AN OPTIMUM APPROACH TOWARDS SEISMIC FRAGILITY FUNCTION OF STRUCTURES THROUGH METAHEURISTIC HARMONY SEARCH ALGORITHM

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ABSTRACT

Vulnerability assessment of structures encounter many uncertainties like seismic excitations intensity and response of structures. The most common approach adopted to deal with these uncertainties is vulnerability assessment through fragility functions. Fragility functions exhibit the probability of exceeding a state namely performance-level as a function of seismic intensity. A common approach is finding some response points of the fragility function and then fitting a typical probability distribution like lognormal through curve fitting estimation techniques. Maximum-likelihood approach is a fitting method to find the probability distribution parameters. Performing this approach for distributions like lognormal which is defined by just two parameters are straight forward while for more complicated distribution which are based on additional characterizing parameters is not feasible, since this approach is based on minimizing an error function through classic mathematical approaches like calculating partial derivations. An applicable modification is to add an efficient optimization approach to determine maximum-likelihood function. In this article, an optimization algorithm is proposed with maximum-likelihood-estimation and the results indicate the efficiency and feasibility of future developments in finding the most appropriate fragility function.

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1. INTRODUCTION

Vulnerability analysis of structures under various intensity of seismic excitation is the objective in performance assessment frameworks. The available vulnerability analysis procedures attempt to consider all uncertainties that exist. In this regards, Moehle and Deierlein [1] proposed a probabilistic framework known as the probabilistic performance based engineering (PBE), for the purpose of considering all uncertainties base on total probability rule. These uncertainties consist of hazard analysis, structural response and decision variable for a comprehensive decision-making framework. In this framework, the seismic hazard analysis based on location characteristic is run, generating the hazard probability curves. Fallowed by it, structural analysis lead to finding the probability structural response as a function of intensity levels, which in turn the probability of damage state of performance limit state (LS) is derived. The outcome of this three steps procedure contributes to decision making analysis, as a consequence of vulnerability analysis.

Determining the unconditional or total probability of a state function of a structural response due to various intensity excitations is an essential issue in this framework. This function is termed as fragility function in seismic engineering terminology, and is widely assessed as a prerequisite of vulnerability analysis. Various analytical approaches are developed to drive fragility function of structures or structural components in previous studies. Most of these approaches can be found in [2,3].

In general, fragility function is a probabilistic expression of not satisfying a state, like performance level, as a function of excitation variable as independent variable. Fragility function is usually expressed as a cumulative distribution function (CDF). Here CDF means the probability of less than or equal to a given value of uncertain quantity. In the case of fragility curves, CDF is an illustration of probability of exceedance of a state like performance level as a function of seismic intensity. Ellingwood et al. [4] used incremental dynamic analysis (IDA [5]) for data collection and then estimating fragility functions based on lognormal regression. IDA is an analytical framework in which various records of real seismic action time-history are chosen based on site specification and hazard analysis. Each one of these records will be scaled step-wise as a set of time-histories to represent range of intensities from very probable earthquake with low intensity to very rare earthquake with high intensity. The given structure will be analyzed in every scaled time-history of the record. Maximum engineering demand parameter (EDP) of each time-history scale step would be identified versus the intensity measure (IM) of that scaled time-history. For this purpose, an ascending curve for each record is generated. For each intensity measure level, conditional probability of limit state of exceedance ($P_{LS|IM=im}$) can be estimated over observed data. The approach for developing fragility function based on IDA is implemented through FEMA-P695 [6].

Shinouzuka et al. [2] introduced statistical study of structural fragility function of bridge structures with lognormal CDF regression. Lognormal distribution is a common choice because it fits structural global and component failures [7-9]. In most cases in seismic PBE common form of fragility function is expressed as a lognormal CDF. This distribution has two definition parameters that are estimated by the maximum likelihood estimation (MLE) over collected data from analyses. Another reason for using lognormal is its inherent simplicity in definition by the first and second moments of distribution (mean and standard deviation parameters).

Fragility functions derived from this methodology are univariate model; this means they are based on a single damage state. However, there is potential for developing multimodal fragility function for considering different damage state in different intensity levels. Recently some studies like Yazdi et al. [10], are conducted to developing fragility function as multivariate model for considering several damage state. In this study because of limitation of MLE, another regression methods were utilized.

MLE method utilize a penalty function and try to find a feasible solution. The mathematical method for solving this function, which is called the classic method in this article, involves finding the minimum point of penalty function. Doing mathematical operation on a generated penalty function for a simple distribution with one or two description parameters is easy to solve. The limitations of the classic MLE method have made it difficult to expand fragility function to higher level function like multivariate and multimodal functions. The purpose of this study is to use an optimization tool during the MLE process. This tool allows for utilizing more complicated functions and precise probabilistic models than the two-parameter lognormal model. Therefore, as a solution the harmony search (HS) optimization algorithm is proposed.

HS as a metaheuristic approach is introduced by Geem et al. and Lee and Geem [11,12], inspired by improvisation in music. The harmony in music is comparable to optimization solution vector and musician improvisations are analogous to the search schemes in optimization techniques. This method is improved by Mahdavi et.al [13]. Different application of this algorithm can be found the work of Kaveh and talatahari [14], Kaveh and Shakuri [15] and Geem [16].

In this study, this algorithm has been investigated to generate lognormal distributions for fragility functions through IDA data set and compared with classic regression solution. Implementing this methodology will make possible to utilizing higher level distribution functions. This framework is illustrated in Fig. 1.
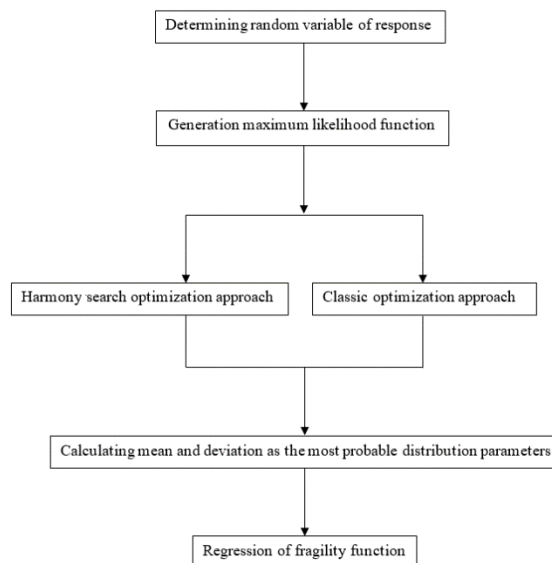

Figure 1. Flowchart for generating fragility curve through closed-form and optimisation approachs

2. SAC-FEMA VUNERABILITY ASSESSMET METHODOLOGY

For determining the probability of fragility of a LS, SAC-FEMA methodology is applied widely in seismic engineering. This methodology is inspired by existing procedures in nuclear engineering proposed by [17,18]. This procedure will be applied through performing incremental dynamic analysis on a nonlinear model of structure. In this method, pseudo spectral acceleration $S_a(T_1, \xi\%)$ corresponding to first period (T_1) and critical damping ratio (ξ) represents the intensity measure of seismic action. This measure is applied to determine structural response, probability of fragility and hazard measure probability, according to each level of intensity.

The process of calculating unconditional or total probability of fragility in the analytical approach of SAC-FEMA failure with respect to all hazard levels can be expressed as Eq (1) which is derived from total probability rule:

$$P_{[LS_i]} = \sum_i P[IM=im] \cdot P_{LS_i|A=a} \tag{1}$$

Where P[IM=im] is the hazard function of intensity measure IM or probability of occurrence of hazard level equal to im. $P_{LS|A=a}$ is the fragility function which represents the probability of reaching to the pre-defined (LS)s when hazard level IM is equal to im. The common and straight form of this function is illustrated in Eq (2).

$$P_{LS|A=a} = \int_0^a \frac{1}{x\beta\sqrt{2\pi}} \ e^{-0.5\left(\frac{\log\left(\frac{x}{\theta_d}\right)^2}{\beta^2}\right)} dx = \Phi\left(\frac{\ln\left(\frac{x}{\theta_d}\right)}{\beta}\right) \tag{2}$$

Where, $\Phi(\cdot)$ is the CDF of standard normal or Gaussian probability distribution, x is the continuous random variable of intensity parameter, θ_d is the lognormal mean of demands in the measure of intensity range and β is the lognormal deviation of demands. Curve illustration of this function for x domain only depends on θ_d and β. Those distribution parameters are expressed with appropriate intensity measures in order to represent the dominant feature of the ground motion [19].

To find a fair distribution of fragility probability in each performance level based on intensity measure, calculating response of structure in various intensities that can lead to fragility is a necessary. For example in IDA, presented by [5], various seismic time history can result in different response histories at the same intensity levels. An illustrative example of this method can be found in Vamvatsikos and Cornell [20]. A comprehensive study in where the best fitting distribution is proved is yet to be conducted. The existing problem is because of difficulty in finding distribution parameter of higher level probability distributions. According to the finding of this study this problem can be solved by applying an efficient optimization algorithm like HS.

3. THE REGRESSION AND ESTIMATION THEORY

In SAC-FEMA methodology in each performance level there are some counts of response of structure equal to the counts of the seismic records. This measured data is of random component where are represented all possible data. Estimation theory is a statistical tool applied in estimating the values of parameters based on observed data. Based on this theory, the descriptor parameter of state space is estimated through a small random sample. The probabilistic approach of estimation (applied in this article) assumes that the measured data is random with probability distribution depending on the parameters of interest. There exist sufficient methods for estimating the distribution parameters like [21]: maximum likelihood estimation, minimum-variance unbiased estimation, Bayes estimation etc. These methods are not without their disadvantages depending on their mathematical approaches.

The most common estimation method for determining distribution parameters of fragility function which is compatible with generating sample data from IDA is MLE. MLE is a probabilistic method in estimating the parameters of a statistical model's given data. By assuming the lognormal probability distribution fragility function with the unknown mean and variance, they are estimated with MLE while only some response point is available through IDA for a set of seismic records. For this set of data and underlying statistical model, MLE selects the set of values of the model parameters which maximizes the likelihood function. This maximization is in agreement of with the observed data, while in random variables space it maximizes the probability of the observed data under the resulting distribution. MLE provides a unified approach for estimation, which is very common in estimating normal and lognormal distributions, which are of two parameters (mean and variance). The MLE method principle is briefed here: Assume that there exist a sample set $\{s_{a_1}, s_{a_2}, ..., s_{a_n}\}$ of IDA in a state of performance. This set should be independent and identically distributed (i.i.d sample) which follows a probability density function of $f_0(\cdot|\Theta)$, where Θ is a vector of parameters for this function. In the case lognormal distribution, parameter vector is $\{\theta, \beta\}$ or the mean and variance. The function f_0 is an unknown distribution which depends on unknown vector Θ. For all possible situations, joint density function for all observations of i.i.d can be expressed as [21]:

$$f(S_a|\Theta) = f\left(s_{a_1}, s_{a_2}, ..., s_{a_n}|\Theta\right) = f_0\left(s_{a_1}|\Theta\right) \times f_0\left(s_{a_2}|\Theta\right) \times ... \times f_0(s_{a_n}|\Theta) \qquad (3)$$

The function f can be observed from a different perspective. If the sample values are fixed parameters and Θ is function of variables, this function is identified by $\mathcal{L}$ and named likelihood function, presented as:

$$\mathcal{L}\left(\Theta; s_{a_1}, s_{a_2}, ..., s_{a_n}\right) = \prod_{i=1}^{n} f\left(s_{a_i}|\Theta\right) = \prod_{i=1}^{n} \Phi(\frac{\ln\left(\frac{s_{a_i}}{\theta_d}\right)}{\beta}) \qquad (4)$$

Where $\Theta = \{\theta_d, \beta\}$. the objective of MLE method, is estimating the Θ vector to estimate a lognormal distribution through the sample space, or to find an estimated $\widehat{\Theta}$ which would be

as close to the true value of Θ as possible. In all possible situations of vector Θ, the best estimated $\widehat{\Theta}$ has largest likelihood or amount of $\mathcal{L}$. Determining the best fit or $\mathcal{L}$ maximum an optimization issue.

3.1 Classic closed form MLE

Finding the $\mathcal{L}$ maximum can be done through a mathematical straightforward procedure, where the derivatives of the main function of likelihood are involved. For normal probability distribution where vector of $\widehat{\Theta}$ has only the two variables of θ_d and β. This procedure is run through calculating the gradient and laplacian operator of likelihood function. The gradient and laplacian are the first and the second partial derivatives of this function:

$$find\ \widehat{\Theta} = (\theta_d, \beta)\ ;\ \nabla L(\widehat{\Theta}) = 0$$
$$if\ \ \nabla^2 L(\widehat{\Theta}) < 0 \tag{5}$$

Calculating these operators in a multi variant function introduce an extremum point of likelihood function which it is not necessarily the global maximum, that is the estimated point in the space of all possible θ_d and β are a local maximums. For more complicated probability distributions which are based on more parameters and have conditional sub spaces this method may face some drawbacks.

3.2 MLE through optimization algorithm

When facing difficulty in calculating the derivations of likelihood function, a numerical algorithm is most appropriate tool. Numerical optimization procedures are widely applied in finding the extreme value of functions. Optimization refers to finding the best element from some set of variables [22]. Optimization problem is involved in maximizing or minimizing a real function by picking input values in systematic manner. In general, optimization includes finding the best available values of an objective function of several variables in a given defined domain. The objective of this study is to find the best regression of a probability distribution on the set of structure response caused by seismic excitations. Adapting an efficient numerical solution as soft computing instead of closed form solution would pave the way to develop fragility function of structures. Common form of this optimization problem is expressed as a maximization format like:

$$\left(\widehat{\Theta}\right)_{MLE} \subseteq \arg \text{Max}\{\mathcal{L}(\widehat{\Theta})\} \tag{6}$$

Where in this expression arguments of the maxima is abbreviated as $\arg$ Max. To simplify computation the likelihood function, $\mathcal{L}$ is substituted with $\ln(\mathcal{L})$; since behavior of logarithmic function is better than the original form of $\mathcal{L}$. By this substitution the domain is restricted to positive real numbers.

There are many numerical algorithms like genetic algorithm (GA), harmony search (HS) which have capability of calculating the estimated extreme value of a function. In this research, an estimation of probability distribution parameter of fragility is calculated through a numerical algorithm with a distribution which has maximum likelihood.

The numerical optimization algorithms are of two major categories: heuristic, and metaheuristic. Heuristic algorithms are mathematical tools for solving problems as an alternative for classical methods. Compared to the classical methods, the heuristic optimization can achieve response more quickly in complicated problems. Metaheuristic is a higher heuristic optimization procedure designed to find solution especially with incomplete or imperfect information or limited computation capacity [23]. Those algorithms generally are of iterative solving process nature. These algorithms generate a sequence of improving solutions which try to find an approximation of the exact solution. All of these methods are nature inspired and their iterative algorithms apply stochastic components accompanied with random variables [24].

All optimization methods have strengths and weakness in solving specific set of problems. The merit of each optimization algorithm is measured against the given problem condition. Among the possible drawbacks of the heuristic algorithms being stack in local optima is the most outstanding, while the metaheuristic methods can often find good solution with less computational effort than heuristic methods. The implementing those two are presented in several studies like [25–27].

4. HS OPTIMIZATION FOR FRAGILITY ASSESSMENT

The two main feature of a metaheuristic solution approach are: diversification, which is a metric for searching all domains, and intensification, which is the capability of focusing on a subset of whole domain where the probability of finding optimum is greater. Metaheuristic optimization algorithms use a compromise of local search and global exploration by means of these two features. The diversification via randomization avoids the solutions being trapped at local optima, while increases the diversity of the solutions [28]. To avoid trapping in local optima, different metaheuristic algorithms like ant-colony (AC), tabu search (TS), HS, and GA are introduced [27]. Due to the specific capability and functionality of each algorithm, choosing the most efficient is difficult. Diversification and intensification features in each algorithm are antithetic, while their balanced combination makes an algorithm efficient. Inordinate diversification makes an algorithm hard to converge, and inordinate intensification traps an algorithm in local optima.

HS algorithm is based on making random harmony (solution vectors), provided that the generated harmony yields better solution than the previous stored harmony. The harmony memory will be updated by a better solution. This process will continue until convergence criteria is satisfied. This process consist of the following five main steps [12]:

- Initializing the optimization problem and algorithm parameters, like defining objective function $f(x)$ where x is the set of each design variable, harmony memory matrix size (HMS) where it is the number of solution vectors in memory, harmony memory considering rate (HMCR), pitch adjusting rate (PAR) and convergence criteria [11,12].
- Initialize harmony memory (HM) matrix which is fed with randomly generated solution vectors and stored by values of the objective function $f(x)$.
- Improvise a new harmony from the HM based on HMCR, PAR and randomization. For example an HMCR of 0.95 indicates that the HS algorithm will choose the variable value from the stored values in the HM with a 95% probability and from the entire feasible

domain with a 5% probability. PAR parameter tries to adjust the final values within a neighbourhood of stored value.

• Update the HM with the best solution and terminate the memory solution vectors.
• Repeat step 3 and 4 until convergence or satisfying termination criteria is met.
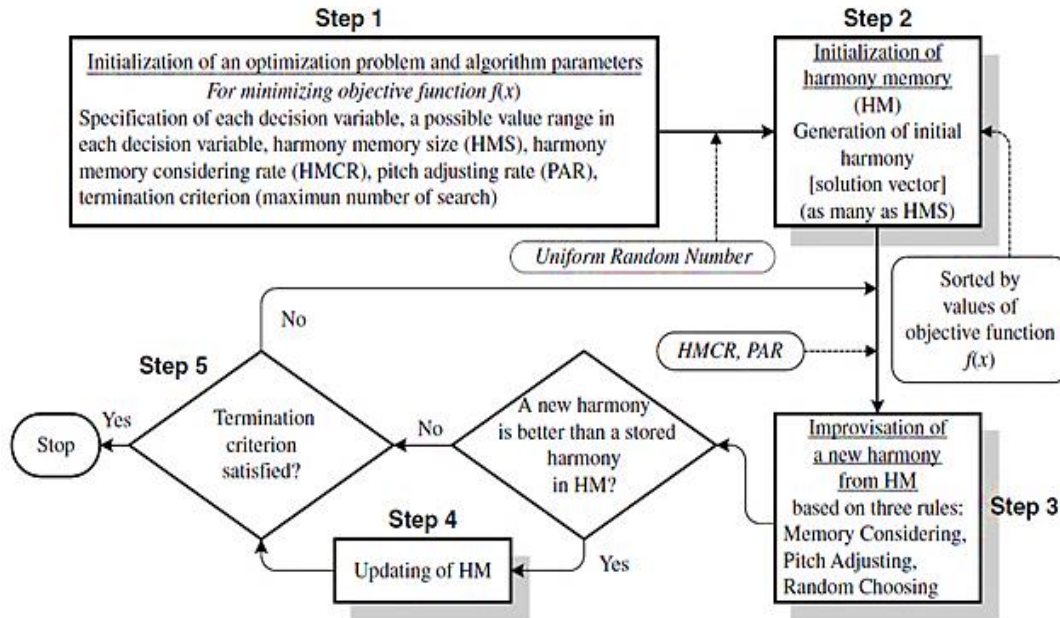   This algorithm is implemented as an optimization code based on Fig. 2, flowchart.

Figure 2. Optimization procedure of the harmony search algorithm [29]

The HS methodology for finding probability distribution of a prototype structure is described as: First, an IDA is implemented. Next the intensity measure of structure is determined for the three performance limit states and then for these data, fragility distribution parameters is determined through closed form classical and harmony search optimization approach for comparison and verification.

5. CASE STUDY

According to assess the fragility probability distribution, the well-known benchmark 3 and 9 story SAC steel structural models (Fig. 3) located in California is selected. More description of this frame model is found in [30–32]. The structural models in this study is a two dimensional nonlinear model with moment resisting frame developed in OpenSees program [33]. Nonlinear behaviour of frame is modelled through the concentrated plasticity of hinges in beams and columns. The second order effects of $P - \Delta$ according to Gupta and Krawinkler [31] is considered in all analyses. The behaviour of plastic hinges is simulated by the modified Ibarra-Krawinkler deterioration model with bilinear hysteretic response [34,35]. The hysteretic response of this material is calibrated with respect to the experimental data of steel beam-to-column connections and multivariate regression formulas
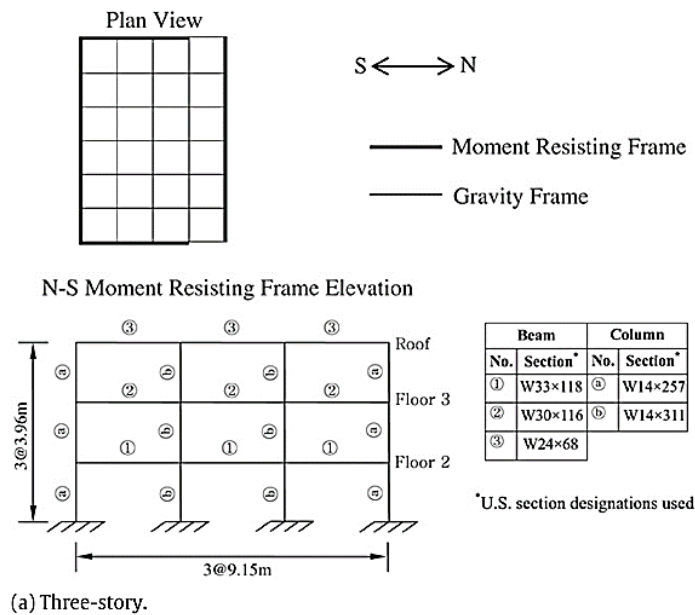
are provided to estimate the deterioration parameters of the model for different connection types. These correlation have been adopted by PEER/ATC 72 [36].

In addition to modelling full nonlinear behaviour of beams and columns with acceptable accuracy, modelling panel zones lead to better estimation of shears, moments and axial forces in members [37]. In this study, panel zones are modelled through the approach introduced by Gupta and Krawinkler [31] as a rectangle composed of eight very stiff elastic beam-column elements with one zero-length element which serves as a rotational spring to represent shear distortions in the panel zone.

IDA is run for the above mentioned model, with a suit of 20 ground motion time history of far field seismic event developed specifically for SAC steel project through hazard analysis [38] are tabulated in Table 1. These ground motions are categorized by their probability of exceedance (or their corresponding mean return interval). In this study ground motions are selected from all 2%, 10% and 50% probability of exceedance in order to consider all seismic frequency content properties in dynamic analyses.

In this study, the first mode spectral pseudo acceleration with 5% critical damping $(s_a(T_1, \xi = 5\%))$ and maximum inter story drift (θ_{max}) is applied as intensity measure and engineering demand parameter, respectively [5,39]. IDA curves for 3 and 9 story frames is presented in Fig. 4.

Performance level LSs are introduced on based on specifications of FEMA-350 [40]. There are three main performance levels according to this guideline: Immediate Occupancy (IO), Collapse Prevention (CP) and Global Dynamic Instability (GI). Here IO performance level is defined as $\theta_{max} = 1\%$, so all intensity measures with $\theta_{max} > 1\%$ lead to exceedance of IO performance level. CP performance is violated when local tangent on the IDA curve reaches 20% of the elastic slope but not far from $\theta_{max} = 10\%$. GI performance level become evident provided that IDA curve get flat.

(a) Three-story.

Plan View

S ⟵⟶ N

▬▬▬ Moment Resisting Frame

─── Gravity Frame

N-S Moment Resisting Frame Elevation

Beam		Column	
No.	Section*	No.	Section*
①	W36×160	ⓐ	W14×500
②	W36×135	ⓑ	W14×455
③	W30×99	ⓒ	W14×370
④	W27×84	ⓓ	W14×283
⑤	W24×68	ⓔ	W14×257

*U.S. section designations used
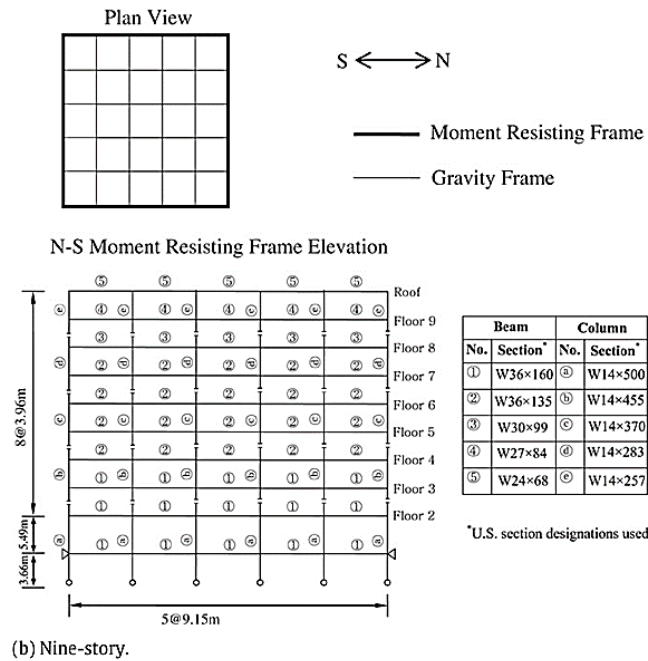
5@9.15m

(b) Nine-story.

Figure 3. (a) 3 and (b) 9 story SAC Steel structural model [32]

The common fragility models assume the following two parameters of lognormal distribution of θ_d and β for simplicity. In this study all calculation are made according to the presented flowchart in Fig. 1, above mentioned calculation of probability distribution parameter through classical closed-form methodology with solving Eq (5), and harmony search optimization method with calculating Eq (6) will be done. Final results are presented in Table 2 where it is observed that there exist a good convergence between classical method and harmony search optimization. These calculated distribution parameters introduce an optimum fragility function curve in Fig. 5.

Table 1: Suit of 20 ground motion time history of far field seismic event [38]

SAC Name	Record	Magnitude	Distance (km)	Scale Factor	Number of Points	DT (sec)	Duration (sec)	PGA (cm/sec2)
LA07	Landers, 1992, Barstow	7.3	36	3.2	4000	0.02	79.98	412.98
LA08	Landers, 1992, Barstow	7.3	36	3.2	4000	0.02	79.98	417.49
LA09	Landers, 1992, Yermo	7.3	25	2.17	4000	0.02	79.98	509.70
LA10	Landers, 1992, Yermo	7.3	25	2.17	4000	0.02	79.98	353.35
LA11	Loma Prieta, 1989, Gilroy	7	12	1.79	2000	0.02	39.98	652.49
LA12	Loma Prieta, 1989, Gilroy	7	12	1.79	2000	0.02	39.98	950.93
LA31	Elysian Park (simulated)	7.1	17.5	1.43	3000	0.01	29.99	1271.20
LA32	Elysian Park (simulated)	7.1	17.5	1.43	3000	0.01	29.99	1163.50
LA33	Elysian Park (simulated)	7.1	10.7	0.97	3000	0.01	29.99	767.26
LA34	Elysian Park (simulated)	7.1	10.7	0.97	3000	0.01	29.99	667.59
LA35	Elysian Park (simulated)	7.1	11.2	1.1	3000	0.01	29.99	973.16
LA36	Elysian Park (simulated)	7.1	11.2	1.1	3000	0.01	29.99	1079.30
LA45	Kern, 1952	7.7	107	2.92	3931	0.02	78.6	141.49
LA46	Kern, 1952	7.7	107	2.92	3931	0.02	78.6	156.02

LA47	Landers, 1992	7.3	64	2.63	4000	0.02	79.98	331.22
LA48	Landers, 1992	7.3	64	2.63	4000	0.02	79.98	301.74
LA49	Morgan Hill, 1984	6.2	15	2.35	3000	0.02	59.98	312.41
LA50	Morgan Hill, 1984	6.2	15	2.35	3000	0.02	59.98	535.88
LA59	Whittier, 1987	6	17	3.62	2000	0.02	39.98	753.70
LA60	Whittier, 1987	6	17	3.62	2000	0.02	39.98	469.07

(a)   (b)
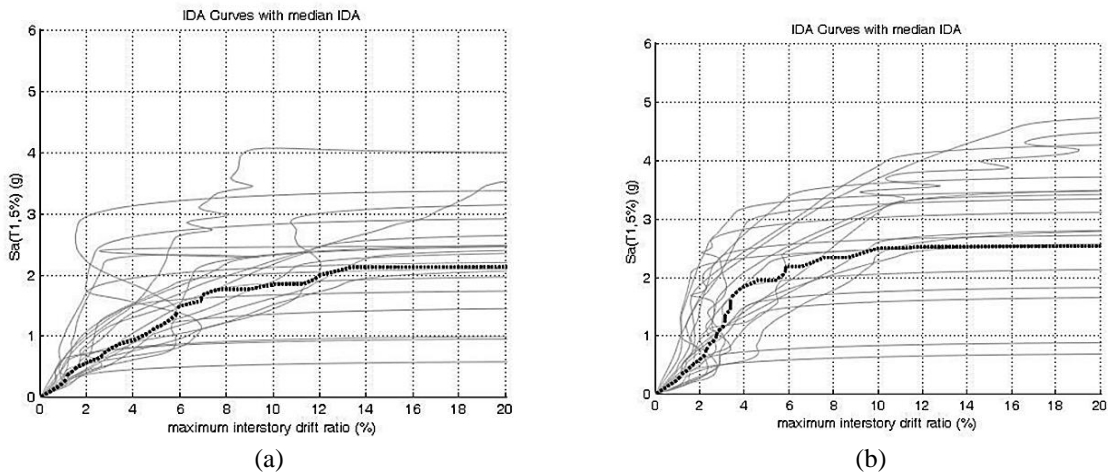
Figure 4. IDA curves for (a) 3 story frame, (b) 9 story frame

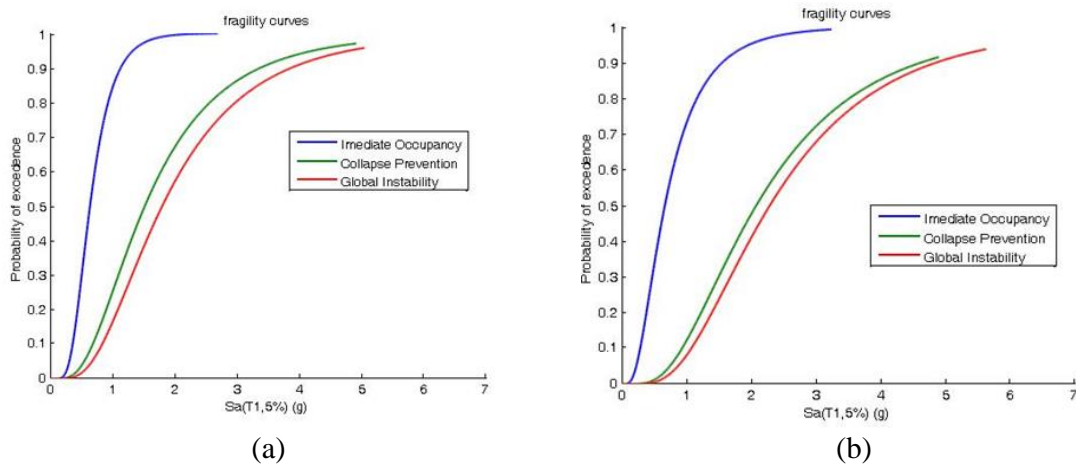(a)   (b)

Figure 5. (a) 3 story frame Fragility function curves, (b) 9 story frame Fragility function curves

Table 2: Comparing fragility curve distribution parameters with both classic closed-form mathematical and harmony search approaches

Frame	Optimization approach	Performance levels					
		IO		CP		GI	
		θ	β	θ	B	θ	B
3 Story	Classic mathematical approach	-0.44840	0.44580	0.41730	0.62270	0.58600	0.59820
	Harmony search approach	-0.44837	0.43456	0.41727	0.60697	0.58603	0.58308
9 Story	Classic mathematical approach	-0.40730	0.66300	0.73060	0.62650	0.82680	0.58980
	Harmony search approach	-0.40426	0.64618	0.73060	0.61066	0.82680	0.57488

6. CONCLUSION

The common form of fragility probability distribution of structurs is calculated through IDA observed data. To determine how these data set can be modeled as a probabilistic distribution curve, a curve fitting approach can be used. Curve fitting is based on the underlying assumption that the observed data is driven by some process that can be modeled as a probabilistic distribution function. maximum likelihood estimation is an common approach of estimating the parameters of a probabilistic distribution given observations, by finding the parameter values that maximize the likelihood of making the observations given the distribution parameters. The closed form mathematical method to find the best fitting probability distribution among collected data for each performance level is based on calculating gradient and laplacian to find argument maxima of likelihood function. This mathematical operation on a generated function for a simple distribution with one or two description parameters is easy to solve. The complexity of determining partial derivation of gradient and laplacian have made it difficult to expand fragility function to higher level function like multivariate and multimodal functions. The purpose of this study is to use an optimization tool during the maximum likelihood estimation process. This tool allows for utilizing more complicated functions and precise probabilistic models than the two-parameter lognormal model. Therefore, as a solution HS optimization algorithm is proposed in estimation process.

As a case study two well-known benchmark structure is chosen. Incremental dynamic analyses of the 2D numerical models lead to collecting sets of observed data in several performance levels. According to flowchart illustrated in Fig. 1, classical approach and optimization approach is implemented to estimating the lognormal distribution parameters that has maximum likelihood. The results indicate a very high accuracy of optimization approach as expected, but this approach has many potentials including the use of complex probabilistic distributions, while the classical approach combines this ability with computational complexity of calculating partial derivations.

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