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THE POSSIBILITY OF USING JERK PARAMETERS AS SEISMIC INTENSITY MEASURE

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ABSTRACT

It is a common procedure to use a single parameter because of its simplicity to represent the seismic action in a particular region and describe its complex nature. This single parameter generally is known as ground motion intensity measure IM. The time derivative of acceleration, commonly known as jerk, is met in a limited number of such studies and specifically in earthquake engineering. For that purpose, this paper presents a study on the performance of using seismic jerk as ground motion IM. Several typical RC frame buildings of different numbers of stories were selected. The nonlinear time-history analysis is performed while the buildings are exposed to twenty-seven natural earthquake records using ETABS software. The maximum displacement at the top of the building is selected as the structural response parameter. Several widely used IMs were defined in addition to the jerk and its based parameters. After performing a large number of nonlinear analyses and applying machine learning, best feature subsets that present relation between response parameter and considered intensity measures were obtained. For structures with low nonlinearity in behavior, jerk- based parameters were shown to be effective.

KEYWORDS: Ground motion intensity measure; Jerk; Time derivation of acceleration; RC buildings; Masonry Buildings.

1. INTRODUCTION

For the reason of seismic vulnerability evaluation and to characterize the possibility of damage initiated by seismic ground motion in terms of fragility curves, a ground-motion parameter called an intensity measure (IM) is typically utilized. In a broad sense, it is a familiar technique to use a single parameter because of its simplicity to represent the seismic action in a specific area and designate its complex nature.

A successful IM should be able to reliably evaluate the structural response without additional ground-motion information such as magnitude or epicentral distance and etc. During years, some significant IMs have been extracted and derived by researchers (e.g. Housner, 1952; Housner& Jennings, 1964; Arias, 1970; Shome et al., 1998 and etc.) using convenient mathematical methods applied to time histories. These parameters can be categorized based on the time histories that they are derived from and are known as acceleration-, velocity-, or displacement-based intensity measures (Riddell, 2006; Buratti, 2012). The majority of these parameters calculate one of the ground-motion characteristics: the amplitude, duration or frequency content of ground motion. Nevertheless, there are roughly other parameters that are established on a combination of the above mentioned characteristics; these parameters are typically identified as energy-based parameters. The duration is another essential characteristic of ground motion that may affect the level of damage experienced by a structure. Conversely, several investigations (e.g., Riddell, 2006; Nanos, 2011; Buratti, 2012; Elenas, 2013) have asserted that various IMs may have altered abilities in predicting structural reactions when being used as a damage state. Thus, one of the most vital purposes put forth in these researches was to ascertain the ground-motion parameter that is best associated with damage which is, in turn, a function of the structural behavior.

Even though study of the those widely known parameters can also be improved in order to grow the spectra characteristic of ground motions, 'jerk' is a measure not intensively addressed as yet. By the abrupt change of building acceleration, the motion may assume an explosive character. During the following decades of the nineteenth century, that dynamic

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phenomenon of motion was identified in many applications of practical interest, and much later in the Seismic Engineering. Currently, it is called jerk in English (Sofronie, 2017). Theoretically, jerk is defined as the changing rate of acceleration with respect to time (Schot,1978), and its international unit is m/s^3. In current years, jerk is applied in the tracking and positioning for Global Positioning System (GPS), the automatic control of high-speed machines, the high-speed dynamic vehicle tracking, and comfort assessment for high speed trains and elevators (Toshiyuki et al,2009; Liu et al,1999; Hrovat and Hubbard,1987).

In structural and earthquake engineering field, a number of investigations tried to examine the influence of jerk on structure's safety and strength. For example, HE et al. (2011), studied the characteristics of jerk response spectra based on the influencing parameters, such as an amplification factor, a site condition, a reduction factor and a ductility factor. The study consequences illustrate that jerk influences the building structures with short or middle periods more observably, and the impact responses can be decreased considerably when the structural ductility is improved; the impact of jerk on long-period structures can be disregarded. Furthermore, HE et al. (2015) confirmed the results of HE et al. (2011) study and asserted that the jerk spectrum has comparable behavior as acceleration spectrum in general, and the amplitude is in relation to the predominant period, particularly for structures with short or medium period. Similarly, Tong et al. (2005) asserted that the large acceleration pulses are surrounded by large TDoA (the time derivative of acceleration of strong ground motion) spikes. They presented a basic evaluation of TDoA and showed that TDoA is one of the essential contributing parameters to some of the reaction difficulties that limit the capability of people to move usually throughout strong earthquakes. They also indicated that peak ground jerk PGJ and peak ground acceleration PGA are kinetically correlated. Large TDoA allied with strong ground acceleration may consequence in nonuniform dynamic loading caused by the stress wave propagation. This outcome may source stress concentration and local damage (Tong et al., 2005). According to the Sofronie (2017), the dislocations, always occur around local structural imperfections by high concentrations of stresses. Each construction material, elastic or non-elastic, has its own intrinsic time of dislocation when stresses are randomly redistributed. That time has to be compared with the jerk's time of action because the action time of jerks is too short for developing deformations. Only then a valid conclusion on the dynamic phenomenon of amplification could be correctly drawn. He asserted that, generally, the seismic jerks occur in the case of buildings with unbalanced masses.

As abovementioned, unlike acceleration, velocity, and displacement, the time derivative of acceleration of ground motion, Jerk, has not been comprehensively addressed for various seismic source mechanisms, ground motion characteristics and engineering applications (Tong et al., 2005). Additionally, the authors couldn't find even a study regarding the role and importance of jerk as ground-motion IM. Hence, the current study tries to find the answer of this question "Can Jerk Parameters Be Used as Seismic Intensity Measures?"

2. METHODOLOGY

A four stage procedure followed to gain the main objectie of this study as shown in Figure 1. Each stage has been intensively discussed in the following sections.

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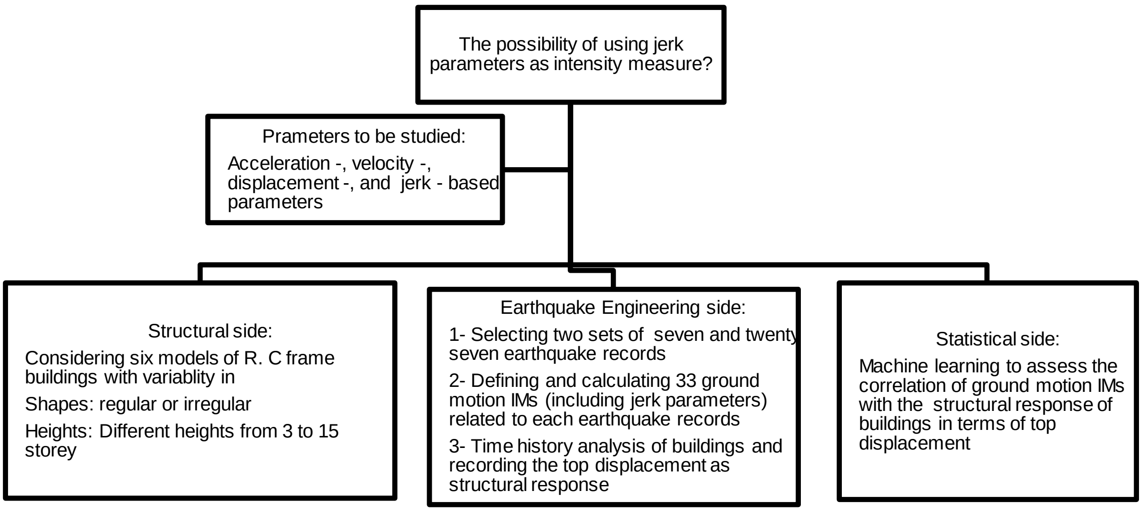

Fig. (1): Flowchart showing the methodology used in the current study

2.1 Ground-motion IMs considered in the present study

To examine which ground-motion IMs are most significant for a given structure in a particular location, the effect of multiple relevant accelerograms must be considered. The IMs chosen for consideration and associated with each accelerogram must be also determined. It is then necessary to determine the correlation between each IM and the damage index related to the structural response of buildings. The IM giving the highest correlation with damage index is the IM that should be chosen. This study has considered a range of widely used ground-motion IMs as presented in Table 1. Furthermore, in addition to the IMs given in Table 1, and toward the study of the importance of jerk as a ground motion IM, the current study defined some new parameters (Table 2) considering the Jerk time history of each earthquake record selected by this study. SeismoSignal (SeismoSoft, 2018) software was used to calculate all the ground-motion IMs.

Table (1): A number of commonly used Ground-motion IMs considered in the current study

IMs*	Name
Acceleration-based	Peak ground acceleration (PGA), root mean square of acceleration (ARMS), Arias intensity (IA), characteristic intensity (IC), cumulative absolute velocity (CAV), acceleration spectrum intensity (ASI), sustained maximum acceleration (SMA), effective design acceleration (EDA), A95 parameter, and average spectral acceleration Sa(ave.)
Velocity-based	Peak ground velocity (PGV), root mean square of velocity (VRMS), specific energy density (SED), velocity spectrum intensity (VSI), sustained maximum velocity (SMV), and Housner intensity (IH)
Displacement-based	Peak ground displacement (PGD), root mean square of displacement (DRMS)
Duration	Predominant period (TP) and mean period (Tm)
Others	Impulsivity index (IP Index) and damage index

* The reader may refer to Kramer (1996),Yaseen (2015), and SeismoSoft (2018) for an explicit explanation of the examined IMs.

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2.1.1 Jerk and Jerk based Parameters

About eleven jerk based parameters were defined in the current study. The definition of these parameters and their mathematical expression are given in this section and are shown in Table 2.

2.1.1.1 Jerk

Currently, jerk sensors are not normally obtainable; thus, attaining jerk information becomes the crucial first step. In this study, and according to (Tong et al., 2005), the jerk j(t) time series are calculated from ground acceleration records by the following mid-point differentiation formula.

$j(t_i) = \frac{a(t_{i+1})-a(t_{i-1})}{2\Delta t} (i = 2, \ldots, N-1)$ Equation 1

Where $a(t_i)$ is the acceleration time series; N is the total number of sampling points; and $\Delta t = t_i - t_{i-1}$ is the time interval between two neighboring points. The $j(t_i)$ is the average jerk in the time interval $2\Delta t$ between the time points i-1 and i+1.

2.1.1.2 Jerk energy

Based on the mathematical expression form of the acceleration energy developed by Qiao (1990), An et al. (2014) presented the so-called jerk energy (JE) that is well-defined as the natural logarithm of the sum of the squares of the sampled average jerk over the entire time history. Based on the An et al. (2014) definition of JE and considering equation 1, in this study, equation 2 is used to calculate the JE.

$JE_i = \log \sum_{i=1}^{N-1} j(t_i)^2$ Equation 2

2.1.1.3 Jerk - bracketed duration

Afterward the bracketed duration of acceleration, the duration of strong ground jerk is reflected as the time span between the first and the last peak within a certain threshold. The duration defined in this research may be interpreted as the time range where jerk makes the human body feel extremely uncomfortable. According to the Tong et al. (2005) review of different studies, if the jerk is larger than 2000 cm/s^3 (2 g/s) (within about 10 Hz), people will become very uncomfortable. So, the threshold of jerk – bracketed duration was set to be 2000 cm/s^3 (2 g/s) in this study. Table 2 show all jerk-based parameters undertaken in the present investigation.

Table (2): Jerk-based parameters considered in the current study

Jerk-based IMs(abbreviations)	Name	Mathematical expression
PGJ (cm/s^3)	Peak Ground Jerk	$max\lvert j(t)\rvert$
$T_{max.}$ (s)	Time of maximum Jerk	
JRMS (cm/s^3)	Root mean square of jerk	$J_{RMS} = \sqrt{\frac{1}{t_{tot}}\int_0^{t_{tot}}[j(t)]^2 dt}$ where t_{tot}=total time of jerk time history
IAJ(m/s^3)	Jerk Arias Intensity	$I_j = \frac{\pi}{2g}\int_0^{t_{tot}}[j(t)]^2 dt$ where g=gravitational constant
ICJ	Jerk- Characteristic Intensity	$I_c = (J_{RMS})^{\frac{3}{2}}\sqrt{t_{tot}}$
JSI (cm/s^2)	Jerk- Spectrum Intensity	$JSI = \int_{0.1}^{0.5} S_j(\varepsilon = 0.05, T)\, dT$ where Sj= Spectral Jerk
SMJ (cm/s^3)	Sustained Maximum Jerk	This parameter gives the sustained maximum jerk during three cycles, and is defined as the third highest absolute value of jerk in the jerk time history
J95 parameter (cm/s^3)		The jerk level below which 95% of the total Jerk Arias intensity is contained
S_j,avg (cm/s^3)		The Average Spectral Jerk is computed as the geometric mean of the spectral pseudo-jerk ordinates for a 5% damping
Tb(2000) (s)	Jerk- bracketed duration	The total time elapsed between the first and the last excursions of a 2000 cm/s^3 of Jerk
JE (cm/s^3)^2	Jerk Energy	Natural logarithm of the sum of the squares of the sampled average jerk over the entire jerk time history

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2.2 Structural response of considered buildings in the current study

The response of a construction influenced by an earthquake can be assessed using a nonlinear dynamic analysis. This technique employs the direct mathematical interaction of the differential expressions of motion by taking the elastoplastic deformation of the structural members. Such nonlinear dynamic analyses are also known as time-history analyses. To create the 3D models and undertake the required non-linear dynamic analyses, the general-purpose finite element analysis (FEA) program ETABS 2016 (Computers and Structures, Inc., 2016) was utilized in this study. The software is able to assess the nonlinear behavior of frames under static or dynamic loadings, taking into account both material and geometric nonlinearities. A key input for such an analysis, dynamic analysis, is a ground motion accelerogram that is suitable for the seismic hazard analysis of the nominated area. A number of ground-motion time histories are required by ETABS software to effectively conduct the time history analyses and predict the structural behavior of the buildings.

Six models of regular and irregular reinforced concrete (RC) frame buildings of different numbers of stories (Table 3) considered in this study. All buildings have a 3m floor-to-floor height and fixed at their supports. Buildings have three spans in the X and Y directions (square plan of 15m × 15m). The evaluated RC frame buildings are designed in such a way that they are only able to resist gravity loads (Live load of 2 kN/m^2 and deal load of 2 kN/m^2(excluding the self-weight)), which is the model widely used in larger cities in the Kurdistan region of Iraq. The slabs of the structures are reflected to be 0.15m thick. Figures 2 to 4 show a two- and three-dimensional view of the nominated RC building frames. Sectional dimensions of columns and beams with the number of longitudinal reinforcement bars are also represented in Table 3.

In ETABS, a nonlinear time history analysis can be conducted utilizing either user-defined nonlinear hinge properties, default hinge properties, or automated hinge properties. Automated hinge properties are determined automatically from the frame element material and section properties according to ASCE 41-17 (ASCE, 2017) criteria. Hinges are assigned at both ends of each element, beams, and columns. The concrete moment (M) hinge type and the concrete axial force-biaxial moment (P-M-M) hinge type are respectively used to account for the behavior of hinges formed in the beams and columns. The material characteristics assigned to the frame element are used to predict the plastic response of the hinges, while the elastic response of the frame elements is calculated by the frame sections assigned to the elements. Hinges are assigned to the 5% and 95% of the length of beams and columns (at their ends). Default values given by ETABS software were considered for nonlinear parameters and other required properties for definition of nonlinear hinges. Time histories were applied in X direction to each model and structural response in terms of top displacement (in X- direction) then were recorded.

Table (3): Detail of the considered buildings in the current study

Type of Structure	Number of storeys	Irregularity in shape	Column section mm	Column Reinforcement mm² *	Beam section mm	Beam Reinforcement mm²	Compressive strength of Concrete MPa	Yield strength of Steel MPa
URM	1	For the purpose of comparison, only results of time history analyses of two unreinforced masonry buildings studied by Yaseen (2015) are considered in this study. For more details on the geometry and materials used in URM buildings and their outcomes refer to Yaseen (2015) PhD thesis						
	2							
Reinforced Concrete	3	Regular	400×4	1600 (8Φ16	400x400	1200 (6Φ16mm at middle and supports)	21	414
	5		500×5	2500			21	414
	7		500×5	3800			28	414
	10		500×5	3800			28	414
	13		600×6	3800			28	414
	15		600×6	3800			28	414
	3	Irregular-	400×4	1600 (8Φ16			21	414

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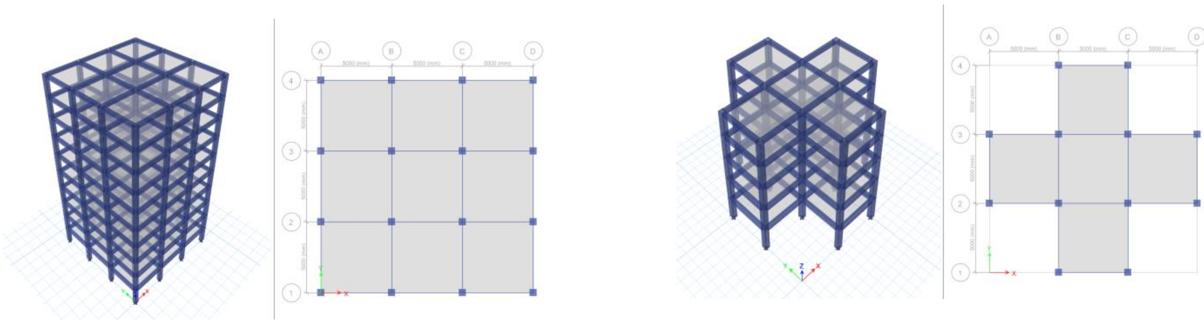
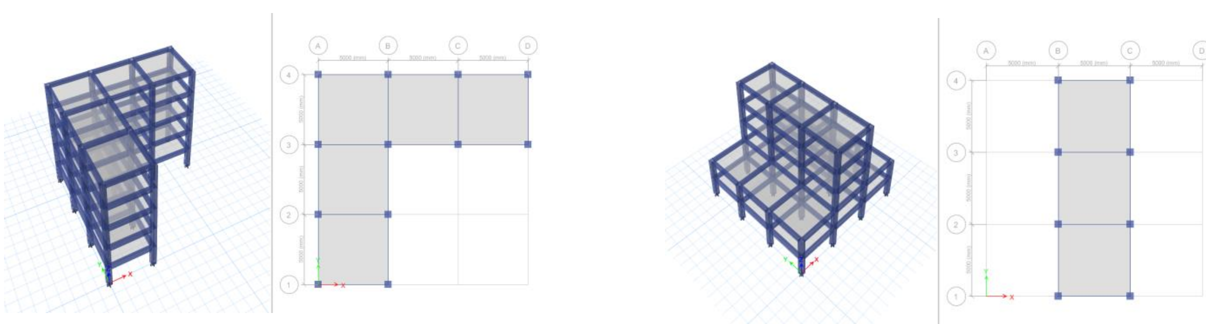
5	Plus shape	500×5	2500	21	414
10		500×5	3800	28	414
15		600×6	3800	28	414
3	Irregular-L shape	400×4	1600 (8Φ16	21	414
5		500×5	2500	21	414
10		500×5	3800	28	414
15		600×6	3800	28	414
3	Irregular-I shape	400×4	1600 (8Φ16	21	414
5		500×5	2500	21	414
10		500×5	3800	28	414
15		600×6	3800	28	414
3	Irregular-Set Back [1]	400×4	1600 (8Φ16	21	414
5		500×5	2500	21	414
10		500×5	3800	28	414
15		600×6	3800	28	414
3	Irregular-Set Back [2]	400×4	1600 (8Φ16	21	414
5		500×5	2500	21	414
10		500×5	3800	28	414
15		600×6	3800	28	414

* For stirrups Φ10 mm at 200 mm used.



(a) (b)

Figure 2 Typical models of (a) regular RC frame (b) Irregular plus shape RC frame



(a) (b)

Fig. (3): Typical models of (a) Irregular L shape RC frame (b) Irregular I shape RC frame

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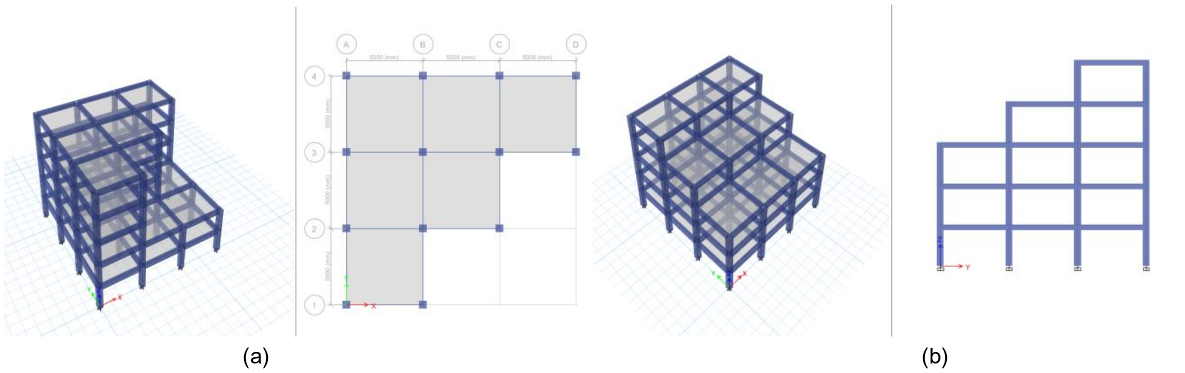

Fig. (4): Typical models of (a) Irregular set back¹ shape RC frame (b) Irregular set back² shape RC frame

2.3 Ground motion records

Despite the high variability in ground motions, it is desirable to choice as few records as possible for these types of analyses. This is mostly due to the nonlinear modeling and dynamic analysis are computationally onerous and highly time-consuming. Although the suitable number of records is still a matter for debate, in practice, it is typical to use seven motions according to EC8 (CEN, 2003) and ASCE/SEI-7 (ASCE, 2010) or eleven ground motions as specified by ATC-58 (2011). The average behavior of the structure is the outcome of the analysis if the aforementioned number of ground motions takes as input to the analysis. Shome et al. (1998) also affirmed that for a medium-rise building, ten to twenty records are adequate to evaluate its seismic demand with great confidence. Hence, in this investigation, and to minimize the bias due to variability in ground motions, two suites of selected seven, and twenty-seven ground motions are chosen in such a way as to be compatible with the seismic characteristics of the Kurdistan Region of Iraq. Nominated motion records were suggested by Yaseen (2015) for Kurdistan Region of Iraq and were derived from PEER Next Generation Attenuation NGA Strong Motion Database (available at http://peer.berkeley.edu/assets/NGA_Flatfile.xls) . Tables 4 and 5 present specifications of the selected ground motions.

Table (4): Specifications of a suite of seven ground motions

No.	NGA Record Number	Earthquake Name	Earthquake Moment Magnitude	Epicentral Distance(km)	PGA(g)
1	126	Gazli, USSR	6.8	12.82	0.6
2	143	Tabas, Iran	7.35	55.24	0.84
3	802	Loma Prieta	6.93	27.23	0.51
4	821	Erzican, Turkey	6.69	8.97	0.5
5	828	Cape Mendocino	7.01	4.51	0.59
6	1086	Northridge-01	6.69	16.77	0.6
7	1602	Duzce, Turkey	7.14	41.27	0.73

Table 5 Specifications of a suite of twenty-seven ground motions

No.	NGA Record Number	Earthquake Name	Earthquake Moment Magnitude	Epicentral Distance(km)	PGA(g)	No.	NGA Record Number	Earthquake Name	Earthquake Moment Magnitude	Epicentral Distance(km)	PGA(g)
1	126	Gazli,USSR	6.8	12.82	0.6	15	983	Northridge-	6.69	13	0.57
2	143	Tabas, Iran	7.35	55.24	0.84	16	1004	Northridge-	6.69	8.48	0.75
3	169	Imperial Valley-06	6.53	33.73	0.24	17	1013	Northridge-01	6.69	11.79	0.51
4	179	Imperial Valley-06	6.53	27.13	0.36	18	1044	Northridge-01	6.69	20.27	0.58

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5	182	Imperial Valley-06	6.53	27.64	0.46	19	1063	Northridge-01	6.69	10.91	0.63
6	184	Imperial Valley-06	6.53	27.23	0.35	20	1085	Northridge-01	6.69	13.6	0.83
7	568	San	5.8	7.93	0.88	21	1086	Northridge-	6.69	16.77	0.6
8	802	Loma Prieta	6.93	27.23	0.51	22	1119	Kobe,	6.9	38.6	0.69
9	821	Erzican, Turkey	6.69	8.97	0.5	23	1197	Chi-Chi, Taiwan	7.62	32.67	0.65
10	825	Cape Mendocino	7.01	10.36	1.5	24	1507	Chi-Chi, Taiwan	7.62	15.42	0.57
11	828	Cape Mendocino	7.01	4.51	0.59	25	1508	Chi-Chi, Taiwan	7.62	21.42	0.49
12	953	Northridge-	6.69	13.39	0.42	26	1602	Duzce,	7.14	41.27	0.73
13	959	Northridge-	6.69	4.85	0.36	27	1605	Duzce,	7.14	1.61	0.35
14	963	Northridge-	6.69	40.68	0.57						

2.4 Machine learning process

As noted previously, the purpose of this study is to find an IM (or IMs) that correlated better with the response of buildings. Due to the number of ground motions being considered and the number of IMs under investigation, the process of determining the level of correlation for each of the IMs is a complex exercise. Machine learning offers tools by which large numbers of data can be automatically analyzed to evaluate such associations. Two methodologies that enable standard machine learning algorithms to be applied to large databases are feature selection and sampling. Both reduce the size of the database-feature selection by identifying the most salient features in the data; sampling by recognizing demonstrative examples (John and Langley,1996). This paper emphasis on feature selection-a process that can benefit learning algorithms regardless of the number of data accessible to learn from. The profits of feature selection for learning can comprise a reduction in the number of data required to complete learning, enhanced predictive accuracy, learned information that is more compact and easily understood, and reduced execution time (Langley and Simon,1995).

Current key choice approaches for machine learning characteristically fall into two broad classes those which assess the worth of features using the learning algorithm that is to eventually be applied to the data, and those which evaluate the worth of features by using heuristics based on general characteristics of the data. The former is referred to as wrappers and the latter filters (Kohavi,1995; Kohavi and John,1996). The wrapper is one of the simplest feature selectors conceptually (though not computationally) and has been found to generally out-perform filter methods (John,1994; Caruana and Freitag,1994). Wrappers are generally considered to be superior to filters as they are tuned to the specific interaction between a learning algorithm and its training data and stand the best chance of finding the "optimal" feature subset. The feature selector is simple and fast to execute. It reduces inappropriate and redundant data and, in numerous circumstances, enhances the effectiveness of learning algorithms. Studies has proven that no single learning method is obviously superior in all cases, and in fact, various learning algorithms often produce similar outcomes (Langley and Simon,1995). Accordingly, in this study, a two-stage technique (subset merging technique) for feature selection is applied to reduce the bias caused by using different types of machine learning algorithms. WEKA workbench (Holmes et al.,1994) was used for that purpose.

A good feature subset is one that contains features (Ground-motion IMs) greatly related with (predictive of) the class (here the response of the buildings to the ground motion time history, yet uncorrelated with (not predictive of) each other. Evaluation of the above hypothesis is accomplished by creating a feature selection algorithm that evaluates the worth of feature sets. Wrapper subset evaluator (Wrappersubseteval), as an attribute selection

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evaluator, is a component of the WEKA workbench (Holmes et al.,1994), which itself is part of ongoing research at the University of Waikato to produce a high-quality process model for machine learning. Wrappersubseteval evaluates attribute sets by using a learning scheme.

Accuracy estimation for the wrapper is achieved through 5-fold cross validation (obtained by trial and error procedure) of the 'training' set. Different types of Classifiers (machine learning algorithms) have been used for estimating the accuracy of subsets and they are: *M5P* (Implements the M5' model tree algorithm.); Random *Tree* (Class that considers k randomly chosen attributes at each node but performs no pruning.); *Linear Regression* (an algorithm that uses linear regression for prediction and which. uses the Akaike criterion for model selection and is able to deal with weighted instances. Attribute selection is carried out by using M5's method (step through the attributes removing the one with the smallest standardized coefficient until no improvement is observed in the estimate of the error given by the Akaike information criterion)); *Gaussian processes* (implements Gaussian processes for regression without hyperparameter-tuning. To make choosing an appropriate noise level easier, this implementation applies normalization/standardization to the target attribute as well as the other attributes); *MultilayerPerceptron* (an algorithm that uses back-propagation to learn a multi-layer perceptron to classify instances. The network can be built by hand or set up using a simple heuristic. The network parameters can also be monitored and modified during training time. The nodes in this network are all sigmoid (except for when the class is numeric, in which case the output nodes become unthresholded linear units). Each represents a different approach to learning. These algorithms are well known in the machine learning community and have proved popular in practice (Holmes et al.,1994).

The following section thoroughly details the outcomes of the study and discusses the significance of the results.

3. RESULTS AND DISCUSSION

Twenty-seven ground motion time histories were applied to six models of regular and irregular reinforced concrete frames having different number of stories. In total, 702 runs of time history analyses were undertaken with the top displacement of each model recorded.

Machine learning applied to the obtained data using WEKA workbench. A forward best first search is used with all variations of wrapper subset evaluation; the forward best first search evaluated fewer subsets than backward elimination. Wrappers evaluate feature subsets by statistical estimation of their accuracy with respect to a learning algorithm. The measure used to evaluate the performance of attribute combinations was root mean square error (RMSE). A RMSE of 0.01 thresholds (default value given by WEKA) has been applied.

In a typical supervised machine learning task, data is represented as a table of examples or instances. Each instance is described by a fixed number of measurements, or features, along with a label that denotes its class. Features (sometimes called attributes) are typically one of two types: nominal (values are members of an unordered set), or numeric (values are real numbers). Each instance is a ground motion time history described in terms of the (numeric) attributes PGA, PGJ, and etc, along with the class label which indicates the response of the buildings in terms of top displacement in X direction. Tables A1 to A5 present the results of time history analyses of models along with showing all 33 ground-motion IMs that are defined and calculated for the different ground motion time histories used in this study. Because of a large amount of data it's not possible to present all of the results graphically, so only the top displacement time history for the earthquake NGA record number 126 (Gazli,USSR earthquake in 1976, Turkey) applied to five story regular RC frame is shown in Figure 5 in addition to its acceleration and jerk time histories.

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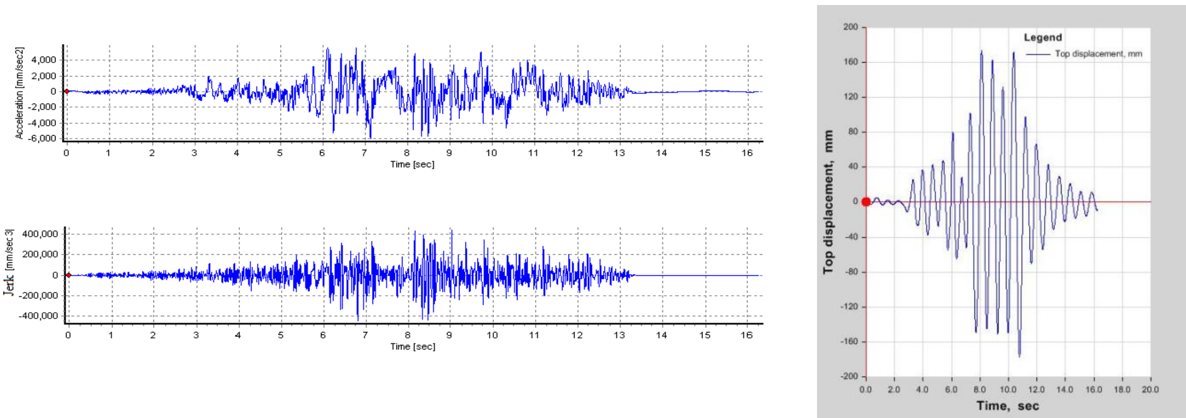

Fig.(5): Acceleration and jerk time histories (left) and top displacement time history for 5 story regular RC frame (right) of earthquake NGA record number 126 (Gazli,USSR earthquake in 1976, Turkey)

Different subsets of features have been selected by using different learning schemes available in Wrappersubseteval within WEKA. Subsets with the higher merit of the accuracy are shown in the Tables 6 and A6. In many cases the number of features is reduced by more than 90%. It's clearly shown in Tables 6 and A6 that thirty-three features (IMs) have been reduced to subsets contain different numbers of features varying from 1 to 6 features according to the learning scheme that gave the higher merit. It's of great importance to mention that different types of machine learning algorithms mentioned in Section 2.4 were examined and the one which give the highest merit was selected in order to choose the best subset of features. Hence it's not study's aim to undertake a comparison among different available learning algorithms and investigate their performance.

Table (6): Subsets of ground-motion IMs obtained from the first stage of feature selection process for the seven earthquake record dataset

Buildings	Three Story Regular	Five Story Regular	Ten Story Regular	Fifteen Story Regular
Subset of ground motion IMs	Sj,avg (cm/s³)	Tb(2000) (s)	JE (cm/s³)²	PGV (cm/s)
	PGV (cm/s)		ASI (m/s)	
	SED (cm²/s)		IH (cm)	
			Sa,ave. (cm/s²)	
Merit	31.05	68	41.37	214.76
Learning algorithm	LinearRegression	M5P	LinearRegression	M5P

Buildings	**Three Story Irregular SetBack¹**	**Five Story Irregular SetBack¹**	**Ten Story Irregular SetBack¹**	**Fifteen Story Irregular SetBack¹**
Subset of ground motion IMs	EDA (m/s²)	Tb(2000) (s)	SMV (cm/s)	PGV (cm/s)
			Damage index	
Merit	34	36	66.86	219.23
Learning algorithm	M5P	LinearRegression	MultilayerPerceptron	M5P

Buildings	**Three Story Irregular SetBack²**	**Five Story Irregular SetBack²**	**Ten Story Irregular SetBack²**	**Fifteen Story Irregular SetBack²**
Subset of ground motion IMs	VSI (cm)	Time of Max. Jerk (s)	IH (cm)	CAV (cm/s)
		JRMS (cm/s³)		IH (cm)
		Tm (s)		SMV (cm/s)
		IP Index		Damage index
Merit	35.8	40	74.5	114.37

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Learning algorithm	M5P	LinearRegression	Multilayer Perceptron	Random Tree

Buildings	Three Story Irregular I shape	Five Story Irregular I shape	Ten Story Irregular I shape	Fifteen Story Irregular I shape
Subset of ground motion IMs	Time of Max. Jerk (s)	Sj,avg (cm/s³)	JSI (cm/s²)	ARMS (m/s²)
		IH (cm)	VRMS (cm/s)	SED (cm²/s)
		SMV (cm/s)	SED (cm²/s)	SMA (m/s²)
		A95 (m/s²)	VSI (cm)	Damage index
		TP (s)		
		Sa,ave. (cm/s²)		
Merit	27	39.54	63.72	136
Learning algorithm	M5P	LinearRegression	Random Tree	Random Tree

Buildings	Three Story Irregular L shape	Five Story Irregular L shape	Ten Story Irregular L shape	Fifteen Story Irregular L shape
Subset of ground motion IMs	VSI (cm)	Tb(2000) (s)	PGV (cm/s)	IH (cm)
				TP (s)
Merit	31.2	74	100.86	146
Learning algorithm	M5P	M5P	M5P	Random Tree

Buildings	Three Story Irregular Plus shape	Five Story Irregular Plus shape	Ten Story Irregular Plus shape	Fifteen Story Irregular Plus shape
Subset of ground motion IMs	VSI (cm)	Tb(2000) (s)	PGV (cm/s)	JRMS (cm/s³)
				PGV (cm/s)
Merit	31.1	68.85	87.76	219.27
Learning algorithm	M5P	M5P	M5P	M5P

Buildings	One story URM	Two story URM
Subset of ground motion IMs	SMJ (cm/s³)	JSI (cm/s²)
	PGD (cm)	J95 parameter (cm/s³)
	SED (cm²/s)	DRMS (cm)
	EDA (m/s²)	ASI (m/s)
	Tm (s)	Tm (s)
		IP Index
Merit	2.39	8.56
Learning algorithm	GaussianProcesses	Random Tree

From the results shown in Tables 6 and A6, it is obvious that jerk based parameters contribute greatly the accuracy for subsets that have been selected within each sets of data. Furthermore, it's clear that the selection of jerk based parameters influenced by the number of the number of storeys. For buildings having less than 10 storeys, it seems that the jerk-based parameters can play a positive role in relating the seismic demand (ground motion time history) to the building capacity (structural response to the seismic action). However, for a specific number of storeys, there are several subsets that contain a different number of parameters depending on the learning schemes used. To minimize that variance and in the second stage of the machine learning process the best subsets corresponding to the number of storeys of different tested buildings are merged together and the merit of this new composite subset is recalculated. If the merit is within 10% of the minimum merit of the subsets obtained in the first stage, the composite is accepted. The results of this stage of analysis are shown in Tables 7, 8, A7 and A8.

Merging feature subsets has made the result

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for the two sets of ground motion records (7 and 27 records) better. It is clear that there are many subsets that contain less numbers of features with a merit equal or close to the highest merit of those subsets obtained in the first stage. Considering the number of features (IMs) selected, improvements in performance can clearly be seen on the 3, 5, 10, and 15 story RC frame datasets for both of 7 and 27 records between Wrappersubseteval with merged subsets and Wrappersubseteval without merged subsets.

For almost all of the determined subsets of significant IMs for the three and five storey RC frame buildings, jerk based parameters are included. Hence, their contribution in gaining higher predictive accuracy of the results (top displacement response of buildings) can't be ignored; especially for those buildings having less than 10 storeys. This becomes much clearer when the results of a seven and thirteen story regular RC frame under application of the 27 records was also added to the other results as shown in Table A6.

To investigate the importance of jerk-based parameters as IM for different type of structures, the results of time history analysis for two URM buildings of Yaseen (2015) thesis were also used here. Top displacements in x direction under the application of the same earthquake records which used here in this study were selected and machine learning applied to data. As shown in Table 6, it can be concluded that with respect to the URM buildings, jerk based parameters lost their importance with comparison to the other considered seismic ground motion parameters since the lower merit was recorded for subsets selected in both sets of 7 and 27 records compared to the RC frame buildings. Thus, it can be concluded that jerk based parameters have less correlation to buildings having a more non-linear high response. On other hand, jerk based- parameters correlate better with short period structures as found for the less than 10 storeys RC frame buildings. This can be discussed as following: if structures have large deformation capability, earthquake energy is absorbed by nonlinear and inelastic behavior; however, for structures with small deformation capability, structural failure may be triggered due to strong ground motion. Hence, for tall and long-period structures that have higher vibration modes, the jerk-based parameter may not be a good choice as an IM to correlate with structural response under earthquakes. The finding of this study agrees well with findings of HE et al. (2011) and He et al. (2015) studies as mentioned in section 1. Furthermore, similarly to other studied mentioned in section 2.4 (e.gLangley and Simon,1995) and as can be seen from Tables 6-8 and A6-A8, no single learning algorithm has been found to be superior to all of the others for the problem discussed in this study.

To this end it should be mentioned that it was out of scope of this study to consider the influence of factors such as ductility, soil-structure interaction, infill walls, distribution of the masses in the building, distance of the buildings from faults with focal depths and etc. Authors tried to perform a typical study in order to find the possibility of using jerk- based parameters as ground –motion IM considering the most important factors affecting such studies and they are the method of structural analysis, type of ground motion and their selection in addition to the number of ground motions and statistical method of data postprocess. Future studies always required to enhance and improve the findings of such type of studies considering all of the aforementioned factors.

Table (7): Subsets of ground-motion IMs obtained for three and five story RC frame buildings from the second stage of feature selection process (sub-merging scheme) (Seven earthquake record dataset)

Three story RC frame	Subset of ground motion IMs	Merit	Learning algorithm	Five story RC frame	Subset of ground motion IMs	Merit	Learning algorithm
Regular	Sj,avg (cm/s^3)	31	M5P	**Regular**	Tb(2000) (s)	68.32	M5P
Irregular SetBack[1]	EDA (m/s^2)	34.6	M5P	**Irregular SetBack[1]**	Tb(2000) (s)	46	Random Tree
Irregular SetBack[2]	VSI (cm)	35.8	M5P		IH (cm)		
Irregular I shape	Time of Max. Jerk (s)	27	M5P		Tm (s)		
Irregular L shape	Sj,avg (cm/s^3)	31.45	linear		Damage		
IrregularPlusshape	VSI (cm)	31	M5P	**Irregular SetBack[2]**	Time of Max.	40	linear

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	Jerk (s)		Regression
	JRMS (cm/s^3)		
	Tm (s)		
	IP Index		
Irregular I shape	Time of Max. Jerk (s)	39.6	Random Tree
Irregular L shape	Tb(2000) (s)	74.8	M5P
IrregularPlusshape	Tb(2000) (s)	68	Multilayer Perceptron

Table (8): Subsets of ground motion IMs obtained for ten and fifteen story RC frame buildings from the second stage of feature selection process (sub-merging scheme) (Seven earthquake record dataset)

Ten story RC frame	Subset of ground motion IMs	Merit	Learning algorithm	Fifteen story RC frame	Subset of ground motion IMs	Merit	Learning algorithm
Regular	SED (cm^2/s)	66	GaussianProcesses	**Regular**	PGV (cm/s)	214	M5P
Irregular SetBack[1]	SED (cm^2/s)	75	GaussianProcesses	**Irregular SetBack[1]**	PGV (cm/s)	219	M5P
Irregular SetBack[2]	JE $(cm/s^3)^2$ SED (cm^2/s)	95	GaussianProcesses	**Irregular SetBack[2]**	PGV (cm/s) IH (cm)	170.18	GaussianProcesses
Irregular I shape	JE $(cm/s^3)^2$ SED (cm^2/s) Damage index	73.5	GaussianProcesses	**Irregular I shape**	ARMS (m/s^2) SED (cm^2/s) SMA (m/s^2) Damage index	136.5	Random Tree
Irregular L shape	PGV (cm/s)	100.86	M5P	**Irregular L shape**	JRMS (cm/sec^3) PGV (cm/s) IH (cm) SMV (cm/s)	209	GaussianProcesses
Irregular plus shape	PGV (cm/s)	87.7	M5P	**Irregular plus shape**	JRMS (cm/sec^3) PGV (cm/s)	219	M5P

4. CONCLUSIONS

Six models of R.C frame buildings dynamically analyzed under application of several ground motion time histories. Machine learning method used to correlate between various types of ground motion IMs and the structural response of buildings in terms of top displacement. With regard to possibility of using jerk and its based paramaters as IM, it has been shown that the jerk-based parameters are only effective when they are used to predict the seismic response of structures with low nonlinearity. Furthermore, it was shown that no single learning algorithm used by machine learning process has been found to be superior to all of the others for the problem discussed in this study. Hence, the bias produced by using different learning algorithms and classifiers should not be ignored.

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Appendix

Table (A1): Jerk-based IMs defined for all the ground motion records considered in this study

NGA Record Number	PGJ (cm/s^3)	Time of Max. Jerk (s)	JRMS (cm/s^3)	IAJ (m/s^2)	ICJ	JSI (cm/s^2)	SMJ (cm/s^3)	J95 parameter (cm/s^3)	Sj,avg (cm/s^3)	Tb(2000) (s)	JE $(cm/s^3)^2$
126	44593.7	6.8	7953.7	16470.6	2860318.8	11820.5	43631.3	44258.0	4060.2	12.7	11.3
143	22223.9	10.0	3831.2	7713.7	1358548.7	18827.5	20383.6	21718.1	5357.1	25.1	10.4
568	15690.9	1.7	2737.2	1082.1	430100.5	12129.4	10985.7	15651.6	3889.2	4.7	10.1
825	47527.1	2.9	3081.0	4556.9	936390.4	21924.2	14124.3	47408.1	4738.8	19.3	10.2
828	13564.0	4.0	1628.2	1527.2	394069.1	7086.3	10447.6	13461.9	2974.1	24.8	9.7
963	15215.0	8.2	1228.9	966.9	272408.4	9967.5	8300.8	15100.4	3350.8	19.4	9.5
983	14689.5	6.8	1806.4	1494.9	410667.0	9891.2	11009.8	14504.8	3737.5	10.7	10.3
1004	26586.9	7.7	1900.4	2762.0	572541.7	10280.3	16224.5	26386.7	4999.2	15.0	10.5
1085	21351.0	3.5	1735.4	1928.7	457203.8	12074.2	12632.3	21190.2	4834.1	19.9	10.4
1086	10960.7	3.9	1020.7	666.9	206183.6	7661.9	5993.4	10878.2	3721.6	10.0	9.3
1197	38478.9	37.9	1675.5	4045.4	650623.9	12027.0	23654.2	38382.6	5033.5	39.2	10.7
1507	21486.4	35.3	2194.1	6937.4	974998.6	13648.8	18934.3	21216.1	3981.9	58.9	10.9
1508	15966.4	35.8	1503.7	3258.5	553185.6	8453.4	14612.7	15684.5	3711.3	44.0	10.6
169	8378.0	8.8	1023.2	1674.7	327129.3	5386.0	7842.5	8101.1	1845.5	28.6	10.0
179	10422.0	5.2	970.5	588.0	188784.2	4127.1	9150.0	10343.5	2136.5	10.1	9.9
182	8333.0	4.8	748.8	330.6	124335.7	4135.1	5295.0	8270.3	3295.2	8.3	9.6
184	15128.0	5.6	1668.6	1736.7	425422.8	9632.9	11379.0	14937.7	2465.6	11.2	10.3
802	13902.7	7.4	1440.0	1326.4	345375.8	7714.3	12564.5	13727.8	3023.6	10.8	10.2
821	15865.0	3.5	1394.9	647.2	237447.7	7927.3	8438.0	15825.3	3455.2	11.3	9.9
953	12534.1	7.4	1324.8	842.5	264018.7	7347.5	10342.3	12439.7	3866.8	9.9	9.7
959	18253.5	6.5	1758.9	1237.5	368697.8	7662.9	10343.0	18116.1	2447.2	12.9	9.9
1013	17719.0	4.7	1584.3	1067.9	325050.6	6817.9	12103.0	17585.6	3668.2	9.7	10.1
1044	17816.5	5.4	1567.2	1572.3	392280.0	12613.4	10713.3	17682.4	3825.1	8.3	9.7

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1063	19332.7	2.4	2985.9	2840.9	727848.0	11591.5	15808.1	19089.5	7251.0	16.9	10.2
1119	10882.5	6.0	1133.0	841.7	244049.9	10363.5	10545.0	10800.6	4675.7	4.9	9.7
1602	21590.0	10.7	1284.3	1476.1	344089.8	12348.8	10829.0	21536.0	3850.3	12.2	10.0
1605	9406.0	3.6	1320.1	722.1	243989.9	7645.6	8986.0	9287.7	2659.8	10.3	10.0

Table (A2): Commonly used ground-motion IMs defined for all the ground motion records considered in this study

NGA Record Number	PGA (m/s^2)	PGV (cm/s)	PGD (cm)	ARMS (m/s^2)	VRMS (cm/s)	DRMS (cm)	IA (m/s)	Ic	SED (cm^2/s)	CAV (cm/s)	ASI (m/s)	VSI (cm)	IH (cm)	SMA (m/s^2)	SMV (cm/s)	EDA (m/s^2)	A95 (m/s^2)	TP (s)	Tm (s)	Sa,ave. (cm/s^2)	IP Index	Damage index
126	6.0	65.4	25.4	1.3	17.8	9.8	4.7	6.2	5172.6	1360.6	4.7	230.2	213.5	5.6	47.1	5.3	5.9	0.1	0.4	5.2	20.5	1581.4
143	8.2	97.8	38.7	1.5	20.8	13.5	11.5	10.3	14190.0	3052.9	8.0	339.3	324.3	6.7	62.3	8.5	8.0	0.2	0.5	7.9	30.0	2034.4
568	8.6	59.3	12.4	1.3	15.8	3.9	2.5	4.5	2248.3	719.8	6.0	240.8	227.6	4.4	48.7	8.2	8.6	0.2	0.6	5.7	12.1	301.3
825	1.47	125.1	39.7	1.1	13.2	10.6	6.0	6.4	5188.0	1416.3	9.3	275.6	231.6	4.1	21.2	16.2	14.7	0.3	0.4	6.1	10.7	1011.9
828	5.8	48.1	21.9	0.8	8.3	4.5	3.4	4.1	2500.9	1518.7	3.6	197.9	161.1	4.2	28.1	5.4	5.7	0.7	0.5	3.7	30.3	479.8
963	5.6	51.8	9.0	0.7	7.3	2.4	2.8	3.4	2110.5	1305.3	5.1	212.4	183.9	4.0	32.5	5.9	5.5	0.3	0.5	4.6	24.8	357.7
983	5.6	76.0	42.4	0.8	16.3	8.7	3.2	4.1	7625.1	1283.9	4.9	244.0	244.4	4.1	64.8	5.5	5.6	0.4	0.8	5.7	16.9	399.9
1004	7.3	78.1	13.4	0.8	9.3	2.9	4.7	4.8	4162.2	1686.2	5.1	318.1	262.5	5.0	43.0	7.3	7.3	0.7	0.6	6.0	21.6	585.3
1085	8.1	117.5	34.5	0.8	14.4	6.9	4.5	4.9	8250.4	1465.5	5.7	306.8	301.4	4.0	52.2	8.4	8.1	0.4	0.7	7.2	12.5	463.9
1086	5.9	78.1	16.8	0.6	10.6	4.0	2.6	3.2	4496.2	1164.9	4.1	259.4	261.2	3.4	49.2	5.6	5.9	0.5	0.8	6.0	14.7	220.4
1197	6.4	72.8	14.7	0.6	7.8	2.9	5.3	4.5	5455.4	2070.0	6.1	312.5	289.6	5.6	56.9	5.8	6.3	0.3	0.6	6.9	28.8	618.0
1507	5.6	44.4	13.8	0.8	8.3	2.9	9.3	6.8	6133.2	3556.9	5.7	238.3	213.2	5.1	38.7	5.6	5.3	0.3	0.4	5.3	80.4	1574.0
1508	4.8	71.7	38.7	0.6	8.8	10.2	5.8	4.8	7047.0	2618.5	4.3	246.1	225.0	3.8	46.0	4.7	4.7	0.7	0.6	5.1	36.8	607.1
169	2.3	26.0	11.9	0.4	6.6	4.4	2.4	2.4	4298.2	2524.7	2.4	115.6	109.3	2.1	20.7	2.2	2.2	0.5	0.6	2.6	96.5	333.5
179	3.5	76.6	59.1	0.4	15.7	12.5	0.9	1.5	9570.9	758.3	2.4	148.6	179.9	2.4	43.4	3.3	3.5	0.2	1.3	4.0	9.9	86.5
182	4.5	109.3	44.8	0.5	16.7	10.7	1.7	2.4	10219.8	795.6	3.1	242.7	265.0	2.2	57.4	4.4	4.5	0.7	1.3	5.8	7.3	79.0
184	3.5	71.3	45.9	0.5	11.5	9.8	1.7	2.4	5147.1	986.9	3.4	151.9	146.6	3.2	44.7	3.4	3.4	0.2	0.5	3.5	13.9	353.7
802	5.0	41.2	16.2	0.5	7.2	3.2	1.5	2.1	2044.6	911.2	3.0	191.3	175.7	3.0	28.5	4.7	5.0	0.2	0.6	4.2	22.2	239.9
821	4.9	64.3	21.9	0.7	14.5	7.3	1.8	2.9	4394.8	868.0	3.9	224.7	217.1	3.2	46.1	4.8	4.8	0.3	0.8	5.1	13.5	145.8
953	4.1	59.0	13.2	0.8	10.9	2.6	3.1	3.9	3572.4	1428.3	3.5	266.3	237.6	3.5	38.7	3.9	4.0	0.5	0.7	5.2	24.2	254.9
959	3.5	32.1	9.1	0.7	8.1	2.8	2.0	2.9	1625.5	1150.0	3.4	149.6	140.1	3.0	28.3	3.6	3.4	0.3	0.5	3.4	35.6	288.7

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1013	5.0	63.7	21.3	0.6	12.0	5.3	1.8	2.7	3795.3	858.6	3.2	245.2	246.0	3.0	42.2	4.8	5.0	0.3	0.9	5.6	13.4	151.0
1044	5.7	75.0	17.8	0.8	9.5	3.5	4.4	4.7	3589.4	1456.8	6.3	240.7	236.6	5.1	42.2	6.3	5.6	0.3	0.5	5.7	19.1	526.3
1063	6.3	160.2	29.6	1.5	23.2	7.7	7.5	8.5	10713.2	1800.4	6.4	505.9	453.8	5.2	50.2	8.0	8.0	0.7	0.8	10.1	11.1	711.6
1119	6.8	68.4	26.7	0.7	11.1	4.1	3.1	3.6	5028.0	1092.0	5.0	317.6	315.5	4.4	51.9	6.5	6.8	0.5	0.8	7.3	16.0	315.8
1602	7.1	56.5	23.1	0.6	8.4	5.6	3.7	3.9	3901.3	1479.6	6.3	235.0	211.4	4.3	40.6	6.0	7.1	0.3	0.5	5.3	26.3	446.3
1605	3.4	60.0	42.1	0.8	19.6	16.2	2.7	3.7	9945.3	1361.2	4.3	173.5	179.2	3.0	55.5	3.3	3.4	0.4	0.7	4.1	22.7	255.0

Table (A3): Top displacement response (in x direction) of regular and irregular set back [1] shape RC frame buildings

NGA Record Number	Top Displacement Three story (mm) Regular	Top Displacement Five story (mm) Regular	Top Displacement Seven story (mm) Regular	Top Displacement Ten story (mm) Regular	Top Displacement Thirteen story (mm) Regular	Top Displacement Fifteen story (mm) Regular	Top Displacement Three story (mm) Set Back [1] shape	Top Displacement Five story (mm) Set Back [1] shape	Top Displacement Ten story (mm) Set Back [1] shape	Top Displacement Fifteen story (mm) Set Back [1] shape
126	69.5	172.4	237.2	334.4	351.4	274.7	65.4	203.8	348.1	268.7
143	94.8	275.7	259.9	391.1	526.9	761.9	129.4	245.9	428.2	756.8
568	106.8	206.7	246.4	292.2	333.7	392.0	92.6	219.4	302.2	381.3
825	128.5	197.7	226.8	311.5	325.3	349.3	128.5	217.6	320.2	366.7
828	84.2	239.8	205.8	169.1	216.7	211.0	66.9	261.0	173.2	219.0
963	80.2	161.6	164.4	260.9	335.6	318.3	86.1	140.3	281.5	307.3
983	55.7	178.0	187.6	261.9	459.8	639.5	62.6	149.8	272.2	661.3
1004	119.4	284.9	359.1	360.8	405.1	397.4	109.4	317.1	370.2	383.4
1085	99.5	213.3	237.7	353.0	459.2	661.4	106.6	228.5	364.2	703.3
1086	110.4	124.5	216.9	321.5	474.5	676.7	102.0	147.4	340.8	698.9
1197	143.3	192.9	340.4	250.1	541.3	634.8	103.3	256.1	257.3	637.9
1507	96.8	153.0	214.6	314.6	278.6	348.4	71.3	158.4	337.0	400.0
1508	84.6	252.0	326.1	276.5	361.4	282.0	104.3	268.3	299.8	285.7
169	50.8	93.9	102.5	119.7	197.2	238.0	57.5	95.7	128.5	240.0
179	47.5	70.8	141.8	217.6	363.4	483.9	48.9	67.4	222.6	504.5
182	66.7	232.4	216.8	323.6	510.8	691.6	78.8	234.7	345.2	691.3

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184	49.0	123.6	76.5	137.6	279.9	445.4	50.5	126.0	146.7	460.2
802	48.9	99.5	136.2	287.6	381.7	395.4	46.0	116.7	297.3	396.4
821	70.4	158.7	179.1	261.0	386.3	484.1	63.5	189.5	264.8	507.2
953	115.6	129.5	323.0	345.0	355.2	314.7	80.8	151.2	357.0	335.8
959	66.3	100.0	114.7	184.1	303.3	327.1	82.6	122.4	190.5	307.4
1013	58.8	146.7	221.6	339.4	452.8	624.5	57.1	148.4	350.2	609.7
1044	109.5	123.7	219.2	396.0	303.1	387.7	75.8	162.1	430.5	390.8
1063	142.2	352.5	559.1	728.4	785.0	775.0	140.3	368.6	742.7	745.4
1119	108.0	234.1	285.2	464.8	647.8	603.2	141.3	262.9	493.1	578.6
1602	130.0	155.4	215.5	218.8	322.8	369.3	125.7	148.3	223.4	384.3
1605	86.2	178.3	172.4	179.6	260.9	306.6	107.3	175.2	194.6	334.4

Table A4 Top displacement response (in x direction) of irregular set back 2 and I shape RC frame buildings

NGA Record Number	Top Displacement Three story (mm) Set Back 2 shape	Top Displacement Five story (mm) Set Back 2 shape	Top Displacement Ten story (mm) Set Back 2 shape	Top Displacement Fifteen story (mm) Set Back 2 shape	Top Displacement Three story (mm) I shape	Top Displacement Five story (mm) I shape	Top Displacement Ten story (mm) I shape	Top Displacement Fifteen story (mm) I shape
126	67.0	195.3	260.3	386.2	61.6	132.7	324.5	490.6
143	102.0	183.1	490.4	776.6	93.4	159.8	488.4	693.5
568	77.9	218.1	311.4	482.3	64.6	184.3	328.5	390.4
825	106.2	208.2	309.6	367.6	92.8	195.0	346.8	372.8
828	59.8	236.6	196.9	233.6	52.0	187.6	254.9	230.4
963	83.5	116.1	215.1	371.5	86.0	130.0	195.0	478.8
983	77.1	132.7	249.2	631.8	64.3	102.9	248.0	522.6
1004	90.5	282.4	414.9	495.4	77.4	236.8	499.8	531.3
1085	84.5	196.7	330.1	606.7	84.7	157.8	451.3	605.2
1086	90.6	164.4	312.4	686.8	71.1	176.4	300.5	560.9
1197	95.0	285.2	359.4	664.0	93.0	252.0	430.9	664.2
1507	76.1	171.0	326.6	347.3	68.8	178.2	331.8	337.9

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1508	88.9	225.4	283.0	367.2	77.2	137.2	349.5	394.9
169	49.3	88.9	110.7	241.1	38.0	66.9	101.6	242.9
179	41.9	55.3	272.2	452.4	31.8	54.2	284.9	454.8
182	77.8	177.7	309.7	723.5	57.8	116.3	336.2	724.9
184	39.0	100.1	154.7	406.2	33.7	63.4	161.9	358.1
802	34.5	112.9	287.6	433.6	33.5	87.3	271.8	480.0
821	54.4	173.6	275.3	550.8	47.1	129.7	301.0	547.3
953	70.0	137.6	438.8	298.1	54.7	137.7	466.0	441.9
959	61.8	135.7	138.4	419.6	43.9	130.2	113.3	355.8
1013	47.8	133.9	477.1	651.9	45.2	111.8	383.4	567.7
1044	74.5	165.2	458.3	405.3	77.4	184.0	420.9	403.1
1063	131.7	333.2	851.9	933.1	117.2	260.1	823.9	1111.8
1119	122.8	255.8	461.7	820.0	85.0	203.7	422.5	795.0
1602	128.7	160.5	213.7	380.8	104.4	206.9	272.7	405.1
1605	109.9	127.1	189.9	301.3	112.1	116.6	192.8	319.6

Table (A5): Top displacement response (in x direction) of URM and irregular L and Plus shape RC frame buildings

NGA Record Number	Top Displacement Three story (mm) L shape	Top Displacement Five story (mm) L shape	Top Displacement Ten story (mm) L shape	Top Displacement Fifteen story (mm) L shape	Top Displacement Three story (mm) Plus shape	Top Displacement Five story (mm) Plus shape	Top Displacement Ten story (mm) Plus shape	Top Displacement Fifteen story (mm) Plus shape	Top Displacement One story (mm) URM Yaseen (2015)	Top Displacement Two story (mm) URM Yaseen (2015)
126	68.3	197.2	438.3	278.4	69.0	177.5	402.1	270.9	9.4	19.8
143	101.0	309.0	428.5	842.7	98.2	288.4	395.6	754.0	18.1	45.6
568	103.7	222.0	309.6	444.3	105.1	217.5	298.6	391.6	15.0	45.6
825	130.1	204.4	322.7	414.5	129.3	202.2	315.6	375.4	23.4	42.6
828	80.0	267.5	179.2	256.9	82.2	252.8	174.2	236.0	7.2	24.1
963	79.7	201.6	314.3	318.4	80.7	189.6	288.0	304.7	8.5	21.5
983	55.1	212.1	317.0	788.0	54.8	198.9	292.5	696.8	9.8	25.6
1004	116.1	314.5	353.1	378.5	117.6	304.2	351.7	355.3	11.7	48.6

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1085	101.9	289.8	467.4	806.9	101.3	269.1	425.8	731.3	13.9	32.4
1086	109.9	182.6	342.0	806.1	110.7	178.6	319.5	715.5	8.7	24.4
1197	139.3	204.0	259.2	667.9	141.8	186.1	233.0	618.8	12.2	32.2
1507	92.2	184.3	431.5	523.1	95.3	171.8	372.5	456.9	9.1	22.8
1508	86.2	278.5	357.6	288.9	86.7	263.4	321.9	263.9	10.7	24.8
169	53.7	104.8	182.3	265.0	52.7	100.5	156.2	232.5	1.2	5.2
179	48.3	82.1	252.6	569.8	48.0	79.5	241.7	530.9	1.1	6.4
182	66.1	268.2	354.8	762.7	66.6	254.5	324.0	712.9	5.9	31.3
184	49.9	139.2	163.6	535.0	49.4	130.3	152.6	486.8	3.5	9.0
802	50.5	94.5	323.3	387.4	49.9	91.5	307.7	377.5	4.2	13.6
821	70.2	168.6	264.2	594.6	70.8	159.2	259.9	516.0	6.4	27.0
953	108.9	172.1	421.1	368.5	113.2	165.2	406.5	348.2	7.6	25.7
959	71.9	106.7	185.8	391.9	69.8	101.9	168.6	309.6	3.2	7.9
1013	59.0	164.4	353.2	689.6	59.6	160.1	333.1	590.9	6.8	26.0
1044	103.2	133.7	406.8	431.3	107.0	131.1	362.7	388.3	11.8	27.8
1063	141.1	400.9	751.1	721.1	141.6	387.5	733.8	717.5	14.4	70.2
1119	118.1	249.5	555.7	572.7	114.1	241.3	497.3	557.0	11.7	27.5
1602	130.6	180.5	241.9	421.7	130.0	173.0	234.0	387.5	11.7	27.4
1605	88.5	202.3	252.2	396.1	88.0	191.6	222.5	357.2	5.0	16.4

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Table (A6): Subsets of ground-motion IMs obtained from the first stage of feature selection process for the twenty seven earthquake record dataset (M5P learning algorithm was the algorithm with higher merit)

Buildings	Three Story Regular	Five Story Regular	Seven Story Regular	Ten Story Regular	Thirteen Story Regular	Fifteen Story Regular
Subset of ground motion IMs	IAJ (m/s^2)	Sj,avg (cm/s^3)	JRMS (cm/s^3)	IH (cm)	PGJ (cm/s^3)	CAV (cm/s)
	JSI (cm/s^2)	PGA (m/s^2)	JSI (cm/s^2)	Tm (s)	IH (cm)	ASI (m/s)
	PGD (cm)	EDA (m/s^2)	Sj,avg (cm/s^3)		Damage index	IH (cm)
	EDA (m/s^2)		PGA (m/s^2)			
			TP (s)			
Merit	24.23	63.46	94.5	115.18	107.98	129.36

Buildings	**Three Story Irregular Set Back ^{1} shape**	**Five Story Irregular Set Back ^{1} shape**		**Ten Story Irregular Set Back ^{1} shape**		**Fifteen Story Irregular Set Back ^{1}**
Subset of ground motion IMs	PGA (m/s^2)	Sj,avg (cm/s^3)		IH (cm)		CAV (cm/s)
	VRMS (cm/s)	IH (cm)				IH (cm)
		Sa,ave. (cm/s^2)				
Merit	24.25	65.59		118.556		131.52

Buildings	**Three Story Irregular Set Back ^{2} shape**	**Five Story Irregular Set Back ^{2} shape**		**Ten Story Irregular Set Back ^{2} shape**		**Fifteen Story Irregular Set Back ^{2} shape**
Subset of ground motion IMs	JE $(cm/s^3)^2$	JSI (cm/s^2)		PGD (cm)		JSI (cm/s^2)
	IA (m/s)	Tb(2000) (s)		VRMS (cm/s)		CAV (cm/s)
	ASI (m/s)	A95 (m/s^2)		IH (cm)		IH (cm)
Merit	22.88	57.84		140.09		144.92

Buildings	**Three Story Irregular I shape**	**Five Story Irregular I shape**		**Ten Story Irregular I shape**		**Fifteen Story Irregular I shape**
Subset of ground motion IMs	JRMS (cm/s^3)	Time of Max. Jerk (s)		VSI (cm)		VSI (cm)
	ASI (m/s)	PGA (m/s^2)				IH (cm)
	IH (cm)	ARMS (m/s^2)				

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		CAV (cm/s)		
Merit	20	45.6	137	161.28

Buildings	**Three Story Ir. L shape**	**Five Story Ir. L shape**	**Ten Story Ir. L shape**	**Fifteen Story Ir. L shape**
Subset of ground motion IMs	EDA (m/s2)	VSI (cm)	IH (cm)	CAV (cm/s)
				IH (cm)
				IP Index
Merit	23.67	71.08	123.15	152.75

Buildings	**Three Story Irregular Plus shape**	**Five Story Irregular Plus shape**	**Ten Story Irregular Plus shape**	**Fifteen Story Irregular Plus shape**
Subset of ground motion IMs	EDA (m/s^2)	PGD (cm)	VSI (cm)	JSI (cm/s^2)
		VSI (cm)	EDA (m/s^2)	IA (m/s)
		TP (s)		IH (cm)
Merit	23.94	67.98	118.46	136.96

Buildings	**One story URM**	**Two story URM**
Subset of ground motion IMs	SMA (m/s^2)	VSI (cm)
	SMV (cm/s)	EDA (m/s^2)
	EDA (m/s2)	
	A95 (m/s^2)	
Merit	4.228	12.3

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Table A7 Subsets of ground-motion IMs obtained for three and five story RC frame buildings from the second stage of feature selection process (subset merging scheme) (Twenty-seven earthquake record dataset)

Three story RC frame	Subset of ground motion IMs	Merit	Learning algorithm
Regular	IAJ (m/s^2)	25.94	Multilayer Perceptron
	ASI (m/s)		
	IH (cm)		
Irregular Set Back 1 shape	JE ($(cm/s^3)^2$)	23.1	Random Tree
	PGA (m/s^2)		
	VRMS (cm/s)		
Irregular Set Back 2 shape	JSI (cm/s^2)	21.5	Multilayer Perceptron
	ASI (m/s)		
Irregular I shape	JSI (cm/s^2)	16.6	Multilayer Perceptron
	ASI (m/s)		
	EDA (m/s^2)		
Irregular L shape	JSI (cm/s^2)	24.5	Multilayer Perceptron
	VRMS (cm/s)		
	ASI (m/s)		
	IH (cm)		
Irregular Plus shape	JE ($(cm/s^3)^2$)	25.73	Multilayer Perceptron
	ASI (m/s)		

Five story RC frame	Subset of ground motion IMs	Merit	Learning algorithm
Regular	Sj,avg (cm/s^3)	46.98	Multilayer Perceptron
	ARMS (m/s^2)		
	TP (s)		
	Sa,ave. (cm/s^2)		
Irregular Set Back 1 shape	Sj,avg (cm/s^3)	52.76	Multilayer Perceptron
	ARMS (m/s^2)		
	VSI (cm)		
	IH (cm)		
	TP (s)		
	Sa,ave. (cm/s^2)		
Irregular Set Back 2 shape	JSI (cm/s^2)	54.98	Random Tree
	Sj,avg (cm/s^3)		
	PGA (m/s^2)		
	A95 (m/s^2)		
	TP (s)		
Irregular I shape	Sj,avg (cm/s^3)	41.97	Multilayer Perceptron
	PGA (m/s^2)		
	PGD (cm)		
	ARMS (m/s^2)		
Irregular L shape	Sj,avg (cm/s^3)	54.47	Random Tree
	TP (s)		
Irregular Plus shape	Sj,avg (cm/s^3)	50	Random Tree
	TP (s)		

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Table (A8): Subsets of ground motion IMs obtained for ten and fifteen story RC frame buildings from the second stage of feature selection process (sub-merging scheme) (Twenty-seven earthquake record dataset)

Ten story RC frame	Subset of ground motion IMs	Merit	Learning algorithm
Regular	PGD (cm)	85.03	Multilayer Perceptron
	IH (cm)		
	EDA (m/s^2)		
Irregular Set Back [1] shape	IH (cm)	91	Random Tree
Irregular Set Back [2] shape	IH (cm)	114.7	Random Tree
Irregular I shape	PGD (cm)	104.23	Random Tree
	VRMS (cm/s)		
	VSI (cm)		
	IH (cm)		
Irregular L shape	PGD (cm)	107.8	Multilayer Perceptron
	IH (cm)		
	EDA (m/s2)		
Irregular Plus shape	PGD (cm)	101.28	Multilayer Perceptron
	IH (cm)		
	EDA (m/s2)		

Fifteen story RC frame	Subset of ground motion IMs	Merit	Learning algorithm
Regular	JSI (cm/s^2)	101.65	Random Tree
	IA (m/s)		
	IH (cm)		
	IP Index		
Irregular Set Back [1] shape	IA (m/s)	106.8	Random Tree
	CAV (cm/s)		
	VSI (cm)		
	IH (cm)		
Irregular Set Back [2] shape	CAV (cm/s)	104.2	Random Tree
	IH (cm)		
Irregular I shape	IH (cm)	130	Random Tree
Irregular L shape	VSI (cm)	145.32	Multilayer Perceptron
	IH (cm)		
Irregular Plus shape	CAV (cm/s)	129.5	Random Tree
	ASI (m/s)		
	IH (cm)		
	IP Index		

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