ESTIMATION OF ECONOMIC LOSSES DUE TO EARTHQUAKE IN LIFELINE SYSTEMS

Morteza BASTAMI
Assistant Professor, International Institute of Earthquake Engineering and Seismology, Tehran, Iran
mbastami@iiees.ac.ir (Corresponding Author)

Ali JAFARIFARD
Student, University of Kurdistan, Sanandaj, Iran
Alijafarifard1381@yahoo.com

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ABSTRACT

In this research, we develop a linear relationship between seismic time-history parameters and earthquake losses to obtain a model that is able to estimate economic losses of lifeline systems including transportation, communication, potable water and waste water, natural gas systems and electric power networks.

We considered economic losses of lifeline systems as a dependent variable and seismic parameters as independent variables. Stepwise multiple linear regressions were used to create a linear equation between the monetary value of losses and the seismic parameters of Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV) and Peak Ground Displacement (PGD) at various earthquakes.

Usually earthquake losses are not limited to physical losses but possible contain very widespread dimensions, example loss of output because of generate abeyance, reduction of consumption because of diminish social activities, etc. Losses linked with effects would be very huge and vaster than those counted just through physical damages.

The method is used in current research is Input-Output (I-O) effect analysis. I-O table is a compendium accounting of all purchases and sales across components in a given zone. In this analysis, Iran is considered as a region. Thus, we use Iran’s input-output table, the indirect losses due to damage of lifeline systems in past earthquakes of Iran evaluated by the inter-industry relation.

INTRODUCTION

Losses from earthquakes are usually associated with building and other property damage. However, many businesses are forced to shut down, even if physically unscathed, when suppliers of lifeline services or other inputs are disrupted, or if their employees are unable to reach the workplace. Likewise, businesses may be forced to curtail operations if orders for their products are canceled by their customers, or if they are unable to deliver their products to market. Moreover, these impacts pertain not only to immediate suppliers and customers, but to successive rounds of upstream or downstream links (Okayama and Chang, 2004).

While significant progress has been made in recent years for the economic analysis of disasters, especially in the field of economic modeling for disaster impact the recent advancements have been more toward short-run impact analysis with the strategies for modeling extensions and modifications to fit them to disaster situations rather than toward evaluation of long-run effect of such events (Okayama, 2014).

Natural hazards, such as earthquakes, reason misadventure when they impacts huge residence example urban zones.

Direct losses including damages in buildings and lifelines can cause non-structural or indirect losses as interruption of business activities and services. Loss estimation methods have been developed to evaluate losses from earthquakes and other natural hazards. Economic losses by severe earthquakes can cause long-term reductions in the growth of a nation's economy and trigger inflation (Kundak, 2004).

To reach a compatible measure, the real failure must be connected to the economic losses, and then Interpretation into direct trade abeyance losses and chain reaction, or ripple effects, that happens all-over the economy. Some of methods have been used to calculation indirect effects. Econometric studies estimate the totality of effects on the economy and therefore conclude indirect effects.

Econometric models have only rarely been used in regional economic loss estimation because of their expense, huge data demands, and difficulty in distinguishing direct and higher-order effects. The statistical rigor of these models requires time series data with at least ten observations (typically years) and preferably many more. Data needed are not usually available at the regional level for this purpose, so various data reduction strategies have been developed, as in the case of Input-Output (I-O) and Computable General Equilibrium (CGE) models (Cummins and Mahul, 2009).

The current method is Input-Output (I-O) effect analysis. It can be transformed into a model capitalizing on the interactions inherent in an economy to show how a decline in economic activity in one sector results in ripple (or multiplier) effects through successive chains of producers and/or consumers. A Process to loss calculation used mathematical optimization methods, which is especially useful for policy-making due to it identifies the potential for loss reduction (Brookshire et al., 1997).

In lifeline systems study, a real time methodology is developed to estimate direct and indirect economic losses, which stems from damages to a power supply system in a probable future earthquake. The methodology integrates physical damage assessment, power flow connectivity, post-earthquake restoration, direct economic loss to system and business interruption for estimating the indirect economic losses. The methodology is new in that it considers all possible path flows that supply power flow to distribution substations, which supply power for customers, and further, the most reliable path flow to each distribution substation is found. This model simulates damage to components of lifeline system and how the situation improves as repairs are made. Indirect economic losses from business interruption are evaluated probabilistically consistent with engineering damage estimation (Bastami, 2007).

MULTIPLE LINEAR REGRESSION

A Multiple linear regression (MLR) model assumes that there is a linear relationship between a dependent variable and independent variables, y. An MLR model can be described using the following equation:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k + \varepsilon \qquad (1)$$

Where $\{X_1, \ldots, X_k\}$ independent variables, β_0 is the regression model constant, β_1 to β_k are the coefficients corresponding to the descriptors X_1 to X_k and *y* is dependent variable. The values for β_0 to β_k are chosen by minimizing the sum of squares of the vertical distances of the points from the hype plane so as to give the best prediction of *y* from *x* (Dumarey et al., 2008; Gavami and Sepehri, 2012).

ANOVA is a statistical method very commonly used in checking the significance and adequacy of the calculated linear regression model. To employ ANOVA in regression, three primary sum-of-squares values are needed: the total sum of squares, SS_T, the sum of squares explained by the regression SS_R, and the sum of squares due to the random error, SS_E. The total sum of squares is merely the sum of squares of the differences between actual y_i observations and the $\bar{y}$ mean:

$$SS_T = \Sigma(y_i - \bar{y})^2 \qquad (2)$$

The total sum of squares $(y_i - \bar{y})^2$ includes both the regression and error effects in that it does not distinguish between them. The sum of squares, due to regression (SS_R), is the sum-of-squares value of the predicted values ($\hat{y}_i$) minus the $\bar{y}$ mean value:

$$SS_R = \Sigma(\hat{y}_i - \bar{y})^2 \qquad (3)$$

Finally, the sum-of-squares error term (SS_E) is the sum of the squares of the actual $\hat{y}_i$ values minus the predicted $\hat{y}_i$ value:

$$SS_E = \Sigma(y_i - \hat{y}_i)^2 \quad (4)$$

As is obvious, the sums of $SS_E$and SS_R equal SS_T:

$$SS_T = SS_R + SS_E \quad (5)$$

R^2, the coefficient of determination, and SS_E, the sum of squares error term, can be used to help find the best subset (k) of x_i variables. R^2 and SS_E are denoted with a subscript k for the number of x_i variables in the model. When R^2 is large, SS_E tends to be small, because the regression variability is well explained by the regressors, so random error becomes smaller.

$$R^2 = 1 - SS_E/SS_T = SS_R/SS_T \quad (6)$$

Another way of determining the best k number of x_i variables is using Adjusted R-squared (Adj. R^2) and MS_E. The mean square error (MS_E) is used to predict the sample variance or $MS_E = S^2$. Where

$$MS_E = \frac{SS_E}{n-2} \quad (7)$$

The model with the highest Adj. R^2 also will be the model with the smallest MS_E. This method better takes into account the number of x_i variables in the model.

$$\text{Adj } R^2 = 1 - \frac{(n-1)SS_E}{(n-k)SS_T} \quad (8)$$

Where SS_E, is the full model error sum of squares; SS_T is the full model total sum of squares; n-1 is the sample size less 1; and n-k is the sample size minus the number of variables in the present model (Verma and Hansch, 2010; Paulson, 2007).

Backward elimination: This method begins with a full set of predictor variables in the model. Each x_i predictor variable in the model is then evaluated as if it were the last one added. Some strategies begin the process at x_k and then, x_{k-1} and so forth. Others begin with x_1 and work toward x_k.

Forward selection: In this procedure, x_i predictor variables are added into the model, one at a time. The predictor thought to be most important by the researcher generally is added first, followed by the second, the third, and so on. If the contribution of the predictor value is unknown, one easy way to find out is to run k simple linear regressions, selecting the largest R^2 of the k as x_1, the second largest R^2 as x_2, and so forth(Brown et al, 2009; Paulson, 2007).

Stepwise regression: It's a very popular regression procedure, because it evaluates both values going into and values removed from the regression model. In this method variables are selected by an elimination stepwise selection procedure, which combines the forward selection and backward elimination approaches. If the inclusion of this variable results in a significant improvement of the regression model, evaluated with an overall F-test, it is retained and the selection continues. In a next step the variable that gives the largest significant decrease of the regression sum of squares, evaluated with a partial F-test, is added. After each forward selection step a backward elimination step is performed. In this step a partial F-test for the variables, already in the equation, is carried out. The procedure stops at the moment that no variables fulfill the requirements anymore to be removed or entered. After this selection procedure classical MLR can be applied on the retained variables to build a predictive model (Gavami and Sepehri, 2012).

LOSS ESTIMATION MODEL

In this research, we create a linear relationship between seismic Time-history parameters and earthquake losses to obtain a model that is able to estimate economic losses of lifeline systems including transportation and communication systems, potable water and waste water systems, natural gas systems and electric power systems in earthquakes by using the seismic data and data lifeline systems economic losses of Rudbar and Manjil 1990, Ardabil 1996, Bam 2003, Silakhoor 2006, East Durood 2010, Varzaghan 2012, Borazjan 2013, Murmuri 2014 and Bastak 2014 earthquakes. They are economic losses Data to the following shown in tables:

Table 1. Economic losses natural gas systems

Earthquake	Date	Economic losses(Million Rials)
East Durood	6/11/2010	1500
Varzaghan	11/8/2012	127100

Table 2. Economic losses electric power systems

Earthquake	Date	Economic losses(Million Rials)
Rudbar and Manjil	20/6/1990	18000
Ardabil	30/12/1996	6500
Bam	26/12/2003	67000
Silakhoor	31/3/2006	13250
East Durood	6/11/2010	3024
Varzaghan	11/8/2012	142050
shounbeh	10/4/2013	170000
Murmuri	18/8/2014	35000

Table 3. Economic losses transportation and communication systems

Earthquake	Date	Economic losses(Million Rials)
Rudbar and Manjil	20/6/1990	3628.9
Ardabil	30/12/1996	530
Silakhoor	31/3/2006	6183
East Durood	6/11/2010	1515
Murmuri	18/8/2014	10000

Table 4. Economic losses potable water and waste water systems

Earthquake	Date	Economic losses(Million Rials)
Rudbar and Manjil	20/6/1990	19221.717
Ardabil	30/12/1996	6800
Silakhoor	31/3/2006	43535.7
East Durood	6/11/2010	9500
Varzaghan	11/8/2012	171920
Shounbeh	10/4/2013	13000
Borazjan	28/11/2013	3500
Bastak	2/1/2014	162000
Murmuri	18/8/2014	364000

Because of Iran's high inflation rate in years that earthquake happen; the monetary value of the losses is different. So the monetary value of losses caused by an earthquake in the lifeline systems calculated according to the annual inflation rate. In this research, base year is considered 2006. Therefore, to estimate economic loss according to the annual inflation rate, we propose a model to estimate the economic losses of earthquakes.

Monetary value of Equivalent (Oskuei Nejad, 1996):

1) The monetary value loss of earthquakes happens before 2006:

$$\mathrm{E}_{\mathrm{i}+1} = \mathrm{E}_{\mathrm{i}} + \left(\frac{\mathrm{N}_{\mathrm{i}+1}}{100} \times \mathrm{E}_{\mathrm{i}}\right) \tag{9}$$

Where E_{i}, The monetary value in year *i*, N_{i+1}, The inflation rate in year *i+1* and E_{i+1}, The monetary value in year *i+1*.

2) The monetary value loss of earthquakes happens after 2006:

$$E_{j-1} = \left(\frac{100}{100+N_j}\right) \times E_j \tag{10}$$

Where E_{j}, The monetary value in year *i*, N_{j}, The inflation rate in year *i+1* and $\mathrm{E}_{\mathrm{j}-1}$, The monetary value in year *j-1*.

In this research, we were considered economic losses of lifeline systems as a dependent variable and seismic parameters as independent variables. Stepwise multiple linear regressions were used to create a linear equation between the monetary value of losses and the seismic parameters of PGA, PGV and PGD.

In statistical terms, the relationship between variables is denoted by the correlation coefficient, which is a number between 0 and 1. Pearson Correlation Coefficient test is used to measure the strength of a linear association between two variables, where the value *r=1* means a perfect positive correlation and the value *r*

=-1 means a perfect negative correlation. If there is no relationship between the variables under investigation (or between the predicted values and the actual values), then the correlation coefficient is 0, or non-existent.

The Pearson's r for the correlation between the Loss and PGD variables is 0.969. This means that there is a strong relationship between two variables and changes in PGD variable are strongly correlated with changes in the Loss variable. In here, Pearson's r is 0.969. This number is very close to 1. For this reason, we can conclude that there is a strong relationship between Loss and PGD variables.

If the Sig (2-Tailed) value is less than or equal to 0.05, we can conclude that there is a statistically significant correlations between your two variables. That means, increases or decreases in one variable do significantly relate to increases or decreases in your second variable. The Sig. (2-Tailed) value in our example is 0.000. This value is less than 0.05. Because of this, we can conclude that there is a statistically significant correlation between Loss and PGD.

Table 5. Pearson Correlations

		Loss	PGA	PGV	PGD
Loss	Pearson Correlation	1	0.511**	0.859**	0.969**
	Sig. (2-tailed)		0.000	0.000	0.000
PGA	Pearson Correlation	0.511**	1	0.696**	0.536**
	Sig. (2-tailed)	0.000		0.000	0.000
PGV	Pearson Correlation	0.859**	0.696**	1	0.917**
	Sig. (2-tailed)	0.000	0.000		0.000
PGD	Pearson Correlation	0.969**	0.536**	0.917**	1
	Sig. (2-tailed)	0.000	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

The Table 6 is "model summary". This is an important one, as it gives us the measures of how well our overall model fits, and how well your prediction, is able to predict dependent variable. The first measure in the table is called R. This is a measure of how well our predictors predict the outcome, but we need to take the square of R to get a more accurate measure. This is R-squared, which is shown in the next column. This gives us the amount of variance in reading scores explained by the independent variable and predictor, dependent variable. R-squared varies between 0 and 1. The value $R^2 = 0.940$ indicates that nearly 94% of the total variability in the dependent variable is accounted by the predictor variable. The high value of R^2 indicates a strong linear relationship between dependent variable and the seismic parameter of Peak Ground Displacement (PGD).

The adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model. The adjusted R-squared increases only if the new term improves the model more than would be expected by chance. It decreases when a predictor improves the model by less than expected by chance.

Table 6. Model summary[b]

Model	R	R Square	Adjusted R Square	Durbin-Watson
1	0.969[a]	0.940	0.939	1.935

a. Predictors: (Constant), PGD b. Dependent Variable: Loss

Table 7 provides the completed ANOVA model of this evaluation. What we do see here is the F-test outcome that we mentioned earlier as giving a measure of the absolute fit of the model to the data. Here, the F-test outcome is highly significant (less than 0.001, as you can see in the last column), so the model does fit the data. A straight line, depicting a linear relationship, described the relationship between these two variables.

Table 7. ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	447400856592.635	1	447400856592.635	825.740	0.000[b]
	Residual	28716353481.743	53	541817990.222		
	Total	476117210074.378	54			

a. Dependent Variable: Loss b. Predictors: (Constant), PGD

The Table 8 gives us some important information, as that is where we will be able to look at the Beta and significance of our predictor (PGD). Standardized regression coefficients remove the unit of measurement of predictor and outcome variables. There are many good reasons to report them: They serve as standardized effect size statistics and allow you to compare the relative effects of predictors measured on different scales.

The column headed "Standardized Coefficients", contains the Beta coefficient. This is 0.969. If you look back at the section on Pearson's r correlation coefficient, you will see that this is in fact the same value. When we look at the relationship between just two variables, Beta in a regression output will always give us the same value as the correlation coefficient.

The final column in Table 8 gives us the statistical significance of the relationship between the independent and the dependent variables. In other words, how likely is it that we would have found a relationship enough strong in our sample, if there was not one in the actual population under study. As we can see, the relationship is statistically significant at the 0.001 level.

Table 8. Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	10153.407	4159.448		2.927	.005
	PGD	413989.141	14406.791	0.969	28.736	.000

So, model based on the standardized coefficient and the annual inflation rate is:

$$\mathrm{Loss_n} = [0.969(PGD)_s \pm \varepsilon_\alpha \sigma] \prod_{\mathrm{i}=2006}^{\mathrm{n}-1} \left(1 + \frac{\mathrm{N_{i+1}}}{100}\right) \tag{11}$$

Where σ is the standard deviation, it is value of the normal distribution curve, 0.991 (Figure 1).
And,

$$(PGD)_s = \frac{PGD - \overline{PGD}}{\sigma_{PGD}} \tag{12}$$

$\overline{PGD}$and σ_{PGD}, are mean value and standard deviation of PGD, respectively. $\mathrm{N_{i+1}}$, is Iran's annual inflation rate (in terms of Percent).

Table 9. Mean value and standard deviation of PGD

	Mean	Std. Deviation
PGD	0.1025615	0.21986828

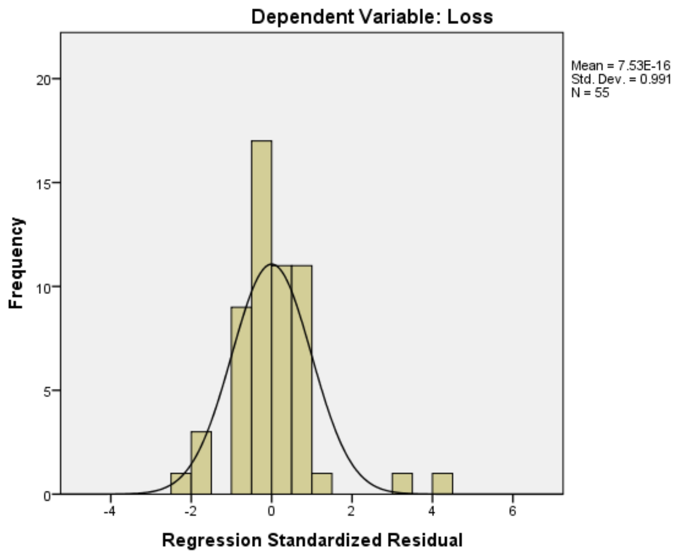

Figure 1. Normal distribution curve

ESTIMATION OF INDIRECT ECONOMIC LOSSES CAUSED BY EARTHQUAKE

Usually earthquake losses are not limited to physical losses but possible contain very widespread dimensions, example loss of output because of generate abeyance, reduction of consumption because of diminish social activities, etc. losses linked with effects would be very huge and vaster than those counted just through physical damages.

Given the possibility of alternative damage patterns across various business sectors, linked business activities are potentially vulnerable beyond sustaining just direct damage. Thus, the term indirect damage means any loss other than that directly produced by a disaster. These potential losses are not confined to immediate customers or suppliers of damaged enterprises. All of the successive rounds of customers of customers and suppliers of suppliers are impacted. In this way, even limited earthquake physical damage causes a chain reaction, or ripple effect, that is transmitted throughout the regional economy (Brookshire et al., 1997).

The current method is Input-Output (I-O) effect analysis. I-O table is a compendium accounting of all purchases and sales across components in a given zone. In this analysis, Iran is considered as a region. Thus, we use Iran's input-output table, the indirect losses due to damage of lifeline systems evaluated by the inter-industry relation.

Such economic loss in *i-th* industry (for example electric power systems), decrease productions of other industries which depend on the products of *i-th* industry, even if their facilities suffered no direct damages by the earthquake. In this study, the ripple effects of direct economic losses is considered as indirect economic losses, and is analyzed through an inter-industry relation analysis(Kawashima and Kanoh, 1990).

An inter-industry relation table has a form of Table 9 in which $\mathrm{I_i}$ represents *i-th* industry. The relation may be written as

$$\underline{A}.\underline{X} + \underline{F} = \underline{X} \tag{13}$$

Where $\underline{\mathrm{A}}$: Input coefficient matrix, $\underline{\mathrm{X}}$: Product vector, and $\underline{\mathrm{X}} = \{\mathrm{X_1}, \mathrm{X_2}, \dots, \mathrm{X_n}\}^{\mathrm{T}}$, $\underline{\mathrm{F}}$: Final demand vector and $\underline{\mathrm{F}} = \{\mathrm{f_1}, \mathrm{f_2}, \dots, \mathrm{f_n}\}^{\mathrm{T}}$.

Table 10. Inter-industry Relation Table (Input-Output Table) (Ronald et al., 2009)

Purchase/Sell		Intermediate Demand							Final Demand	Products
		$\mathrm{I_1}$	$\mathrm{I_2}$	$\cdots$	$\mathrm{I_i}$	$\cdots$	$\mathrm{I_j}$	$\cdots$		
Intermediate Sales	$\mathrm{I_1}$									
	$\mathrm{I_2}$									
	$\vdots$									
	$\mathrm{I_i}$	$\cdots$	$\cdots$	$\cdots$	$\mathrm{X_{ii}}$	$\cdots$	$\mathrm{X_{ij}}$	$\cdots$	$\mathrm{f_i}$	$\mathrm{X_i}$
	$\vdots$									
	$\mathrm{I_j}$	$\cdots$	$\cdots$	$\cdots$	$\mathrm{X_{ji}}$	$\cdots$	$\mathrm{X_{jj}}$	$\cdots$	$\mathrm{f_j}$	$\mathrm{X_j}$
	$\vdots$									
Gross Value Added		$\cdots$	$\cdots$	$\cdots$	$\mathrm{V_i}$	$\cdots$	$\mathrm{V_j}$	$\cdots$		
Products		$\cdots$	$\cdots$	$\cdots$	$\mathrm{X_i}$	$\cdots$	$\mathrm{X_j}$	$\cdots$		

In this analysis, Iran is considered as a region. Thus, we use Iran's input-output table, the indirect losses due to damage of lifeline systems evaluated by the inter-industry relation.

Table 11 shows the direct loss and indirect loss in the lifeline systems (in terms of Percent). Because most of activities are dependent on Electric power, in that Electric power has the maximum amount of indirect loss (Nearly 52.35%).

Table 11. Share of direct losses and indirect losses (%)

Lifeline system	Indirect Economic loss	Direct Economic loss
Electric power	52.35	47.65
potable and waste water	40.99	59.01
communication	24.07	75.93
natural gas	32.15	67.85

CONCLUSIONS

In this short article we have attempted to obtain a model that is able to estimate economic losses of lifeline systems and estimate economic loss according to the annual inflation rate. We use multiple linear regression techniques to assess the model estimated direct loss and propose a model to estimate the economic losses of earthquake.

In this research, obtained a model based seismic parameter PGD, because the correlation between the Loss and PGD variables is a strong relationship. The value R^2 indicates that nearly 94% of the total variability in the dependent variable is accounted by the predictor variable.

The estimation of economic losses lifeline systems is important in earthquake loss estimation. It has demonstrated the importance of estimation indirect as well as direct losses in understanding the total economic impact of an earthquake. However, we were emphasized, especially in linking physical damage and economic loss lifeline systems.

For analyzing economic losses effects an earthquake, an analytical method with use of the inter-industry relation check, which has been was applied to the earthquake. Indirect loss is very important for assessing an extent of the hit effect of earthquake.

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