2008a). Given that uncertainties are inherent in geotechnical engineering practice, approximation methods like ANN can be applied effectively in such problems (Tsompanakis et al. 2008b). Over the last decade an increasing number of articles presenting applications of ANN in geotechnical engineering have been published. Most of these studies are focused on liquefaction potential under seismic excitations, which is a very computationally intensive task and therefore suitable for ANN. Recently, some of the studies in this field are examining the applicability of ANN in soil dynamic analyses as well. A detailed literature review on the recent implementation of various metamodels in the field of geotechnical engineering can be found in Tsompanakis et al. 2008b.

In general, embankments (earth dams, tailings dams, solid waste landfills, etc) constitute large-scale geostructures of great importance, the safety of which are directly related to environmental and social-economical issues. This type of structures became subject of systematic research following the 1994 Northridge and the 1995 Kobe earthquakes after which extended investigations took place examining the failures occurred in embankments due to seismic action. In geotechnical earthquake engineering practice, the slope stability of an embankment is evaluated in the majority of the cases utilizing the pseudostatic method, in which the horizontal and vertical pseudostatic inertial forces are included in the safety factor calculations (EC8). On the other hand, vulnerability analysis of structures is becoming a very useful tool for assessing their performance. The core of contemporary vulnerability analysis is the development of fragility curves for the damage-states in question. There are two basic approaches to develop a fragility curve: either based on the lognormal assumption of the response or using reliability analysis methods. The Monte Carlo Simulation (MCS) method is the most widely applied reliability analysis method requiring though enormous computational effort. In a recent article by the authors it was found that MCS based fragility analysis, compared to the simplified approaches (lognormal assumption), offers a more accurate approach into this emerging field (i.e., geotechnical applications) in earthquake engineering (Tsompanakis et al. 2008c).

In the present work efficient ANN based metamodels are used for estimating the safety factor required for the slope stability analysis under pseudostatic conditions of a typical embankment, and subsequently are applied, in the framework of MCS based reliability analysis, in order to develop damage-state fragility curves. Randomness related to the soil mechanical properties and the geometry of the embankment as well as the seismic intensity is considered in this work. The ANN is trained utilizing available information generated from selected pseudostatic analyses of the geostructure. In the sequence, the trained ANN is used to accurately predict the factor of safety against slope instability of the examined geostructure, replacing the conventional analysis procedure. Two approaches are implemented in this work: in the first approach a different neural network is trained for each intensity level, while in the second one a single neural network is employed for approximating the seismic response over the entire range of seismic intensity levels.

2. SEISMIC SLOPE STABILITY

Large-scale geostructures, such as earth dams, highway embankments, solid waste landfills are of extreme importance due to the high risk (socio-economical, environmental, etc) related to their potential failure. In regions with high seismicity the aforementioned risk is even more pronounced. In order to investigate the seismic response of an embankment, as well as the related seismic instability issues, it is more realistic to perform probabilistic slope stability analysis in order to determine the effect of the seismic excitation on the geostructure's seismic behaviour. Since the failure of embankments is related to slope instabilities (either of the embankment mass or its foundation), seismic slope stability analysis is certainly considered as a critical component of the geotechnical seismic design process. Engineering practice in seismic slope stability analysis is based on three main categories of methods; namely: *stress-deformation analysis*, *permanent deformation analysis*, and *pseudostatic analysis*. Stress deformation analyses are mainly performed utilizing the finite element method incorporating complicated constitutive models to describe the potential nonlinear material behaviour. However, the parameters required for the definition of the models are not easily quantified in the laboratory or in situ. On the other hand, permanent deformation analyses are based on the calculation of seismic deformations through the *sliding block approach* proposed by Newmark (1965).

Due to their complexity, the two aforementioned methods are usually excluded from the seismic design of embankments. Most frequently, the assessment of seismic slope stability is obtained via pseudostatic analyses. Based on the *limit equilibrium concept* of static slope stability analysis, and including horizontal and vertical inertial forces, the results are provided in terms of the minimum factor of safety (FoS). The basic limitation of this method is the selection of the proper value of the seismic coefficient, as this value controls the inertial forces on the soil masses. In contemporary seismic norms (e.g., Eurocode 8 (EC8 2004), Greek Seismic Code (EAK 2000), etc) pseudostatic slope stability analysis is conducted using a proper value for the corresponding seismic coefficient (the so-called pseudostatic horizontal acceleration or PHA) equal to a specific portion of the design peak ground acceleration (PGA) at the site of interest. However, when using the pseudostatic approach the actual dynamic response of the structure is not taken into account, and thus, the real response and stability of the geostructure cannot be accurately assessed during a moderate or severe seismic event. Therefore, in special cases of non-symmetric embankments, cases of loose foundation and when local site conditions play an important role, it is advisable to use more sophisticated non-linear dynamic analysis procedures (Zania et al. 2008a).

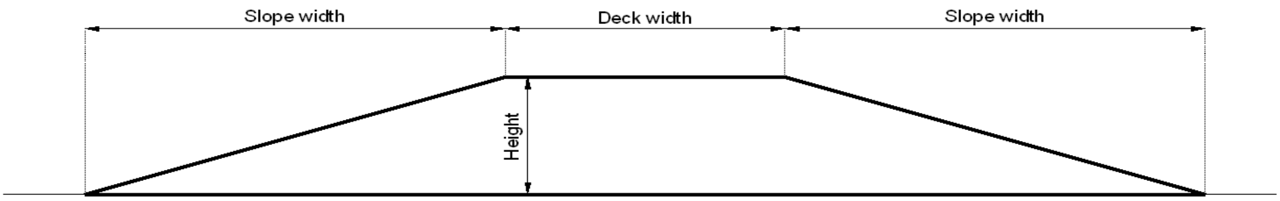


Figure 1 Geometry of the examined embankment.

In this study the symmetric trapezoid embankment shown in Figure 1 is examined. The probabilistic calculations involved for the construction of the geostructure's fragility curves, especially if dynamic analyses had to be performed, are extremely time-consuming. Thus, in the current investigation pseudostatic analyses are conducted, in which the required numerical analyses are performed using a FORTRAN code developed by the authors (Zania et al. 2008b). The code utilizes Bishop's method for slope stability analysis, and is capable of randomly modifying the mechanical and geometrical characteristics of the model, as well as the acting pseudostatic horizontal acceleration values throughout the probabilistic analyses via the MCS technique.

3. SEISMIC VULNERABILITY ANALYSIS OF EMBANKMENTS

Fragility analysis is considered nowadays as a useful computational tool for determining the structural behaviour (of a slope in particular) over a range of the seismic intensity levels. Specifically, a fragility curve provides the probability that the slope exceeds a given damage level for a certain seismic intensity level. In general there are two approaches to perform fragility analysis: based on the empirical assumption that the demand values follow the lognormal distribution or based on the Monte Carlo simulation technique performing a reliability analysis of the slope for each intensity level (Tsompanakis et al. 2008c).

The main objective of the present investigation is to perform probabilistic slope stability analysis of a characteristic geostructure based on the pseudostatic method. In particular, four fragility curves are developed. In order to perform probabilistic fragility analysis the examined embankment is assessed over a number of different PHA levels. Therefore, seven different hazard levels (namely: 0.01g, 0.05g, 0.10g, 0.20g, 0.30g, 0.40g, 0.50g) ranging from low PHA to severe PHA seismic intensity were studied. To obtain discrete damage-states, according to the above perspective, a properly selected range of the geostructure's Damage Index (DI) must be specified. The correlation of the geostructure FoS and the related DS is a crucial factor for the construction of the fragility curves. The Damage States (DS) considered are defined by means of safety factor for the embankment slope stability and cover the whole range of structural damage from slight, to moderate, to extensive and finally to the onset of collapse, i.e. for corresponding intervals of the following values of FoS=2.0, 1.4, 1.3, 1.0 following the guidelines of the Greek Seismic Code (EAK 2000). Certainly, the behaviour and the corresponding DS of a geostructure, in terms of deformation and instability, may differ substantially from the values in the case of various "sensitive" materials (clay, loose sand, organics, waste, etc), wherethe DS should be determined more elaborately.

In the present study, as briefly described in the sequence, the reliability analysis based approach has been implemented, where fragility curves are developed as functions of PHA in order to represent the intensity of the seismic ground motion. The use of PHA for this purpose is reasonable, since in the present study the pseudostatic slope stability approach is used. Fragility analysis based on MCS requires the solution of a reliability problem for each seismic intensity level examined. Structural reliability methods have been developed significantly over the last twenty years. However, despite the improvement in the efficiency of these methods, they still require disproportionate computational effort for treating practical problems. This is the reason why in most cases numerical investigations in the field of structural reliability analysis are restricted to small-scale plane frames and trusses. Structural reliability analysis can be performed either with simulation methods, such as the Monte Carlo simulation method, or with approximation methods. First and second order approximation methods lead to formulations that require prior knowledge of the means and variances of the component random variables and the definition of a differentiable failure function. Nevertheless, MCS appears to be the only universal method that can provide accurate solutions for problems involving nonlinearity, large number of random variables, large variation of uncertain parameters, etc. The major advantage of MCS is that accurate solutions can be obtained for any problem, while the main disadvantage is the computational cost. It is obvious that the computational cost for developing fragility curves based on MCS is enormous, especially when earthquake loading is considered.

The MCS with Latin Hypercube Sampling (LHS) has been employed for performing probabilistic fragility analysis, since it has been proved efficient in calculating the probability in question. Computational efficient methodologies have been implemented for the generation of fragility curves by means of MCS, for a characteristic embankment considering uncertainty in material properties, geometry and seismic intensity. For each simulation pseudostatic analysis of the embankment is performed and the safety factor is calculated, a simulation is characterized as successful if FoS is less than a threshold value that defines the damage state. The probability that the performance of the geostructure exceeds a target safety factor is given by:

$$p_{exc} = \frac{N_H}{N_{SIM}} \tag{3.1}$$

where N_H and N_{SIM} are the number of successful and total simulations, respectively.

4. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN), expert and fuzzy systems as well as evolutionary methods are the most popular soft computing techniques; which are used to increase the computational efficiency of conventional techniques. The most popular paradigms that can be solved by means of SC techniques are: simulation, inverse simulation and identification problems. In this study, ANN are used for estimating the seismic response of the geostructure. Over the last two decades SC techniques, such as ANN, have emerged as a powerful tool that can be used to replace time-consuming procedures in many engineering applications. Some of the fields where ANNs have been successfully applied are: pattern recognition, regression (function approximation/fitting), optimization, nonlinear system modeling, identification, damage assessment, etc. In general, function approximations involve approximating the underlying relationship from a given input-output data set of finite size. Feed-forward ANN, such as multi-layer perceptrons and radial basis function networks, have been widely used as an alternative approach to function approximation since they provide a generic functional representation and have been shown to be capable of approximating any continuous function with acceptable accuracy. A trained neural network presents some distinct advantages over the numerical computing paradigm. It provides a rapid mapping of a given input into the desired output quantities, thereby enhancing the efficiency of the standard analysis approach. This major advantage of a trained ANN over the conventional procedure, under the provision that the predicted approximations fall within acceptable tolerances, leads to results that can be produced in a few clock cycles, is representing orders of magnitude less computational effort than the conventional computational process.

In the present work the ability of ANN to predict characteristic measures that quantify the seismic response of a geostructure considering uncertainties is presented. More specifically, the aim of the present study is to examine in detail the efficiency of the ANN in predicting slope stability failure (i.e. in terms of safety factor) and, using the results of the ANN-based approximations, to develop fragility curves. This objective comprises the following tasks: (i) define the suitable neural network architecture; (ii) select proper training and testing sets and (iii) training/testing the neural network. The learning algorithm, which was employed for the training, is the well-known Back-Propagation (BP) algorithm (Lagaros and Papadrakakis 2004). An important factor governing the success of the learning procedure of ANN architecture is the selection of the training set. A sufficient number of input data properly distributed in the design space together with the output data resulting from complete analyses are used in the BP algorithm to provide satisfactory approximations (Papadrakakis and Lagaros 2003).

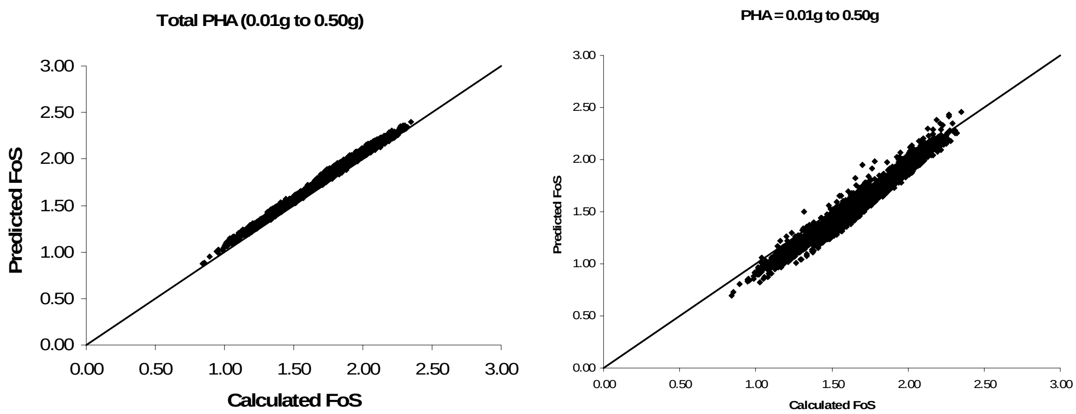
5. NUMERICAL STUDY

In the current investigation, numerical pseudostatic slope stability analyses of the embankment shown in Figure 1 were performed, using the Bishop's method in conjunction with the MCS technique to take into account the uncertainties of the problem. Note also that for the performed pseudostatic slope stability analyses not only the pseudostatic horizontal acceleration (PHA) was used, but the pseudostatic vertical acceleration (PVA) was also taken into account. In accordance to contemporary seismic norms, vertical acceleration was set equal to: PVA = ±0.50*PHA, to account for the vertical pseudostatic inertial force.

Table 5.1 Probabilistic data for the mechanical and geometrical properties of the embankment.

Variable	Distribution	Mean	COV
Cohesion (kPa)	Normal	5	10%
Friction angle (°)		30	
Unit weight (kN/m^3)		22	
Height (m)		20	20%
Deck width (m)		40	
Slope width (m)		60	
PHA	Lognormal	0.01g to 0.50g	10%

Generally, in earthquake engineering applications, the reliability problem can be defined as a problem of two separate types of random variables, representing the demand and the capacity. In this work uncertainty both on capacity and demand has been considered. Uncertainty on capacity is taken into consideration through the soil mechanical properties and more specifically the unit weight (γ), friction angle (φ) and cohesion (c) as well as the embankment's geometry while on the demand through the seismic intensity levels. The geometry of this simple trapezoid example is determined using three parameters: height, slopes and deck width (see Figure 1). In this work two distinct cases were examined: in the first the dimensions of the geostructure were considered deterministic implementing the mean values of the dimensions, while on the latter the dimensions were also considered as random variables. In geotechnical engineering practice there are four probability density functions that are most commonly used: uniform, triangular, normal and lognormal distributions (Lacasse and Nadim 1996). In this study, the normal distribution is used for the basic parameters encountered in pseudostatic slope stability analyses (i.e., geometry, unit weight, friction angle and cohesion), while the lognormal distribution is used for the seismic coefficient (PHA) levels. The mean values and the corresponding coefficient of variation (COV) values for the soil mechanical properties the geometry and the seismic demand coefficient (PHA) for the seven examined cases are given in Table 5.1.



(a) (b)

Figure 2 ANN-predicted versus exact FoS for the deterministic geometry case using: (a) separate metamodels for each PHA level (ANN1), and (b) the same metamodel for all PHA levels (ANN2).

5.1. Safety factor calculation via ANN metamodels

The ANN predictions of the safety factor are used to replace numerical slope stability analyses and subsequently to develop the fragility curves. In this work two different ANN models are employed, in the first one (ANN1) a different neural network is trained for each intensity level while in the second one (ANN2) a single neural network is employed for approximating the seismic response over the entire range of intensity levels. The input data that are employed in the ANN metamodel are the random parameters of the examined embankment: cohesion, friction angle, specific weight, geometry along with the PHA values (only for ANN2 model), whereas the output in both neural network metamodels is the factor of safety value. In general, when applying ANN in the simulation of structural response, especially under dynamic loading conditions and including material nonlinearity, it is difficult to find the best configuration of ANN architecture. The ANN configurations employed for all the test cases examined in this study is selected to have one hidden layer fully connected with the input and output layers, since increasing the size of the ANN architecture since increasing the size of the ANN architecture didn't alter much its exceptionally accurate results. After a preliminary study concerning the number of nodes of the hidden layer, the architecture for the ANN1 model was set as [3-7-1] while for the ANN2 model was set as [4-10-1] for the case that the geometry is deterministically define. When the three additional variables associated with the geometry (see Table 5.1) are also randomly determined, then the neural network configurations for the two types of metamodels were set to [6-15-1] and [7-20-1], for ANN1 and ANN2, respectively.

The selection of appropriate training and testing sets determines the quality of the prediction, thus emphasis has to be given on the selection of the training samples. The training and the testing sets, for both ANN1 and ANN2 approaches, consist of groups of the random variables. All samples were produced via Latin Hypercube Sampling (LHS), to ensure that the whole sampling space is covered. More specifically, for the ANN training 100 triads and 200 hexads are generated for each intensity level for the deterministic and probabilistic implementations of the ANN1 approach, respectively. On the other hand, 200 quarts and 400 heptads are generated for the implementation of the ANN2 metamodel for deterministic and probabilistic dimensions, respectively. Moreover, by using LHS in a similar manner, 10 triads per hazard level (ANN1) and 20 quarts (ANN2) have been generated for the testing set for the deterministic geometry, which for the probabilistic case 20 hexads (ANN1) and 40 heptads (ANN2) have been used to test the quality of the ANN training.

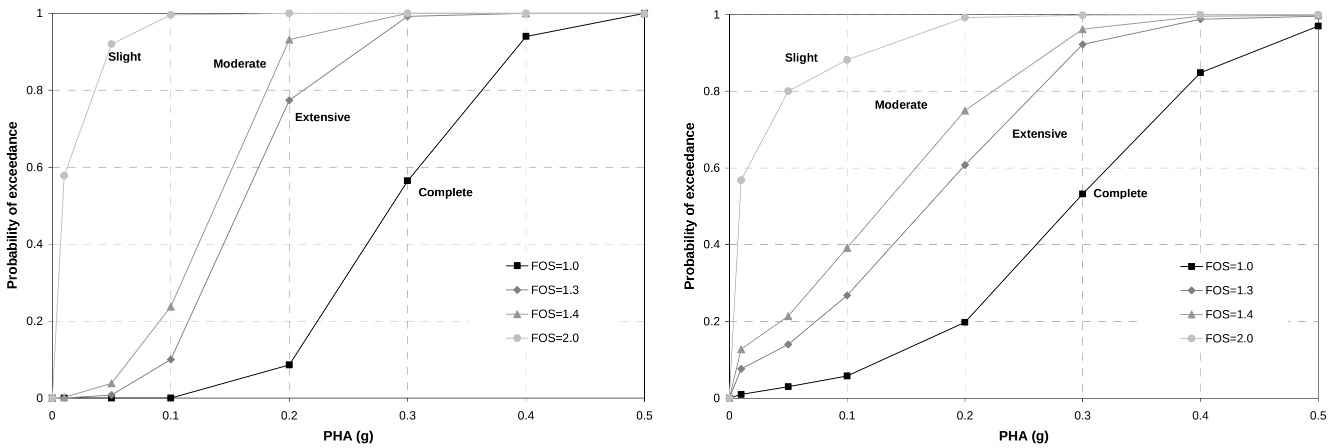
The results presented in Figure 2 correspond to the deterministic definition of the geometry dimensions for the metamodels ANN1 and ANN2, respectively. By inspecting plots 2a and 2b it is evident that both approaches provide excellent approximations of the FoS for all seismic intensity levels. The same trend is encountered when the geometrical properties are considered as random variables. When comparing the two plots of Figure 2 it can be seen that the single scheme (ANN2) seems to marginally underestimate the FoS values, while the independent PHA level scheme (ANN1) seem to produce slightly overestimated FoS values compared to the calculated ones. From the same plots it is also evident that the predictions of the seven different ANN1 models are slightly more accurate than the ones obtained from the single ANN2 model. However, both approaches presented excellent accuracy, having maximum tolerance of less than 10% only in a very few runs for the most severe PHA levels, as depicted in Figure 2.

5.2. Fragility curves generation via ANN metamodels

Fragility assessment under seismic loading using a MCS based method is a computationally intensive problem, especially when small probabilities are sought. The proposed methodology, allows the derivation of improved fragilities in terms of accuracy compared to the commonly used empirical approach (Tsompanakis et al. 2008c), while the computational cost practically remains the same if efficient approximation schemes, as the proposed ones, are applied. For instance, for the test cases considered the number of the simulations required to obtain a single value of probability of exceedance ranges from 100 to 2,000 simulations.

The computational effort of the standard Monte Carlo simulation and that of the two proposed ANN methodologies are shown in Tables 5.2 and 5.3 for deterministic and probabilistic geometry, respectively. The

ANN2 model is superior to the ANN1 models since it requires almost three times less computational effort, while as aforementioned the differences in accuracy of the approximations are marginal. Depending on the limit-state considered, the computational cost can be reduced by two orders of magnitude. It can be seen that for higher limit-states, the computational effort of the standard MCS is rapidly increased, while the effort required by the proposed methodology remains the same. Furthermore, worth noting is the fact that the ANN has to be trained only once in order to produce reliable probability estimates for any limit-state. Figure 3 depicts the fragility curves developed for the case that the geometry was considered as deterministic and as random, respectively. As it can be seen there is significant difference for the lower intensity levels, and more frequently occurred, intensity levels, especially for the lower damage states.



(a) (b)

Figure 3 ANN Fragility curves for the embankment with: (a) deterministic, and (b) stochastic geometry.

Table 5.2 Comparison of computing times for the case with deterministic geometry.

Damage State	Standard MCS method		ANN1 method		ANN2 method	
	No of analyses	Time (hours)	No of analyses	Time (hours)	No of analyses	Time (hours)
Slight	3300	14.11	500	2.14	200	0.86
Moderate	10500	44.89	500	2.14	200	0.86
Extensive	12400	53.01	500	2.14	200	0.86
Complete	16200	69.26	500	2.14	200	0.86

Table 5.3 Comparison of computing times for the case with probabilistic geometry.

Damage State	Standard MCS method		ANN1 method		ANN2 method	
	No of analyses	Time (hours)	No of analyses	Time (hours)	No of analyses	Time (hours)
Slight	3300	14.11	1000	4.31	200	1.73
Moderate	10500	44.89	1000	2.31	200	1.73
Extensive	12400	53.01	1000	2.31	200	1.73
Complete	16200	69.26	1000	2.31	200	1.73

6. CONCLUSIONS

In this study it has been presented that robust seismic vulnerability analysis of geostructures can be implemented via the Monte Carlo simulation technique. Nevertheless, the computational effort involved in MCS based methodology for obtaining fragility curves for various damage states becomes excessive. In this work efficient neural network based metamodels are proposed for obtaining inexpensive estimates of stability assessment of large-scale geostructures under pseudostatic loading conditions in terms of safety factory highly accurate estimations. These estimates are subsequently used for the vulnerability assessment of the embankment via the generation of its fragility curves. The presented implementations involved the consideration of random variability of geometrical and mechanical properties as well as the seismic intensity levels. It was found that there is a substantial discrepancy between the fragility curves obtained when the dimensions are considered deterministic or random variables. It has been demonstrated that the use of ANN metamodels for the numerical generation of fragility curves can be very effective both in terms of time and accuracy. The use of ANN can practically eliminate any limitation on the sample size and lead to extremely accurate estimates of the fragilities without using any simplifying assumptions. Conclusively, it is evident that by incorporating efficient ANN based metamodels into the time-consuming process of fragility curves construction it is possible to increase the MCS sample size and predict more accurately the possibility of failure of a geostructure within a fraction of time compared to the conventional procedure. Thus, ANN offer a precise and efficient way to determine a geostructure's performance and the evaluation of its seismic vulnerability for multiple hazard levels and multiple damage states, in the viewpoint of the performance-based earthquake engineering.

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