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RELIABILITY BASED OPTIMIZATION OF A SEISMICALLY ISOLATED STRUCTURE USING ARTIFICIAL NEURAL NETWORKS AS THE RESPONSE SURFACE METHOD

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Abstract

One of the efficient methods in seismic resistant design of medium height buildings is applying seismic isolation systems at the base of the structures to mitigate the response of structure. In this study an effective numerical reliability-based optimization technique is presented for the optimum design of isolation system under random time history earthquake loading.

Friction Pendulum System (FPS) as one of the popular types of seismic isolation devices is considered to protect delicate equipment installed on the floor of a specific concrete building. So the object is to minimize the probability of failure of the base-isolated building subjected to design performance criteria in terms of the story acceleration of the superstructure.

Due to stochastic nature of variables such as input ground motion; a novel method is proposed to predict the reliability of the supposed structure using artificial neural networks (ANN). The reliability of the system in the format of probability of failure (*Pf*) is calculated using a simulation based method which is an effective tool for an isolated structure subjected to random earthquake excitations.

A 2D concrete frame three story building isolated with FPS, representing critical facilities, such as a data center, is considered as the super structure.

Random excitations are applied by the means of artificial earthquake ground motions generated through the superposition of the long period and high frequency components of the earthquake.

The probability of failure for a particular set of structure and isolation parameters is calculated using Monte Carlo Simulation by time history structural analysis at first. Then a set of neural networks were trained to predict the peak responses of the structure and furthermore to predict the probability of failure. Then using a meta-heuristic optimization algorithm the design parameters of the structure and isolation systems are obtained.

Keywords: Neural Network, Reliability Based Optimization, Base Isolation, Friction Pendulum

1. Introduction

In recent decades, many of engineers' attentions have been attracted to “base isolation” as an effective technology for seismic protection of building structures. Using isolation bearings at the base of structures elongates their period of vibration, dissipates seismic input energy and controls structural response.

Among different types of implemented isolators, Friction Pendulum System (FPS) is an approved system that was invented by Zayas in 1986 [1]. FPS consists of a spherical concave sliding surface and a slider as an innovative bearing that exerts friction as supplemental damping. Plenty of studies were conducted on this type of isolation systems and other developed generations of FPS later [2-5].

Castaldo and Tubaldi analyzed the influence of FPS isolator properties on the seismic performance of base-isolated building frames. The uncertainty in the seismic input was simply taken into account by considering a set of natural records with different characteristics scaled to increasing intensity levels [6]. Bucher discussed the analysis of all types of friction pendulum isolators and compared their behavior with respect to isolation capacity and device displacements [7]. These studies were mainly developed through deterministic analyses while the isolation system characteristics, structural system properties, earthquake characteristics, and device properties have inherent uncertainties.

Stochastic nature of variables such as input ground motion encouraged the scientists to apply the probabilistic analyses in structural dynamics, structural reliability methods, and reliability based analysis [8-10].Thus several studies have been conducted on the design analysis of isolated structure considering uncertainties in structure, base isolation and ground motion characteristics.

Su and Ahmadi[11] studied the responses of a rigid structure with a frictional base isolation system subjected to random horizontal-vertical earthquake excitations. Constantinou and Papageorgiou [12] discussed the stochastic response of practical sliding isolation systems. Alhan and Gavin [13] studied the reliability requirements of isolation system components for the protection of the critical equipment from earthquake hazards. They considered a four-story structure representing a critical facility on isolated raised floor at the second level of building. Stochastic seismic response analysis and reliability evaluation of base-isolated structures were conducted combining the physical stochastic ground motion model and the probability density evolution method by Chen et al. in 2007 [14].They concluded that the response and earthquake action on the super structure could be reduced by one degree of intensity in comparison to fixed based structure. Their investigations showed that stochastic seismic response analysis and reliability assessment could provide indices for decision making more objective than just a few selected deterministic ground motions as usually employed in practice. Taflanidis and Jia proposed a versatile, simulation-based framework for risk assessment and probabilistic sensitivity analysis of base-isolated structures. a sampling-based approach was also introduced for establishing a probabilistic sensitivity analysis to identify the importance of each of the uncertain model parameters in affecting the overall risk [15]. In 2014 Palazzo et al. evaluated the seismic reliability of a base-isolated structure with FPS considering both isolator properties and earthquake main characteristics as random variables. They used Latin Hypercube Sampling (LHS) as the sampling method for Monte Carlo simulations[16].

In this study the main objective is to economically design the isolated structures with regards to satisfaction of desired reliability targets. This will leads to a reliability based design optimization problem. Xiao et al. [17] in 2010 presented an effective numerical reliability-based optimization technique for the design of base-isolated concrete building structures under spectrum loading. Huang and Ren presented a dynamic reliability-based optimization technique for the seismic design of base-isolated structures. Analytical solutions of stochastic seismic response under the Kanai-Tajimi spectrum loading were obtained applying on a 3-story isolated building [18]. Jia et al.[19] optimized the floor isolation system based on reliability criteria, where the reliability of the system is quantified by the plausibility that the acceleration of the protected contents will not exceed an acceptable performance bound, and is calculated using stochastic simulation.

The objective function considered as the probability of failure of the isolated structure with FPS. Protecting delicate facilities in structures as one of the applications of seismic base isolation is chosen for desired performance of the structure. Therefore as an innovative study, the limit state is defined on the maximum acceleration response of the equipped floor beside the maximum relative story displacement and the base isolation total displacement.

To fully observe the effect of nonlinear behavior of FPS isolators, time history analysis is inevitable. So for reliability analysis, best estimates can be achieved by simulation based methods via dynamic time history model of the isolated structure. Simulation based methods of reliability analysis is an effective tool to calculate the probability of failure (P_f) or reliability index (β) of an isolated structure subjected to random earthquake excitations[13]. One of the main issues in simulation based reliability methods is computational cost. For complex systems that derivation of their joint probability distribution function is difficult, the probability of failure is evaluated via Monte Carlo Simulations (MCS). In fact, P_f is the ratio of the number of realizations with non-positive limit states to the total number of simulations. Mostly the required number of simulations is too large and for complex dynamic analysis it would take a long time to perform the reliability analyses. Regarding this fact several modified MCS methods have been developed to reduce the size of calculations. For this reason variety of sampling variance reduction techniques have been developed in order to improve the computational efficiency of the method by minimizing the sample size and reducing the statistical error that is inherent in MCS. These techniques can be summarized as; importance sampling, adaptive sampling technique, stratified sampling, Latin hypercube sampling, antithetic variate technique, conditional expectation technique, average sampling and asymptotic sampling [20-22].
Other efficient newly developed methods of simulation based reliability analyses that can significantly reduce the amount of computations are based on the estimation of the limit states by response surface[23, 24]. These methods are generally called Response Surface Methods (RSM) that are mainly used in Reliability Based Design Optimization (RBDO) [25]. One of the most applicable tools in RSM is Artificial Neural Network[26, 27]. Papadrakakis and Lagaros [28] examine the application of neural networks (NN) to reliability-based structural optimization of large-scale structural systems. The failure of the structural system in the mentioned study is associated with the plastic collapse. There are also studies that shows efficiency of neural networks (NN) as a useful tool to estimate the limit state function [29]. This study attempts to use the efficiency of NN in structural reliability of seismic isolated structures. Simulating Annealing as a meta-heuristic optimization algorithms is applied to solve the optimal problem.

2. The Selected Model and Assumptions

2.1. Super Structure

In this study a two dimensional isolated three story concrete frame (see Fig. 1) is purposed for optimization process. The sensitive computer servers are installed on the third floor of the supposed structure.

The structure is subjected to ground motions generated randomly through the combination of the low-frequency (long period) and high-frequency components of the ground motion following the recommendation by Mavroeidis and Papageorgiou [30].

At first, all the loads and resistant parameters of the structure assumed as random variables, however, to reduce analysis time, only crucial variables are selected as random by using sensitivity analysis.

The failure of the structure is occurred when the structural responses pass one of these three thresholds:

1- The facility floor acceleration equal to A_f
2- The relative story displacement equal to X_r
3- The Isolation (or 1st floor) displacement equal to X_I

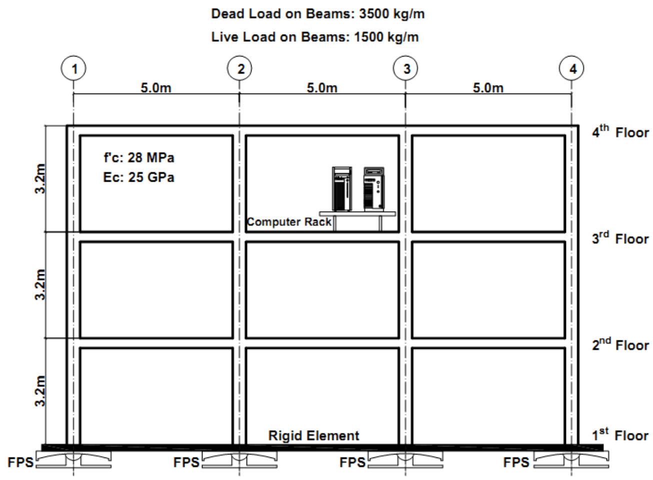

Fig. 1-2D 3-story concrete frame modeled for simulations

Acceleration levels in the range of 100–200 milli-g are specified by computer producers for sensitive computers as the limit where they fail to operate [13]. Here A_f is considered to be equal to 100 milli-g. For the relative story displacement, according to common building codes the allowable drift ratio equal to 0.004 is considered and the allowable isolation displacement X_I equal to 10 cm is chosen for the analyses.

3. Input Ground Motion

There are two approaches available applying time history dynamic analysis of structures subjected to random earthquakes: (1) dynamic response-history analysis using a set of recorded ground motion time histories and (2) stochastic dynamic analysis employing generated synthetic stochastic ground motions.

Considering the recommendations by Mavroeidis and Papageorgiou [30], the synthetic near-fault ground motions are produced to evaluate the probability of failure using Monte Carlo simulations.

Artificial or synthetic ground motions are generated in a way to describe the coherent (long-period) component of motion and the stochastic (or engineering) approach to synthesize the incoherent (high frequency) seismic radiation.

Since not-all near-fault excitations exhibit a velocity pulse (long period component), the probability of occurrence of such a pulse needs to be incorporated into the excitation model. This is established by the indicator I_P with possible outcomes [1 or 0] (the former corresponding the existence of pulse) with the probability of having pulse recommended by Shahi and Baker [31]. It is assumed that the seismic hazard is originating from strike-slip faults, and the probability model adopted is:

$$P(I_P = 1 | r, s) = \frac{1}{1 + e^{(0.624 + 0.167.r - 0.075.s)}} \tag{1}$$

where s is defined as the distance between the epicenter and the site projection on the fault plane surface and r is the closest distance to vertical projection of the rupture surface.

Finally the proposed methodology consists of the following steps (see Fig. 2) considering the pulse velocity (long period component):

1. Generate the long-period component of acceleration time history applying the equations suggested by Mavroeidis and Papageorgiou [30]
2. For the selected fault–station geometry, generate synthetic high frequency component of the acceleration time history considering the method proposed by Boore [32]
3. Calculate the Fourier transform of the synthetic acceleration time histories generated in steps 1 and 2.

4. Subtract the Fourier amplitude spectrum of the synthetic time history generated in step 1 from the Fourier amplitude spectrum of the synthetic time history produced in step 2.
5. Construct a synthetic acceleration time history so that (1) its Fourier amplitude spectrum is the difference of the Fourier amplitude spectra calculated in step 4 and (2) its phase coincides with the phase of the Fourier transform of the synthetic time history generated in step 2.
6. Superimpose the time histories generated in steps 1 and 5. The near-source pulse is shifted in time so that the peak of its envelope coincides with the time that the rupture front passes in front of the station.

Even though in the simulation process of high frequency component of the ground motion the white noise is generated randomly, to fully apply Monte Carlo simulation method, uncertainty of the main variables should be included. Here, fifteen mostly effective random parameters lined up as:

$M, r, k_0, f_a, f_b, f_{\max}, \varepsilon, T_{GM}, \varepsilon_w, \eta, I_P, \mathrm{e}_{A_P}, \mathrm{e}_{T_P}, \nu_P, \gamma_P$.

The first ten parameters are used for random generation of high frequency component and the last five parameters are applied for long period component of synthetic random earthquake. Each of these parameters are described briefly in the following:

The uncertainty in moment magnitude, M, is modeled by the Gutenberg–Richter relationship truncated to the interval $\left[M_{\min}, M_{\max}\right] = [4.5, 7]$ with the regional seismicity factor selected as $b_M = 0.9\ln(10)$. So the random generation of moment magnitude would be done by the following equation using CDF of moment magnitude:

$$M = \ln(1 - U(1 - \exp(-b(\mathrm{M}_{\max} - \mathrm{M}_{\min}))) / (-\mathrm{b}) + \mathrm{M}_{\min} \tag{2}$$

where U is uniformly distributed random variable on the interval [0,1].

The uncertainty of closest distance to vertical projection of the rupture surface (r) is modeled considering fault as a line source. The cumulative density function of this variable is define as following equation [33] by assuming the closest horizontal distance between site and source is 10 kilometer:

$$F_r(\tilde{r}) = P(r < \tilde{r}) = 2\frac{\sqrt{\tilde{r}^2 - 10^2}}{L_F} \tag{3}$$

where the length of fault projection is $L_F = 10^{-3.55+0.74M}$ [34].From Eq. (3), r would be generated randomly by the following equation:

$$r = \left[(UL_F / 2)^2 + 10^2\right]^{0.5} \tag{4}$$

Other random variables have median values with the probability distribution listed in Table 1.

Table 1-Random variables and their distribution used in earthquake generation [30-32, 35]

Parameter	**Description**	**Median Value**	**Coefficient of Variation (C.O.V)**	**Distribution Type**
k_0	site diminution parameter	0.03	-	Uniform on [0.02,0.04]
f_a	corner frequency	$10^{2.181-0.496M}$	0.2	Lognormal
f_b	corner frequency	$10^{2.41-0.408M}$	0.2	Lognormal
$f_{\max}$	site diminution parameter	100	0.2	Lognormal

ε	moment ratio	$10^{0.605 - 0.255M}$	0.2	Lognormal
T_{GM}	Duration of ground motion	$0.5/f_a + 0.05R$	0.4	Lognormal
ε_w	temporal parameter	0.2	0.4	Lognormal
η	temporal parameter	0.05	0.4	Lognormal
Parameter	**Description**	**Median Value**	**Standard Deviation**	**Distribution Type**
I_P	Pulse existence indicator	-	-	Discrete
e_{A_P}	signal amplitude parameter	0	0.187	Normal
e_{T_P}	prevailing pulse period parameter	0	0.143	Normal
ν_P	phase angle	-	-	Uniform on [0,π]
γ_P	oscillatory characteristic	1.8	0.3	Normal

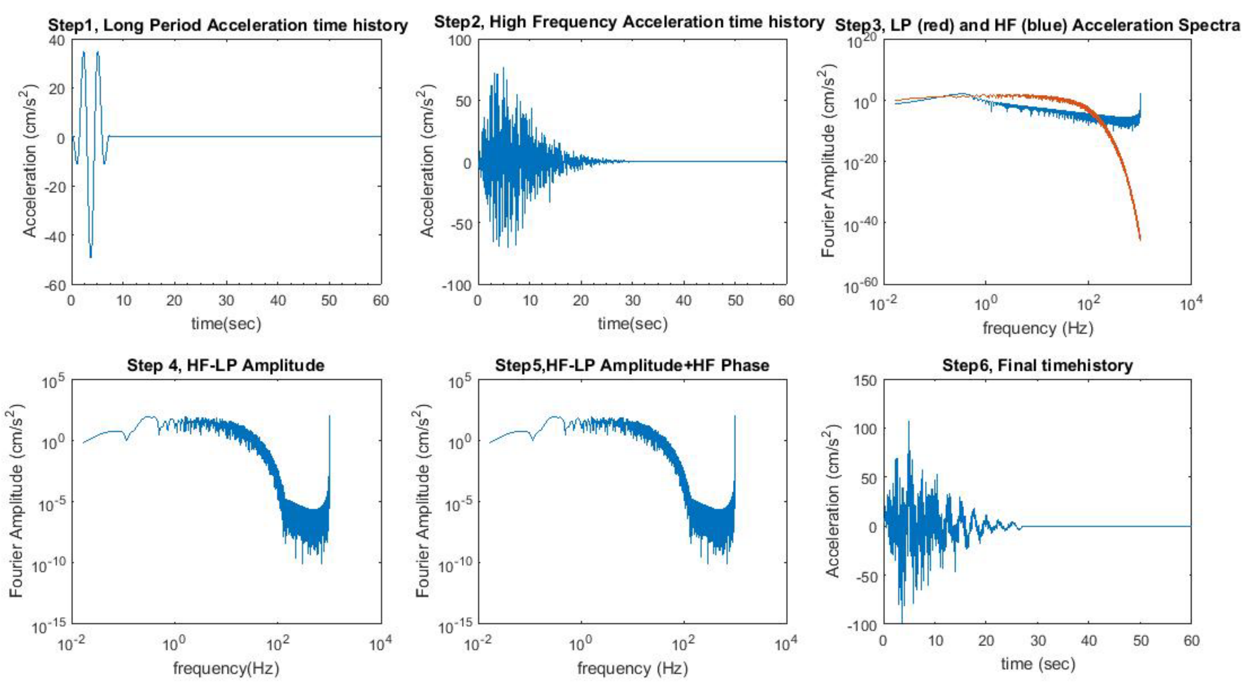

Fig. 2- Six steps of simulating ground motion using Mavroeidis and Papageorgiou method. M= 7 and r= 25 km and other parameters are based on the recommendations in mentioned studies

4. Neural Networks

Neural networks (NN) are numerical algorithms inspired in the functioning of biological neurons. This concept was firstly introduced by McCulloch and Pitts [36] who proposed a mathematical model to simulate neuron behavior [37]. Nowadays NN has found its way into practical applications in many areas. Numbers of computational structures technology applications, that are heavily dependent on extensive computer resources, have been investigated, showing the range of application of neural network capabilities. The basic idea of applying NN here is to use it as the RS as an evaluation for the limit state in MCS. The major advantage of a trained NN over the conventional numerical process, is that results can be produced in a few clock cycles, requiring orders of magnitude less computational effort than the conventional computational process. More detailed introduction to NN may be found in[38].

4.1. The NN Training and Assumptions

Herein, the efficiency of the proposed method in application of the NN is investigated to predict the structural maximum responses in the context of reliability analysis. This objective comprises the following tasks:

- (i) Select the proper training set.
- (ii) Find suitable network architecture.
- (iii) Determine the appropriate values of characteristic parameters.

The Back Propagation (BP) algorithm according to Levenberg-Marquardt optimization [39] is used as the learning algorithm that updates weight and bias states.

The number of neurons to be used in the hidden layers is not known in advance and usually is estimated by trial and error .But the number of 100 hidden layers shows good results in output estimations.

The convergence of the training process is controlled by the prediction error. This is done either with a direct comparison of the predicted with the target results computed by means of the root mean square (RMS).

For the purpose of validation and testing, 30% of I/O training pairs are randomly extracted (each one 15%) and the training is done with the remained 70% I/O training pairs.

For the purpose of optimization, beside the variation of the fifteen parameters of random motion generation, the variation of structural and FPS properties are in consideration. So the parameters of random motion generation plus structural and base isolation device properties are considered as the input variables for the NN; and the outputs are maximum responses of the structure.

In the optimization process, it is considered that the dimensions of all columns and beams are the same and all FPS have the same properties including radius of curvature and coefficient of friction. So the structural and FPS properties are limited to five variable parameters including dimensions of square column (D_C), height of beams (H_B), width of beams (W_B), radii of curvature of FPSs (R) and friction coefficients of FPSs (μ).

In fact these are the five design variables in the optimization process. Due to the negligible effect of the uncertainty of these five parameters in the probability of failure they are considered as certain variables and other fifteen parameters of random motion generation are considered as uncertain variables. However all of these twenty variables are considered as input variables of the NN.

For the outputs of the neural network, due to the definition of the failure, the NN should be capable of estimating five maximum responses of the structure. These five responses are the maximum displacement of all stories and the maximum floor acceleration of the facility floor so five different neural networks are designed separately.

To design the NN at first 200,000 set of input variables were generated randomly in accordance with variable ranges. The five mentioned variables were randomly generated so that $D_C \in [30_{cm}, 100_{cm}]$, $H_B \in [30_{cm}, 100_{cm}], W_B \in [30_{cm}, 100_{cm}], R \in [0.1_m, 10_m], \mu \in [0.02, 0.2]$.

Then using direct time history analysis the outputs (or maximum responses of structure) were obtained. Using these 200,000 I/O pairs, the NN was trained.

Fig. 3 and Fig. 4 show the concordance of NN and direct time history analysis results. The results are shown in the format of Cumulative Density Function (CDF) of maximum structural responses of a specific structure (D_C =40 cm, H_B =40 cm, W_B =30cm, R =1 m, μ =0.11).

After the selection of the suitable NN architecture and the performance of the training procedure, the network is then used to produce predictions of structural responses corresponding to different values of the input variables. The designed neural networks are then processed by means of MCS to calculate the probability of failure P_f that is needed for optimization process.

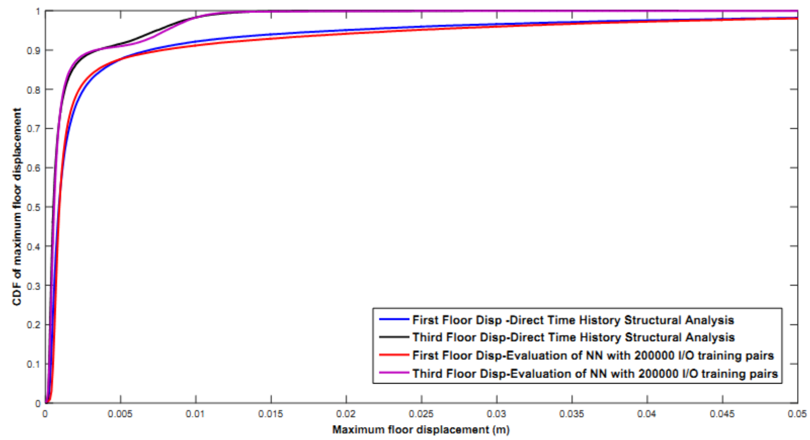

Fig. 3- Comparison of NN and Direct time history Monte Carlo simulation results by means of CDF of maximum floor displacement for first and third floor of a specific structure

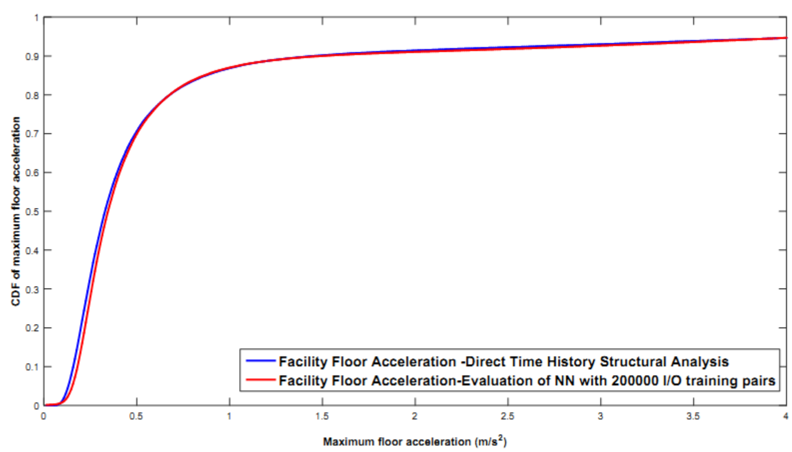

Fig. 4- Comparison of NN and Direct time history Monte Carlo simulation results by means of CDF of maximum facility floor acceleration of a specific structure

5. Reliability Based Design Optimization Problem

5.1. Design Variables

The base isolated structure consists of the super structure and the base isolation system. The structural member sizes including dimensions of square columns, height of beams and width of beam are taken as the design variables of super structure. Radius of curvature and coefficient of friction of FPSs are taken as design variables for the base isolation system. Assuming the same size of beams and columns for different stories and also same FPS at the base of the structure, these five variables can be taken as design variables: dimensions of square column (D_C), height of beams (H_B), width of beams (W_B), radii of curvature of FPSs (R) and friction coefficients of FPSs (μ).

The range of the design variables are taken as: $D_C \in [30_{cm}, 100_{cm}]$, $H_B \in [30_{cm}, 100_{cm}]$, $W_B \in [30_{cm}, 100_{cm}]$,

$R \in [0.1_m, 10_m], \mu \in [0.02, 0.2]$.

5.2. Objective Function

The main objective of this study is to minimize the probability of failure of the structure that is a function of five design variables.

5.3. Problem Definition

For the base isolated concrete building the optimal design problem of minimizing the total probability of failure subjected to the design constraints can be explicitly expressed in terms of design variables as:

Minimize P_f subject to $D_C \in [30_{cm}, 100_{cm}]$, $H_B \in [30_{cm}, 100_{cm}]$, $W_B \in [30_{cm}, 100_{cm}]$, $R \in [0.1_m, 10_m], \mu \in [0.02, 0.2]$

6. Optimization Algorithm and Results

6.1. Optimization Algorithm

Simulated Annealing (SA) is applied in this study to find the optimum solution. (SA) is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimization in a large search space. Simulated annealing interprets slow cooling as a slow decrease in the probability of accepting worse solutions as it explores the solution space. Accepting worse solutions is a fundamental property of metaheuristics because it allows for a more extensive search for the optimal solution. The method was independently described by Kirkpatrick and Vecchi in 1983[40] and by Cerny in 1985[41].

6.2. Results

The main goal of this study is to minimize the P_f for all considerable super structures. This problem is solved applying a SA algorithm with a set of the design variables (D_C, H_B, W_B, R, μ) and the objective function P_f.

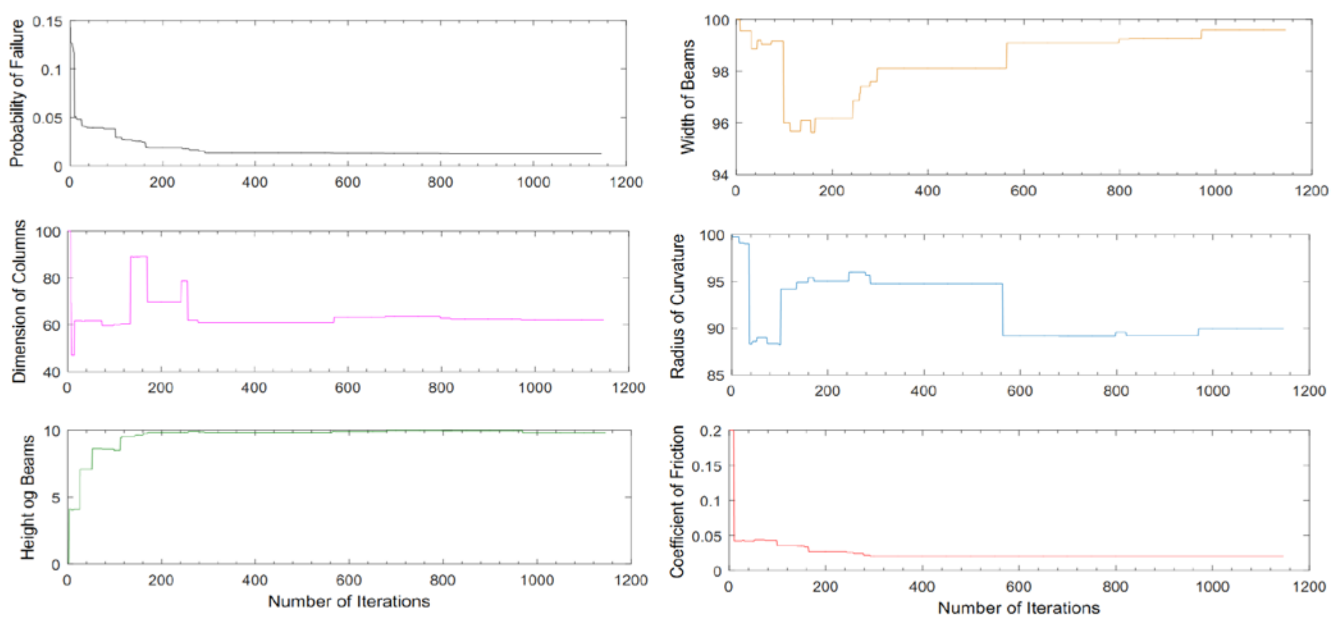

Fig. 5- Optimization processes to find the minimum considerable target probability of failure P_{fb}^*

Fig. 5 shows the solutions results for this problem after 1146 iterations of optimization algorithm. The Optimum design variables are (99.5885, 62.1327, 89.9206, 9.8209, 0.02) and the minimum objective function value is $P_f = 0.0129$. This optimum point is reaches after 1140 iterations of SA algorithm. The minimum

7. Conclusions

According to the results of neural network training, the CDF of the structure maximum response that obtained by means of NN have good compatibility with the ones obtained by means of direct structural time history analysis. This method can significantly reduce the time of the calculation of probability of failure using Monte Carlo simulation. This advantage can significantly improve the efficiency of optimization algorithms in reliability based design of isolated structures.

The optimization process is done using SA algorithm. The optimum value of the radius of curvature for FPS is close to its upper bound and the optimum value of the friction coefficient is its lower bound. It means that the acceleration of the equipped floor play the key role in the value of the probability of the failure. Also the large values of the optimum column dimensions and optimum beam height reduced the portion of P_f related to the story drifts. Thus with different values of A_f, X_r and X_I the optimum point will change significantly.

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