Seismic Performance Assessment of Reinforced Concrete Building Stock Using Artificial Neural Network and Linear Regression Analysis

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ABSTRACT

Istanbul is located on extensive piece of land which is susceptible by seismic activity. In the last half century, Turkish earthquake codes for designing building under earthquake loads went through many modifications and editions (TEC1975, TEC1997, TEC2007, and TBEC2018). Hence, there are many buildings existing that has been built in accordance with old regulations since improvements in the recent earthquake code. Therefore, the need of a quick assessment method to identify the building seismic performance level in accordance with the latest seismic code is extremely vital. For this purpose, this research is aiming to prepare a database for the quick estimation on building seismic performance by constructing an artificial neural network model that is capable of this, relating building material properties, geometry, designed standard, site class, and peak ground acceleration to the building seismic performance levels. In order to meet these objectives, 540 reinforced concrete building models with various parameters are modeled with respect to TEC1975, TEC1997, TEC2007, TBEC2018 and seismic performance obtained from the analysis in accordance with TBEC2018. Data obtained are used to train and validate the constructed artificial neural network (ANN) model. Also, several training algorithms performed with various number of hidden layers and comparison between them is discussed in order to figure out the optimum number of hidden layers and best train method which gives the highest accuracy of prediction for the performance assessment of the buildings. Since the artificial neural network model created for the performance level estimation of the existing buildings, validity of the created model is checked by the application through the existing buildings as a case study with various parameters within the range of considerations according to the existing study. The data obtained from the analysis is used to perform multiple linear regression analysis (MVLRA) as well. Results indicate that ANN can be a very profound technique in predicting the seismic performance levels with a determination coefficient (R^2) of 0.8786. Furthermore, identification of the significance of the predictor variables according to their effect on seismic assessment have been done with several methods which are widely used in literature as well.

Keywords: ANN, TBEC2018, Pushover, Performance.

ÖZ

Istanbul deprem hareketleri ile kritik durumda bulunan büyük bir bölgedir. Bu bağlamda son zamanlarda depreme dayanıklı yapı tasarımı konusunda birçok araştırma ve geliştirmelerle birlikte Türk Deprem Yönetmelikleri tasarlanmıştır. Buna rağmen, farklı tasarım ve yaklaşım öngörüleriyle önceden inşa edilmiş birçok mevcut yapı bulunmaktadır. Bu doğrultuda, yapıların yeni deprem yönetmeliğine göre yapı performans seviyesinin belirlenmesi adına hızlı değerlendirme yönteminin geliştirilmesi hayati bir ihtiyaç haline gelmiştir. Bu çalışmanın amacı yapay sinir ağı modeli ile binaların farklı malzeme özellikleri, geometrisi, tasarım yönetmeliği, zemin çeşidi, yer ivmesine göre bina performans seviyesi hakkında hızlı değerlendime metodu geliştirmektir. Bu bağlamda, TDY1975, TDY1997, TDY2007 ve TBDY2018 kullanılarak belirtilen farklı parametreler doğrultusunda 540 betonarme bina modellenmiş ve TBDY2018 ile bina performans analizi yapılmıştır. Analizlerden elde edilen veriler yapay sinir ağı modeli öğretiminde ve doğrulamasında kullanılmıştır. Buna ek olarak, yapay sinir ağı farklı öğrenim algoritmaları ile modellenip en doğru performans tahmini elde edilen öğrenim algoritması ile çalışan yapay sinir ağı modeli belirlenmiştir. Analizden elde edilen veriler ile doğrusal regresyon analizi de yapılmıştır. Sonuç olarak yapay sinir ağı modelinin doğruluk payı anlamında çok etkili bir teknik olduğu ve modelin doğruluk oranı (R^2) 0.8786 olarak bulunmuştur. Buna ek olarak, çalışmada kullanılan farklı parametrelerin performans seviyesinin belirlenmesindeki etkisi bağlamında önem sırasına göre sıralanması adına literatür araştırması ile yaygın olarak kullanıldığı belirlenen farklı metodlar uygulanılmıştır.

Anahtar Kelimeler: ANN, TBDY2018, İtme, Performans.

To My Family…

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
bfg	BFGS Quasi-Newton Backpropagation
BKS	Building Usage Category
br	Bayesian regularization backpropagation
BYS	Building Height Category
cgb	Conjugate Gradient Backpropagation with Powell-Beale Restarts
cgf	Conjugate Gradient Backpropagation with Fletcher-Reeves Updates
cgp	Conjugate Gradient Backpropagation with Polak-Ribiere Updates
DTS	Building Design Category
GD	Collapse Case
gd	Gradient Descent Backpropagation
gda	Gradient Descent with Adaptive Learning Rate Backpropagation
gdm	Gradient Descent with Momentum Backpropagation
GO	Collapse Prevention
KH	Controlled Damage
KK	Immediate Occupancy
lm	Levenberg-Marquardt Backpropagation
MVLRA	Multiple Variable Linear Regression Analysis
oss	One-step Secant Backpropagation
PGA	Peak Ground Acceleration
RC	Reinforced Concrete
rp	Resilient Backpropagation
scg	Scaled Conjugate Gradient Backpropagation

TBEC2018	2018 Turkish Building Earthquake Code
TEC1975	1975 Turkish Earthquake Code
TEC1997	1997 Turkish Earthquake Code
TEC2007	2007 Turkish Earthquake Code
AC	Checked peak ground acceleration (0.2g, 0.3g, 0.4g, and 0.55g),
AD	Designed peak ground acceleration (0.1g, 0.2g, 0.3g, and 0.4g),
CG	Grade of concrete (C16, C20, and C25),
EQ	Earthquake standard (TS1975, TS1997, TS2007, and TS2018),
IR	Irregularity type (Regular, A1, A2, A3, B1, and B2),
PER	Performance level (KK, KH, GO, and GD),
SC	Checked soil type (Za, Zb, Zc, Zd, and Ze),
SD	Designed soil type (Za, Zb, Zc, and Zd),
SG	Grade of steel, (S220 and S420).

LIST OF SYMBOLS

∇_k	Function gradient at point k.
A_0	Peak ground acceleration in terms of g.
A_0	Peak ground acceleration in terms of g.
A_k^{-1}	Approximation of the hessian matrix that its value is updated through iterative approach.
B_k	Modification coefficient of the direction function.
C_R	Spectral displacement ratio
$D_{1,max}^{(X)}$	The maximum displacement of the modal single degree of freedom system
F_e	Elastic strength demand
f_y	Yield strength
J^T	The Jacobean matrix that is developed based on the sum of square root error derivative
N_D	Number of rows in the matrix.
N_P	Number of columns in the matrix.
P_k	The direction functions.
r^2	Zero-Order Correlations coefficient.
$R^2(M\backslash S)$	Difference in between the accuracy determined by the multilinear regression with all predictor variable data and and the accuracy obtained from the multilinear regression analysis model by removal of relating predictor variable.
$R^2(M \cup S)$	Accuracy obtained by the model with data that is used considering all predictor variable.

$R^2(S)$ Accuracy determined by the model with data that is used including removal of relating variable.

$R_a(T)$ Ductility factor for the reduction of the seismic forces.

R_y The yield strength reduction coefficient.

$S_{ae}(T_1)$ Elastic spectral acceleration at the first natural period of vibration

S_{de} Elastic design spectral displacement

S_{di} Nonlinear spectral displacement

T_1 The first natural vibration period for the lateral force resisting system

W_j^2 Squared current weight of the trained neuron.

x_1 First independent predictor variable

X_I The input values for a given variable.

X_I The input values for a given variable.

X_k Data point at point k.

Y_I Output of the data set.

A_{1-9} Fitting coefficient which are presented in Table 2.

A_I The regression coefficient obtained by multiple variable linear regression analysis.

α_i' The standardized regression coefficient.

α_{y1} Yield acceleration

β_0 The intercept

β_1 Coefficient of first predictor variable

∇ The gradient descent coefficient.

$\nabla f(x_k)$ The gradient of the function.

C Lateral load coefficient.

Dx_{k+1} Partial derivative of the input data.

e	Unit vector of the network error.
$F(X_I)$	Predicted output.
I	Importance factor which depends on the function of the building.
I	Importance factor which depends on the function of the building.
K	Structural type coefficient which depends on the ductility of the structure.
Lr	Learning rate.
Per	Performance of the training.
S	Spectral coefficient which depends on the site class and the natural period of vibration of the structure.
S(T)	Spectral coefficient which depends on the site class and the natural period of vibration of the structure.
S(w)	Regulation function.
$\mathrm{Sign}(\nabla f(x_k))$	Sign of the gradient only without considering its magnitude.
T	Transpose of the matrix.
V	Base shear force which acts on the structure.
W	Total weight of the structure.
Y	Dependent outcome variable
Y	The corresponding output of x_i.
Y	The corresponding output of x_i.
ε	Error
Λ	Constant diagonal element varies between 0 and 1.
$\mu(R_y, T_1)$	Ductility demand with respect to the yield strength and natural vibration period.

Chapter 1

INTRODUCTION

1.1 General

Reinforced concrete building structures that are subjected to earthquake are expected to dissipate high input energy without failure to assure controlled damage performance level. Errors of providing enough capacity leads to catastrophic failure and in most cases to disasters. Turkey as a country is prone to many earthquakes' excitations since it is hovering over multiple faults such as Anatolian Fault etc. (Soyluk & Harmankaya, 2012). Therefore, its important to update the performance of these old buildings continuous against most recent standards as a part of vulnerability assessment to prevent this disaster from happening.

The recent development achieved over the last few decades in the field of technology has indeed impacted our lives. Day by day new methods are being introduced to the literature trying to overcome certain difficulties and obstacles with the help of these improved technologies. Nowadays, many efforts are being spent on developing new interpolation techniques to improve their modeling capability and reduce their uncertainty represented in most cases by what so called "coefficient of determination" which is represented as (R^2).

Artificial neural networks (ANN) is a new computing system of interpolation which was created in similar aspect to the human brain neurons. In such a method the program is trained to recognize certain pattern by means of “learning” in order to be capable of performing the required tasks. As a part of the model development high amount of data is expected to be supplied to the system. These data are categorized into three parts which are used to train, validate and test the constructed mathematical expressions. This method is usually handled in different computer software.

Another approach is multiple linear regression analysis which is commonly used technique in most of the research in literature. Due to the usage of more than one and several independent variable parameters in the analysis of the existing case study, it is called as multiple linear regression analysis. It is mainly the relationship between several independent input variable parameters and one dependent output variable parameter. The main objective of this technique is to fit an equation to the real case data and get the closest regression line with respect to all data points of the analysis of existing case study in order to minimize error of prediction as well.

1.2 Previous work done

There are existing studies on the analysis and the performance assessment of the various building structure types under seismic loadings by using several structural software programs. Regarding this, prediction based tools are widely used in literature in order to meet the objectives of the related studies such as ANN and linear regression analysis as well. Several studies regarding these are summarized below.

Arslan (2010) conducted a study on determining the most effective parameters in designing reinforced concrete structure. He focused on the concrete and steel reinforcement strength, the role of infill walls, the influence of short columns and strong column weak beam, in addition to the ratio lateral resisting elements with respect to the floor area. He conducted several analysis on building with variable number of floors and perform pushover analysis which is implemented in building performance estimation. He constructed an ANN and found that the substantial parameters that might alter the performance of building is the ratio of the lateral resisting elements and the development of short columns.

Chatterjee et al. (2017) they tried to develop a new predictive ANN model which has the ability to give precise assessment of the building performance, using a data base of 150 reinforced concrete buildings designed using STA4CAD. Pro v8i in accordance with IS 456-2000. They consider multiple parameters such as parapet wall height, thickness of infill walls, dimensions of the structural elements in addition to their volume and their reinforcement area. They concluded that their ANN model can be very powerful technique in the determination process of seismic performance of buildings.

Another research study conducted by Arslan (2009) investigated the effectiveness of the ANN model in the prediction of the base shear and displacement at failure under lateral loads using different parameters. For this purpose, several RC buildings with numerous parameters are analyzed by conducting a static nonlinear pushover analysis. The parameters include the reinforcement ratios of the columns and beams, the axial loads acting within column and structural elements dimensions. Also, he included the effect of the compressive strength. He found that ANN perform very well in prediction of the base shear and displacement at failure considering his suggested parameters regardless of the training technique.

Kameli et al (2011) used artificial neural network to predict target displacement and base shear at the target displacement of reinforced concrete buildings. In order to achieve this objective, numerous reinforced concrete buildings are analyzed using finite element method. The input parameter for the collected data were the number of frames, number of floors, thickness of the infill walls, the presence of soft story and the spectral accelerations. Results indicate that ANN predicted the actual target displacement and the base shear at target displacement with high accuracy.

Arslan et al (2015) implemented the use of ANN for quick predication of the building performance. For this purpose, several number of reinforced concrete buildings are analyzed in accordance with the Turkish earthquake code 2007. The input parameters that have been considered are the material grades, loading condition, and the geometrical properties of the structures. Researchers concluded that ANN can be extremely handy and cheap tool in the estimation of building performance where it yields an accuracy of 64%.

Estêvão (2018) investigated the likelihood of neural network model to predict the capacity curve of reinforced concrete structure in accordance with Eurocode 8. SeismoStruct software is used to obtain the capacity curve of large set of reinforced concrete buildings. Results indicate that the performance of ANN is strongly linked to the data set which is used to train the network. Nevertheless, it can be concluded that the results obtained by the ANN is accurate enough for rapid determination of the capacity curve of concrete reinforced buildings.

Morfidis et al (2018) investigated the reliability of ANN in the prediction of reinforced concrete building subjected to seismic activity. For this purpose, 35 reinforced concrete buildings are analyzed under 65 different ground motions records. The input parameters are divided into two main categories which are structural properties (i.e. concrete grade, columns alignment, etc.) and the ground motion characteristics. The output parameters were inter-stories drift, and building damage index. It was concluded that ANN can provide very accurate rapid prediction tool for the assessment of existing buildings.

Ozcebe et al, (2004) studied the effectiveness of statistical discriminate data analysis in the assessment of building vulnerability in seismic region of low to mid rise buildings. The aspects which he used in the creation of the mathematical models are building elevation, stiffness, strength, presence of soft story, and cantilevers ratio, they validated their models wıth the help of data base collected from the buildings located in Düzce region after the earthquake took place in 1999. Results proved that statistical discriminate data analysis is highly effective in seismic vulnerability prediction.

Yakut (2004) suggested a method of assessing the preliminary seismic vulnerability of an RC structure with moderate ductility. As a part of the applications, orientation, size and concrete class of the lateral load resisting system is entered to the analysis using a statistical approach by considering the effect of seismicity and site class as well.

Hassan & Sozen (1997) suggested a method for finding the buildings that are characterized with high vulnerability in a region of RC buildings. In the present study, the dimensions of the structures serve as an input together with its location in a 2D plot. The function of the proposed approach can be used to rank a set of buildings against a certain earthquake. These ranks can be modified later to consider the importance of the structure and other building properties.

1.3 Aim and scope

The aim herein is to find adapted this improved technology in the field of structural engineering by means of developing a quick performance assessment method based on the recent Turkish building earthquake code 2018. As a part of the study, about 540 case is to be considered to cover the most significant parameters that has effect on the performance of the buildings including Turkish earthquake code which is designed, peak ground acceleration (PGA), soil class, concrete grade, steel grade, several types of irregularities in plan and elevation. In general, this model is expected to help structural engineers who are trying to check the performance of the existing structures constructed with the guidelines of previous Turkish earthquake code and to assess their deficiency against the most recent one.

1.4 Organization of the thesis

There are six main chapters that the research is composed of which are;

- The present chapter which includes general overview regarding the topic through some back ground information, and the current work existing in the literature. In addition, the aim and scope of the study is presented.
- Second chapter illustrates the fundamental differences between the considered earthquake standards. In addition, it presents detailed information regarding the nonlinear pushover analysis procedure in accordance with TBEC2018, and it highlights how the different performance levels are estimated.
- Third chapter gives description about artificial neural network, and presents the different training procedure which are followed in the current research. In addition, multiple linear regression analysis and several techniques for the identification of variable importance are presented as well.

- Fourth chapter describes the research methodology by presenting the considered locations within Istanbul province, building geometries, assumptions and analysis method.
- Fifth chapter argues the analysis results and highlights the significant training method, the optimum hidden layer number and the important predictor variable.
- Sixth chapter summarizes the whole dissertation perspective, research and highlights its outcomes. In addition, it discusses the suggestions for future studies.

Chapter 2

TURKISH EARTHQUAKE CODES AND PUSHOVER ANALYSIS

2.1 Introduction

A large part of Turkey is situated in an active earthquake zones which causes devastating consequences both on human lives and serious damage to structures due to earthquakes. Due to this, designing structures in a way safety and resisting against earthquake is revised during past years and researches will continue on. Therefore, in this chapter improvements on earthquake codes in Turkey since 1975 up to now will be discussed.

2.2 1975 Turkish earthquake code

For a period of 20 years the TEC1975 Seismic design of building in disastrous area has been valid. Hence, many of the buildings existing in Turkey are designed and constructed according to this standard. It was the first code to present the term of ductility in the calculation of the lateral loads. Additionally, the lateral loads are derived from the spectral acceleration coefficient, the natural period of the building and the site class. The code enhanced many aspects in seismic design consideration which are listed as follow:

• Imposing restriction for reinforcement details.

• Defining restriction for the structural elements cross-sections and reinforcement ratios.

• Presenting reinforcement detail requirements for the purpose of confinement.

• Describing shear design procedure for the connection between beams and columns.

• Presenting the contribution of natural period of vibration in the calculation of base shear of the structure.

• Describing building irregularities.

• Presenting limitation for equivalent (H<75 m)

• Defining restriction for the shear walls additional longitudinal reinforcement towards the end and base of the wall. However, confining these longitudinal bars was not mandatory.

• Calculated lateral forces were applied with 5% eccentricity along the orthogonal direction.

The lateral base shear force coefficient is calculated in accordance with equation 2.1

$$C = A_0 KIS \leq \frac{A_0}{2} \tag{2.1}$$

where;

A_0: It is peak ground acceleration in terms of g.

K: Structural type coefficient which depends on the ductility of the structure.

I: Importance factor which depends on the function of the building.

S: Spectral coefficient which is a function of the building frequency and the soil type of the region.

C: Lateral load coefficient.

2.3 1997 Turkish earthquake code

In 1997 new code standard was released to accommodate the recent experienced earthquake which was considered a breakthrough in terms of designing earthquake resistance structure (TEC, 1997). In addition, to maintain the public in a safer environment. The key point that distinguished this code from the TEC1975 are presented as follow:

- Presenting earthquake peak ground accelerations in terms of occurrence possibilities.
- Imposing restriction for the building performance under the application of the considered lateral seismic loadings.
- Creating the Idea of elastic design spectrum.
- Defining the live load contribution factor.
- Defining new considerations for the building ductility.
- Imposing more requirements on reinforcement details to ensure confinement of the structural elements.
- Presenting detailed definitions for building irregularities.
- The idea of designing strong columns weak beams is presented.
- The shear capacity of the structural element within the structure were restricted to be larger than the building capacity to ensure ductile failure.

The base shear force is calculated in accordance with equation 2.2

$$V = W\frac{A_0 IS(T)}{R_a(T)} \geq 0.10A_0 IW \tag{2.2}$$

where;

V: Base shear force which acts on the structure.

A_0: It is peak ground acceleration in terms of g.

W: Total weight of the structure.

I: Importance factor which depends on the function of the building.

$S(T)$: Spectral coefficient which depends on the site class and the natural period of vibration of the structure.

$R_a(T)$: Ductility factor for the reduction of the seismic forces.

2.4 2007 Turkish earthquake code

Most of the structures were inspected in terms of their safety under seismic activity and some buildings were modified as well after the earthquake happened in 1999. On the other hand, while analyzing and retrofitting existing structures, engineers were doing assumptions and following incorrect approaches as well due to the missing information in standards regarding earthquake assessment criteria. According to this, retrofitting process and earthquake assessment of the existing structures have been studied in detail and revision of designing reinforced concrete structures have been done in the new version of seismic design code which is established in 2007. Significant improvements in seismic code 2007 compared to the previous codes as follows;

- Addition of the detailed study regarding assessment of the existing structures under earthquake and retrofitting.
- Addition of linear elastic method for the assessment of the structures under earthquake regarding the inelastic behavior due to allowable capacity ratios given according as damage level.
- Addition of performance-based evaluation principles in assessment of the existing structures under earthquake and retrofitting.
- Addition of performance levels such as immediate occupancy, life safety and collapse prevention and earthquake design levels such as service, design and maximum earthquake to be used for structures.
- Single-mode and multi-mode pushover analysis methods are added for the assessment of the existing structures under earthquake and retrofitting.
- Addition of the nonlinear time history analysis method.

- Addition of principles regarding various retrofitting techniques such as strengthening, concrete jacketing, shear wall addition.

To sum up, performance assessment of the structures under earthquake is depending on the damages of structural members which damage levels are identified due to the concrete compressive strain, tensile reinforcement strain obtained from the rotations of plastic hinges when pushover analysis has been done.

2.5 2018 Turkish building earthquake code

Since turkey is located in highly seismic region the development of new Turkish standard is necessary to accommodate the data obtained from recent seismic activities and new researches discoveries. The main key point differences between 2007 and 2018 are listed in the following bullet point;

- Introducing two more site classes according the shear velocity propagation in the ground (Za, Zb, Zc, Zd, Ze, and Zf).
- Dividing building into ten categories with respect to their elevation from the ground surface.
- Introducing performance base design for the first time where in old standard it was limited for the elastic spectral design only.
- The spectral acceleration calculation is based on the short period and the one second period not on the giving peak ground acceleration.
- Presenting more detailed sections for the ductility reduction factor of the seismic forces.
- Increasing the minimum dimension of the column and beams to be 30 cm.
- Increasing the minimum concrete compressive strength to be C25.

- Adding more detailed restrictions on the required elastic seismic performance of the building.
- Presenting detailed procedure for conducting nonlinear pushover and time history analysis.
- Adding more restriction on selection the ground motion records and the number of the selected records (11 minimum).
- Adding more restriction on reinforcement details to increase the confinement of the structural element.

2.6 Seismic Analysis of RC Structures

Engineers during the design phase of their structure restrict the internal stresses in such manner so that no exceedance of the yielding stress of the building material is achieved, which is a faster method and requires small amount of computational effort. However, under unexpected severe loading conditions (i.e. seismicity with high magnitude) the yielding stress of the structural element material is exceeds causing the structural elements to act in non-linear conditions. Thus, researchers and scientists developed both linear and non-linear analysis methods that can simulates the various behaviour of the structural elements within a given building. Figure 1 presents a flowchart that summarize the various types of seismic analysis methods.

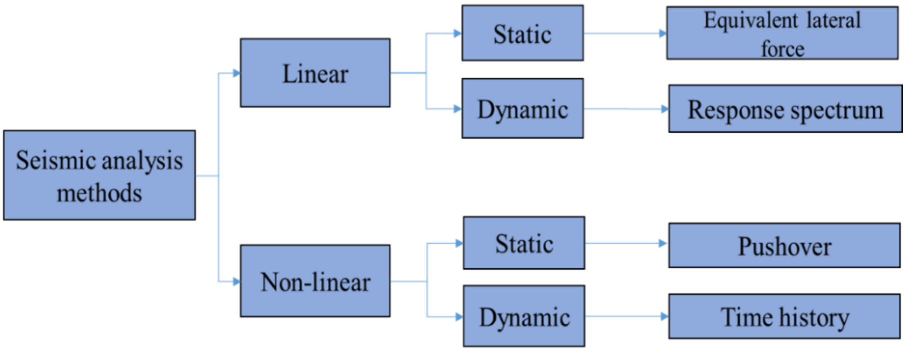

Figure 1: Seismic analysis methods

2.6.1 Equivalent lateral force method

The main purpose of this procedure is to substitute the dynamic earthquake forces with an equivalent static lateral force. This method basically estimates the base shear with respect to the overall structure mass, the structure frequency of considered direction of load application, the response acceleration transmitted to the building and the ductility of the building.

2.6.2 Non-linear static pushover analysis

This method is accounted to be one of the most applied techniques for determining the plastic behaviour of RC structure. In general, this method requires high computational effort unlike the linear static method, since the stiffness matrix of the structure varies with respect to the applied loads. It is an iterative method where forces are subdivided into multiple steps. At each step the stresses which are resulted within the primary elements are checked and the stiffness matrix is modified accordingly. This iterative approach continues until the limit state is reached (target displacement).

Ultimately, the performance-based design allows the structural elements to exceeds their yielding stresses up to a certain criterion is achieved (rotation). This procedure can be subdivided into the following categories:

- Force controlled; the structure roof is pushed until a predefined magnitude of base shear force is achieved.
- Displacement controlled; which involves pushing the structure top story until a target displacement is achieved. This procedure is suggested by most standards to estimate the building performance.

2.6.3 Non-linear static pushover analysis in accordance with TBEC2018

Earthquake modal displacement is obtained from the maximum displacement of the single modal degree of freedom system which is represented by the modal capacity diagram under earthquake. Maximum displacement of the single degree of freedom modal system is defined as nonlinear spectral displacement which is presented in equation 2.3

$$d_{1,max}^{(X)} = S_{di}(T_1) \tag{2.3}$$

where:

$d_{1,max}^{(X)}$: The maximum displacement of the modal single degree of freedom system

S_{di}: Nonlinear spectral displacement

T_1: The first natural vibration period for the lateral force resisting system

Furthermore, nonlinear spectral displacement at the first natural vibration period for the lateral force resisting system is expressed as presented in Equation 2.4.

$$S_{di}(T_1) = C_R S_{de}(T_1) \tag{2.4}$$

where:

S_{de}: Elastic design spectral displacement

C_R: Spectral displacement ratio

Moreover, spectral displacement ratio is defined in Equation 2.5.

$$C_R = \frac{\mu(R_y, T_1)}{R_y} \tag{2.5}$$

where:

$\mu(R_y, T_1)$: Ductility demand with respect to the yield strength and natural vibration period.

R_y: The yield strength reduction coefficient.

The yield strength reduction coefficient is representing the yield strength obtained directly from the pushover analysis for the strength based design approach which is presented in Equation 2.6.

$$R_y = \frac{f_e}{f_y} = \frac{S_{ae}(T_1)}{\alpha_{y1}} \tag{2.6}$$

where:

f_e: Elastic strength demand

$S_{ae}(T_1)$: Elastic spectral acceleration at the first natural period of vibration

f_y: Yield strength

α_{y1}: Yield acceleration

Ductility demand of earthquake is equal to the yield strength reduction coefficient for the lateral force resisting systems with low rigidity with respect to the equal displacement rule as shown in Equation 2.7.

$$\mu(R_y, T_1) = R_y \qquad T_1 > T_B \tag{2.7}$$

In addition, the equation for the lateral force resisting systems with high rigidity is given in Equation 2.8.

$$\mu(R_y, T_1) = 1 + (R_y - 1)\frac{T_B}{T_1} \qquad T_1 \leq T_B \tag{2.8}$$

So, the Equation 2.9 are derived by using the spectral displacement ratio and ductility demand which is defined above.

$$C_R = 1 \qquad\qquad T_1 > T_B$$
$$C_R = \frac{1 + (R_y - 1)\frac{T_B}{T_1}}{R_y} \geq 1 \qquad\qquad T_1 \leq T_B \tag{2.9}$$

Modal capacity diagram, modal displacement versus modal acceleration in terms of coordinates and with respect to the first vibration mode is given and also linear earthquake spectrum with spectral displacement versus spectral acceleration as coordinates is given on the same plot as shown in Figure 2.

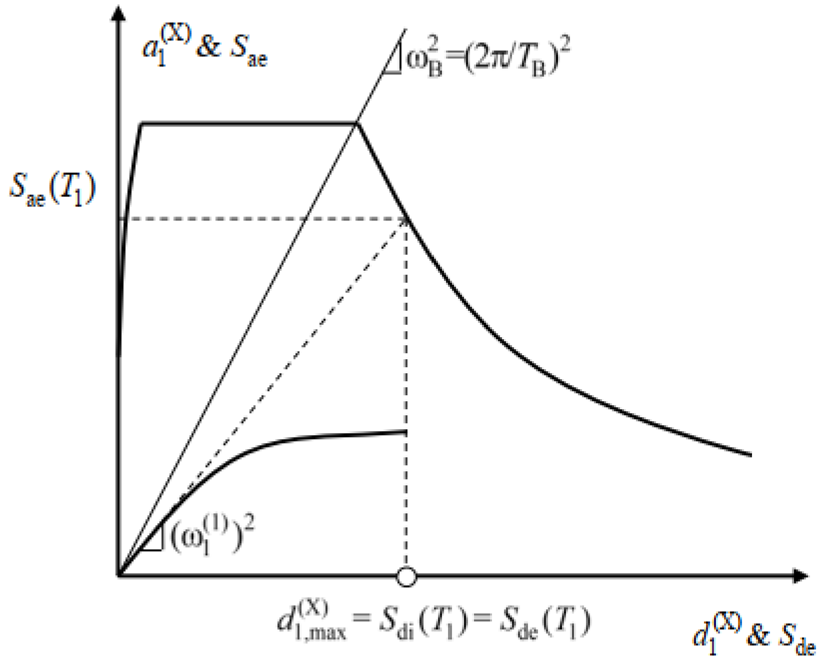

Figure 2: Capacity demand curve calculated in accordance with TBEC2018

2.6.4 Performance level determination in accordance with TBEC2018

Performance of existing buildings are related to the expected damage that occurred within the building under seismic forces applied which are categorized as four main damage conditions.

2.6.4.1 Limited damage performance level

It is only allowed to have maximum 20% pronounced damage on beams after the calculation for each direction of earthquake applied in any storey of a building. In case there are brittle damaged elements, retrofitting is needed. Buildings that are satisfying these conditions are to be considered in Limited Damage Performance Level.

2.6.4.2 Controlled damage performance level

Controlled damage performance level is determined when given three conditions are satisfied and retrofitting is applied to the brittle damaged elements.

It is only allowed to have maximum 35% advanced damage on beams (except secondary beams) and the regulation specified for vertical elements regarding advanced damage zone should be satisfied after the calculation for each direction of earthquake applied in any storey of a building.

Ratio of the summation of shear forces carried by the vertical elements that are in advanced damage zone on the top storey to the summation of shear forces of all vertical elements at the same storey should not exceed 40%.

The ratio of the summation of shear forces that are carried by the vertical elements in any storey which are exceeded pronounced damage zone at both top and bottom sections to the summation of shear forces of all vertical elements within the same storey should not exceed 30% while all other elements are within the limited damage zone or pronounced damage zone.

2.6.4.3 Collapse prevention performance level

At most 20% of the beams (except secondary beams) can exceed collapse zone after the calculation for each direction of earthquake applied in any storey of a building.

The ratio of the summation of shear forces that are carried by the vertical elements in any storey which are exceeded pronounced damage zone at both top and bottom sections to the summation of shear forces of all vertical elements within the same storey should not exceed 30% while all other elements are within the limited damage zone, pronounced damage zone or advanced damage zone.

The usage of building with its existing condition is threatened in terms of life safety.

2.6.4.4 Collapse case

If the building is not satisfying collapse prevention performance level conditions, then it is collapse case. The usage of building with its existing condition is threatened in terms of life safety.

Chapter 3

ARTIFICIAL NEURAL NETWORK, LINEAR REGRESSION ANALYSIS AND VARIABLE IMPORTANCE

3.1 Introduction

In this chapter, artificial neural network and multiple variable linear regression analysis are explained in detail which are the two methods used in order to determine quick performance level estimation of buildings under seismic loads. In addition, predictor variable importance determination methods are explained since several input variables are considered in the study.

3.2 Artificial Neural Network

According to the literature study that have been done by (Setyawati, et al., 2002) states that artificial neural networks (ANNs) are networks of artificial neurons which in other words are processing elements. These artificial neurons are sets of three different types of layers such as input layer, hidden layer and output layers. The input layers have the input data and variable parameters. Hidden layers have the neurons which perform the computations and output layers which is the solution takes place. Furthermore, learning algorithm is needed in order to train the network. So, multilayer feedforward network is the most widely used popular network type among several types such as single layer feedforward networks, recurrent networks, lattice structures and so on. The main aim of training the network is to find out the weights (parameters) of the neural network model in order to minimize the output errors of the model. So, back propagation is the most widely used supervised learning method due to the nonlinearity of the model in the parameters and need of a nonlinear algorithm. One minor disadvantage is the approach is slow due to its learning speed (Setyawati, et al., 2002). According to (Elhag & Boussabaine, 1998), artificial neural networks (ANNs) are advanced methodology against traditional techniques in cost prediction since it has learning ability as well as to generalize solutions. (Elhag & Boussabaine, 1998), according to a literature study of ANN by (Hecht-Nielsen, 1990) states that, neural computation is a methodology used to learn, generalize and represent the knowledge. It gives information from the existing data by learning.

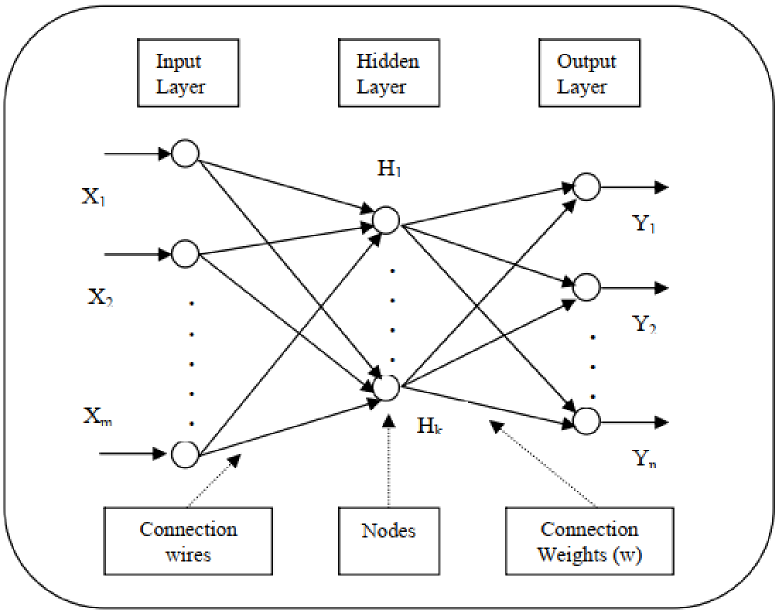

Figure 3: ANN modelling system

A back-propagation neural network is simply defined as a network with number of layers synthesized with processing elements called neurons. There are input layers consists of input data or parameters of a problem, hidden layers which the information is processed by trial and error due to the complexity of the problem and output layers which gives the solution of the problem. Each neuron receives inputs, processes and generates an output (Elhag & Boussabaine, 1998).

As the cost estimation of a construction project is one of the most important issue for the decision making about the building design process and its parameters, it is very important to have an accurate and reliable cost prediction depending on the client's requirements and data to develop the model as well (Elhag & Boussabaine, 1998).

(Elhag & Boussabaine, 1998), indicates that some traditional techniques for estimation such as functional unit, cube method, superficial area, superficial-perimeter, story-enclosure, approximate quantities, elemental analysis, interpolation, resource analysis, cost engineering, which are found out by a literature survey (Brandon, 1990; Raftery, 1994; Seely, 1996) are suffering in case of imprecision and uncertainty of data and variables. On the other hand, other developed techniques such as linear/dynamic programming, regression analysis, simulation/risk analysis, expert systems are able to deal with complex input-output relationships, imprecision and uncertainty of variables that are affecting cost of constructions.

Due to the restricted properties of the traditional knowledge-based systems, Artificial Neural Networks started to be used as a complement and advanced applications since eighties especially in civil engineering. One of the most important property of ANNs which makes it useful for engineers is to be able to learn from examples and generate solutions. (Rafiq, et al., 2001), states that neural network tries to imitate human brain learning activities. Examples with input data and known output data involves in training process and the system adjusts the weights of the internal connections and minimize the errors between known output and network output. Design of a simple artificial neural network structure is composed of three main phases such as modeling, training and testing phase. Therefore, the process is like the study of neurons in the human brain. After it is trained and tested in a way satisfactory, the system is able to generalize rules and able to predict required output data, within the domain covered by training examples.

(Rafiq, et al., 2001), studied on comparison of three different types of Neural Network which are multi-layer perception (MLP), radial basis function networks (RBF) and normalized RBF (NRBF) in terms of speed of training and ease of use via practical example of a reinforced concrete slab design.

3.2.1 Methods of Training

3.2.1.1 Back-propagation learning methods

Back propagation is applied through gradient descent method which can be quite inefficient in terms of speed. Especially, when the research data point is extensive and the patterns of the points has many spikes and sharp curvature (Gill et al.1981). For this purpose, multiple methods are suggested to enhance the speed and accuracy of the optimized model.

3.2.1.2 BFGS quasi-newton backpropagation

This training algorithm is used for solving nonlinear optimization problem which is constraint by no means through iterative solutions (Fletcher et al.2013). The method uses the Quasi-Newton approach which seeks a point on the curve which is designated with preferably two differentiable functions. The solution is achieved when the gradient reaches value near the zero or as defined by user (Curtis et al.2015) the training function is presented in Equation 3.1.

$$x_{k+1} = x_k - A_k^{-1} \nabla f(x_k) \tag{3.1}$$

where;

A_k^{-1}: Approximation of the hessian matrix that its value is updated through iterative approach.

x_k: Data point at point k.

$\nabla f(x_k)$: The gradient of the function.

3.2.1.3 Bayesian regularization backpropagation

This method is more efficient than the traditional backpropagation methods since it can decrease or even eliminate the need of cross-validation where it alters the nonlinear regression into well-ordered statistical problem that is characterized by ridge regressions (Burden et al. 2008). There many advantages of the Bayesian regularization such as;

- Overtraining or overfitting is not a major concern due to its unique procedure where it eliminates the need for validations and it stop the training whenever the training criterion is reached.
- The structure of the neural network doesn't play major role in the fitted results obtained by this method. However, the structure of the neural network should be relatively minimal.
- It does not acquire test set since it can generate a mathematical model which can represent all the data used in the model.

The training function of the method is described in Equation 3.2

$$S(w) = \sum_{i=1}^{N_D} [y_i - f(X_i)]^2 + \lambda \sum_{i=1}^{N_P} w_j^2 \tag{3.2}$$

where;

$S(w)$: Regulation function.

y_i: Output of the data set.

$f(X_i)$: Predicted output.

λ: Constant diagonal element varies between 0 and 1.

w_j^2: Squared current weight of the trained neuron.

N_D: Matrix row dimension (Order).

N_P: Matrix column dimension (Order).

3.2.1.4 Conjugate gradient backpropagation with Powell-Beale restarts

This method is preferred by many researchers since it is minimizing the number of required functions to represents the variables. In addition, it does not require any storage to store matrices. This causes the convergence rate to have linear nature. However, if the procedure is restarted repeatedly the convergence might be nonlinear. The method depends highly on the norms of the data points slops which is represented in Equation 3.3 (Saini et al. 2002).

$$|\nabla_{k-1}^T \nabla_\mathrm{k}| \geq \alpha \|\nabla_\mathrm{k}\|^2 \tag{3.3}$$

where;

∇_k: Function gradient at point k.

α: Varies between 0.9 and 0.1(usually 0.2 is selected).

T: Transpose of the matrix.

3.2.1.5 Conjugate gradient backpropagation with Fletcher-Reeves updates

This method is starts by defining the steepest gradient along the decreasing direction then it modifies it using the coefficient presented in Equation 3.4 where the new direction function is present in Equation 3.5 (Chatterjee. 2019).

$$B_k = \frac{\nabla_k^T \nabla_\mathrm{k}}{\nabla_{k-1}^T \nabla_\mathrm{k-1}} \tag{3.4}$$

$$P_k = -\nabla_\mathrm{k} + B_k P_{k-1} \tag{3.5}$$

where;

P_k: The direction functions.

B_k: Modification coefficient of the direction function.

∇_{k}: Function gradient at point k.

T: Transpose of the matrix.

3.2.1.6 Conjugate gradient backpropagation with Polak-Ribiére updates

The method is very similar in nature Conjugate gradient backpropagation with Fletcher-Reeves updates. However, the modification function is slightly altered as presented in Equation 3.6 (Charalambous. 1992).

$$B_k = \frac{\nabla_{k-1}^T \nabla_{\mathrm{k}}}{\nabla_{k-1}^T \nabla_{\mathrm{k-1}}} \tag{3.6}$$

where;

B_k: Modification coefficient of the direction function.

∇_{k}: Function gradient at point k.

T: Transpose of the matrix.

3.2.1.7 Gradient descent backpropagation

This method is rather hard to apply and slow to converge since it requires differentiable functions for all of input data, weight and transfer functions. However, this method is rather characterized by its simple structure. The gradient is represented in Equation 3.7 which is multiplies by every single parameter (Silva, 1990).

$$\nabla = lr \frac{d\,Per}{dx} \tag{3.7}$$

where;

∇: The gradient descent coefficient.

lr: Learning rate.

Per: Performance of the training.

3.2.1.8 Gradient descent with adaptive learning rate backpropagation

This method is quite similar to the Gradient descent backpropagation the only difference that it is highly sensitive to the learning rate where high learning rate may cause the model to oscillate. On the other hand, slow rate will cause the convergence process to be rather slower. Gradient is described in Equation 3.7 (Riedmiller. 1994).

3.2.1.9 Levenberg-Marquardt backpropagation

This method basically works on the basis of minimizing the sum of square roots error since it uses as function for the performance of the model. Unlike Quasi-Newton this method is conducted without the development of the second order hessian matrix. The gradient of this method is obtained by the multiplication of the transpose of the Jacobean matrix by unit vector of the error of the network as shown in Equation 3.8. The Jacobean matrix is developed by taking the derivative of sum of square root error with respect to both weight and biases of the network (Sapna. 2012).

$$\nabla = J^T e \tag{3.8}$$

where:

∇: The gradient descent coefficient.

J^T: The Jacobean matrix that is developed based on the sum of square root error derivative

e: Unit vector of the network error.

3.2.1.10 One-step secant backpropagation

The methods of conjugate gradient algorithm require small number of storages unlike the BFGS method. For this purpose, one-step secant backpropagation method is developed among to overcome this problem between the other two methods. This is achieved by assuming that the hessian is the identity matrix for every iteration which would eliminate the need of finding the inverse of the matrix. Although, the storage is reduced using this method, the conjugate gradient still faster and requires less storage (Upadhyay. 2013).

3.2.1.11 Resilient backpropagation

When constructing multilayer network, the transfer functions are often turned into what is defined as squashing function. Since the function try to compress the infinite set of data into a finite set. This causes the gradient of the data set to approach zero as the input magnitude increases. Which will yield no to small variation in the weights and biases upon iterations. Thus, resilient backpropagation algorithms is constructed to bridge over these problems. Where this method eliminates the magnitude of the derivative and rather focus on the sign of the gradient as shown in Equation 3.9 (Naoum. 2012).

$$dx_{k+1} = (x_{k+1} - x_k)\ sign(\nabla \mathrm{f}(\mathrm{x_k})) \tag{3.9}$$

where;

dx_{k+1}: Partial derivative of the input data.

$sign(\nabla \mathrm{f}(\mathrm{x_k}))$: Sign of the gradient only without considering its magnitude.

3.3 Multiple Linear Regression Analysis

Basically, linear regression can be defined as the relationship between two variables where the main aim is to fit an equation to a real case data. It is clear that an excellent relationship in between variables without any error is not expected. On the other hand, expectation is to build a useful equation due to the aim and a strong relationship in between variables in order to get the reliable prediction for the case with high accuracy. So, statistical programs build regression line for the given data such that determines the equation that will give the closest line for the given data points. It is somehow minimizing the error of prediction or it is said to be squared deviations. Error of prediction or squared deviation is the difference between the regression line and the actual data points. The length between each data point and regression line is squared and added to get the summation of the squared deviations which represents the error of prediction for the data set in a study. It is noted that these values should be squared in calculation because they might be positive or negative and they sum to zero when it is not squared. So, that's why the regression line is the closest line determined to all the data points in order to minimize the squared deviations by means of minimizing the error of prediction.

3.3.1 Methodology of analysis

Multiple linear regression analysis is widely used statistical methodology in many research fields in order to determine the relationship between one continuous dependent variable and a set of data which is made of two or more independent predictor variables for the predictions. The main reason why it is called as multiple regression is that there are more than one and many independent variable parameters which is used in the analysis. There are several approaches to build regression model according to the aim of the study. Therefore, it is possible to build the best model to perform in accordance with the aim of the specified study due to the expectations. Moreover, two principles are applied to regression modelling in general. One is that, each and every variable should explain its own statistically significant amount of variance in the outcome variable. Another one is, it should be expected that some of the predictor variables will be correlated with one another as well as the dependent outcome variable in case of dealing with multiple predictors. Addition or removal of a variable to the model probably will affect the coefficients of all the variables in this case. So, it is possible to comment about significance of one variable in terms of prediction in a model that is including other variables as well instead of commenting on one variables significance in terms of prediction alone in the outcome regardless of other predictor variables.

Linear regression model equation is given as;

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \tag{3.10}$$

where,

y: Dependent outcome variable

β_0: The intercept

x_1: First independent predictor variable

β_1: Coefficient of first predictor variable

ε: Error

Multiplication of the observed independent predictor variable parameters with its coefficients and addition of these to the intercept leads to calculate the predicted outcome. The difference between the predicted outcome and the observed predictor variable is error in any case study. The main aim of the determination of coefficients is to minimize the error. The error is the difference between the regression line and the data point.

3.4 Identification of Predictor Variable Importance

There are several methods to determine the statistical significance in prediction of predictor variables that have been used in a multiple linear regression model. In other words, it is important to notice that, there is no unique solution for the assessment of variable importance. Therefore, as mentioned in literature, it is possible to follow any of these approaches which is suitable for the data under the related condition that is specified in order to reach reliable results.

3.4.1 Standardized regression coefficient

Standardized regression coefficients are measurement of the transformation that take place in the variable criterion for every single standard deviation variation in a predictor variable while maintaining the other predictors in the model as constant. Regression weights are called as Beta weights as well when the predictor variables are standardized. Each of them is representing the total effect of an independent predictor variable which measure each of the independent variables involvement to the regression equation while the variance contributions of all other predictors in the regression model have been calculated for. The standardized coefficient of each predictor states its importance. It is the often used valid methodology in the assessment of predictor variable importance in literature. Also, it is recommended in literature to start multiple regression analysis due to the advantages such as the ease of application with statistical software at the initial stage in order to assess variable importance order of contribution (Nathans, Oswald, Nimon, 2012). The formula which is used in converting the normal coefficients into standardized ones is presentenced in Equation (3.11).

$$\alpha_i' = \alpha_i \sqrt{\frac{x_i^2}{y^2}} \qquad (3.11)$$

where;

α_i': The standardized regression coefficient.

α_i: The regression coefficient obtained by multiple variable linear regression analysis.

x_i: The input values for a given variable.

y: The corresponding output of x_i.

3.4.2 Zero-order correlation method

Zero-order correlations are indicating the direct effect of each predictor variable which means that the measurement of the involvement of each independent predictor variable to the regression equation while measured separately from other independent predictor variables. Zero-order correlations shows the bivariate correlation between independent predictor and dependent outcome variables. The correlation coefficient displays both the magnitude and direction relations between two independent predictor variables. Zero-order correlation method is preferred to use as well due to the determination of true contribution of variables to the variance among other methods and ordering the independent predictor variables by their importance. In addition, there are several advantages to use this method such that it is more sensitive against errors than other methods. Also, it is the only method that determines how much variance is directly shared between the independent predictor and dependent outcome variables (Nathans, Oswald, Nimon, 2012). The zero-order correlation method for each and every predictor variable is evaluated by the raw data obtained from the performance analysis results using Equation 3.12.

$$r^2 = \left(\frac{\sum y x_i}{\sqrt{\sum y^2 \sum x_i^2}} \right)^2 \tag{3.12}$$

where;

r^2: Zero-Order Correlations coefficient.

x_i: The input values for a given variable.

y: The corresponding output of x_i.

3.4.3 Product measure of standardized regression coefficient and zero-order correlation

According to Nathans, Oswald and Nimon (2012), the product measure is calculated by the multiplication of the variable's zero order correlation by its beta weight which is standardized regression coefficients obtained from the multiple linear regression analysis. Thus, the product measure turns out to be the consideration of both direct and total effects in one statistic. So, this method is recommended to use due to the ease of computation method of partitioning R^2 even in the existence of correlated predictors.

3.4.4 Determination of predicting variable importance using P-value

Boslaugh (2012) explained as the p-value is the probability of obtaining a result as extreme as the one in current analysis data. Level of significance is specified by the 'α' (alpha) which is set at 0.05. The value 0.05 was determined which is explained as the tolerability of 5% error in literature of statistics as a cutoff point while determination of significance. Regarding these, the criteria followed is that if the p-value of the relating variable is smaller than 0.05, it is considered as statistically significant and the lower the p-value is, the higher significance of the relating variable among all predictor variables by means of sorting them according to the importance.

3.4.5 Variable elimination method

The main idea of this method is to identify the difference between the R^2 obtained by the multiple linear regression analysis and R^2 determined by the removal of one predictor variable in order to see the significance on the model which is expressed in the Equation 3.13 below;

$$R^2(M\backslash S) = R^2(\mathrm{M} \cup \mathrm{S}) - R^2(\mathrm{S}) \tag{3.13}$$

where:

$R^2(M\backslash S)$: Difference in between the accuracy determined by the multilinear regression with all predictor variable data and and the accuracy obtained from the multilinear regression analysis model by removal of relating predictor variable.

$R^2(\mathrm{M} \cup \mathrm{S})$: Accuracy obtained by the model with data that is used considering all predictor variable.

$R^2(S)$: Accuracy determined by the model with data that is used including removal of relating variable.

Chapter 4

RESEARCH METHODOLOGY

4.1 Introduction

Detailed descriptions of the selected cases in terms of their geometry and the numerical modeling of the structural elements is presented in this chapter. In addition, to the construction of the adopted ANN model for the prediction of building seismic performance.

4.2 Research Approach

The aim of this study is to developed two different methods for the seismic performance assessment through artificial neural network and multiple linear regression analysis as well in order to predict buildings seismic performance that are located in Istanbul province in accordance with TBEC2018. For this purpose, 5 story reinforced concrete buildings with both regular and irregular plans are designed in accordance with the Turkish earthquake codes (TEC1975, TEC1997, TEC2007 and TBEC2018) under different ground acceleration and different ground types (various spectral acceleration from Istanbul region). Followed by seismic performance assessment in accordance with TBEC2018. The large collected data are used as input and output for the training of the ANN where its prediction results are validated afterwards. Also, application for a case study with various parameters within the range of existing study is considered in order to check the validity of the created performance prediction method. In addition, multiple linear regression analysis is conducted by using the same data as an alternative method as well. Moreover, input parameters are sorted in accordance with their significance by using several methods since there are several input parameters in the study which has effect on the performance of the existing buildings under earthquake loads. Summary of the research approach is presented in flow chart form (Figure 4).

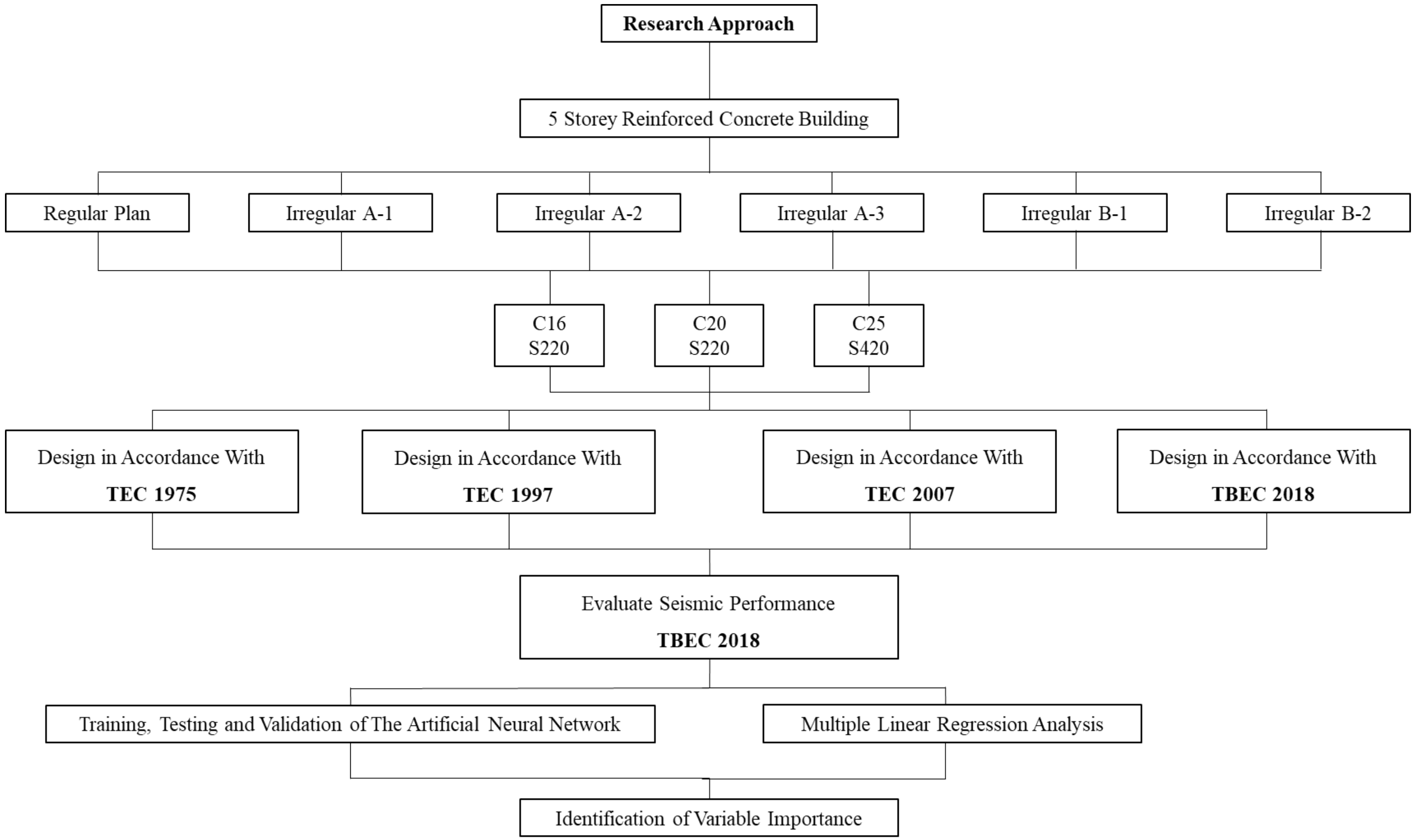

Figure 4: Flow chart of the research approach

4.3 Location of the Assumed Buildings

The buildings are located at various location of Istanbul province in order to cover wide ranges of ground peak acceleration ranging between 0.2g-0.55g (10% of exceedance within 50 years) in addition to various types of site classes ZA, ZB, ZC, ZD, and ZE (TBEC 2018). Figure 5 presents the diversity of shear wave velocity in Istanbul.

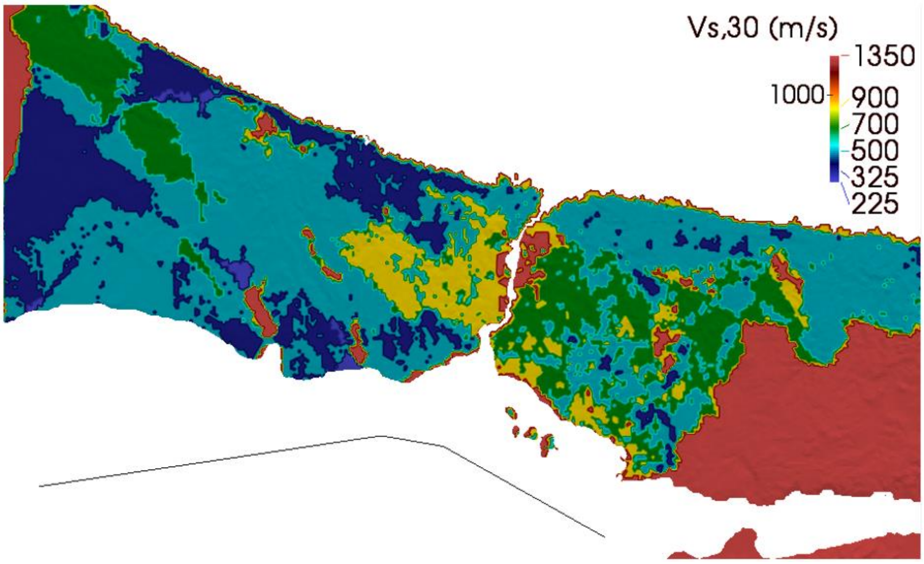

Figure 5: Shear velocity at various location in Istanbul province (Özgül, 2011)

4.4 Buildings Geometry

The 5 story RC buildings with a max span of 5 meters are in orthogonal directions. The typical stories and ground story height is set to 3 meters in most cases. This considered geometries are presented as follow;

4.4.1 Regular building

The building is assumed to be symmetric along both axis with a typical span between the column of 5 meters expect around the stair case where the span is reduced to 4 meters. The building is regular along both plan (center of rigidity matches with the center of mass) and elevation where all floor height are 3 meters. The building plan is presented in Figure 6, and the three-dimensional representation is displayed in Figure 7.

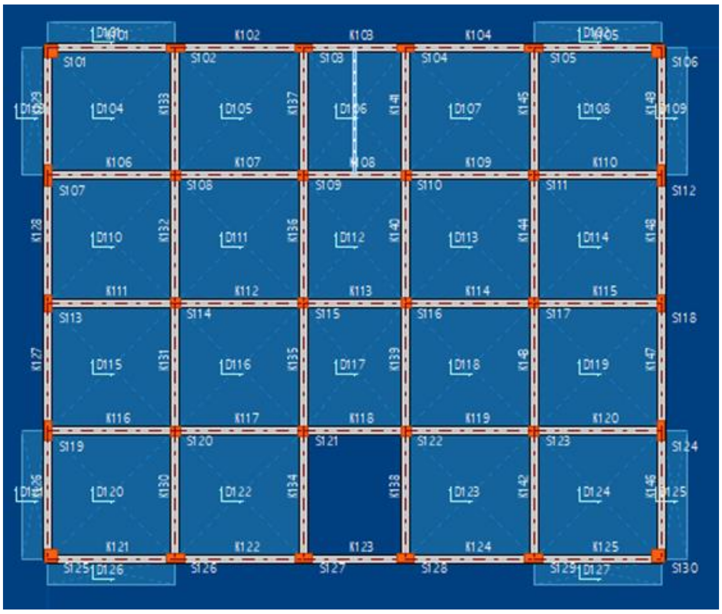

Figure 6: Geometric plan of the regular building

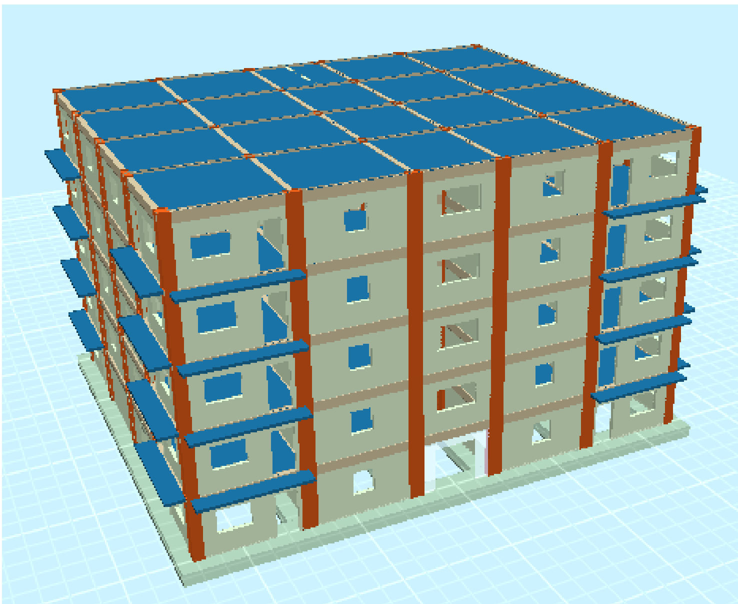

Figure 7: 3D view of the considered regular building

4.4.2 Building with torsional irregularities (A1)

Building is considered to be torsional irregular when the ratio of max displacement to the minimum displacement of a given story is larger than 1.2 (TBEC2018). This was achieved by increasing the column dimensions unsymmetrically causing the center of rigidity to shift upwards as shown in Figure 8. Ultimately the height of the story is kept constant (3 meters) which can be observed in the 3D representation of the structure in Figure 9.

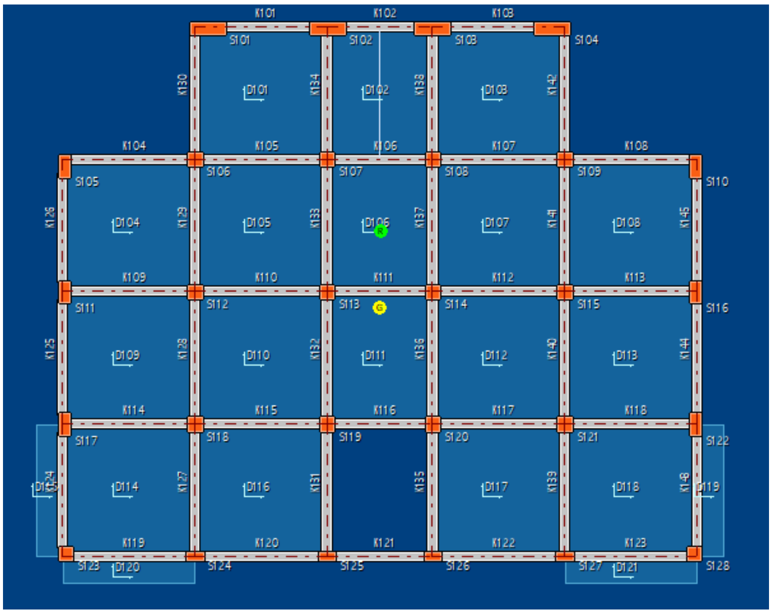

Figure 8: Geometric plan of the torsional irregular building

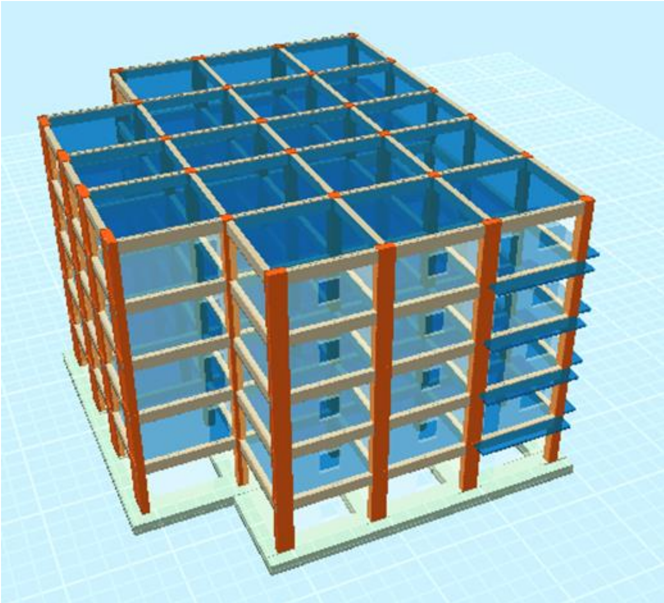

Figure 9: 3D view of the considered torsional irregular building

4.4.3 Building with slab discontinuity irregularities (A2)

A building is considered to be irregular from type A2 along the plans when the total area of the openings within a given floors exceeds one third of the total area. This was achieved by equipping the building with large lightwell (which is used for sustainability measures) as shown in Figure 10 and Figure 11.

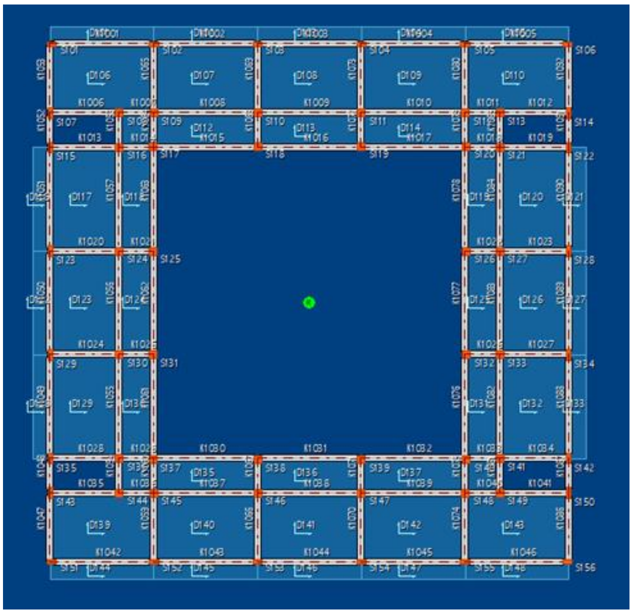

Figure 10: Geometric plan of the slab discontinuity irregular building

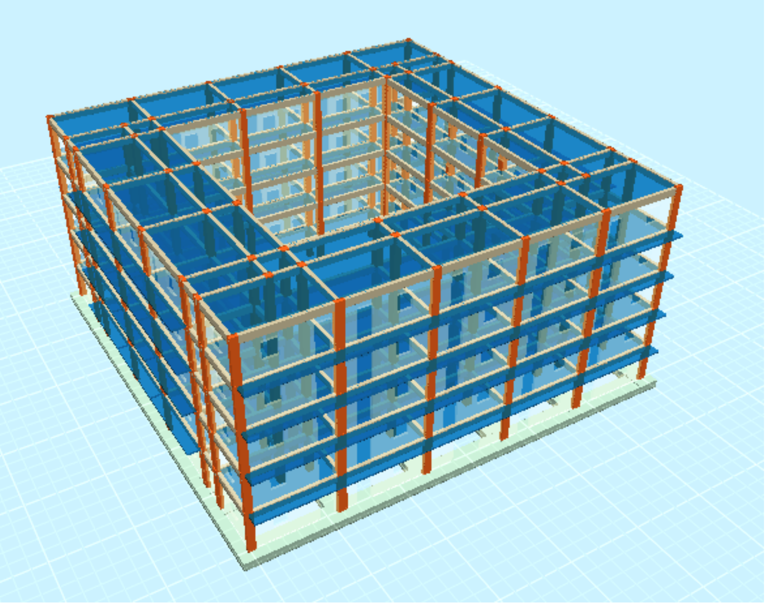

Figure 11: 3D view of the slab discontinuity irregular building

4.4.4 Building with projection in plan irregularities (A3)

Building is considered to be irregular from category A3 when the discontinuity along the plan exceeds the 20% ratio of the tallest parallel length. This was achieved by modeling unsymmetrical building with an L shape as presented in Figure 12 and Figure 13.

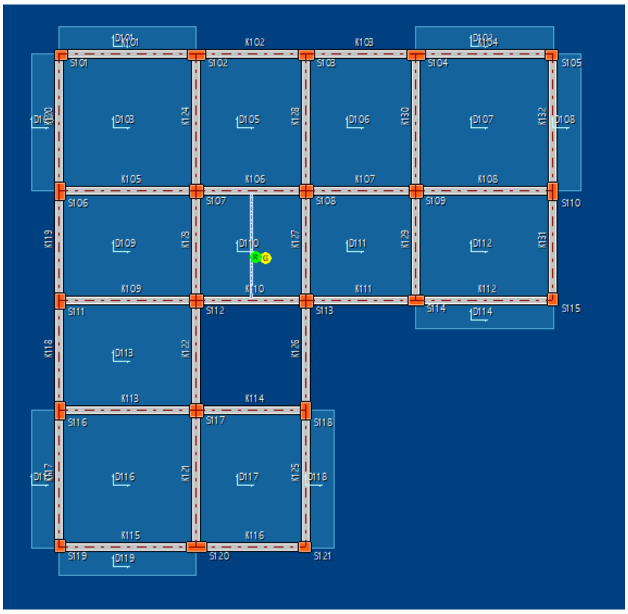

Figure 12: Geometric plan of the projection in plan irregular building

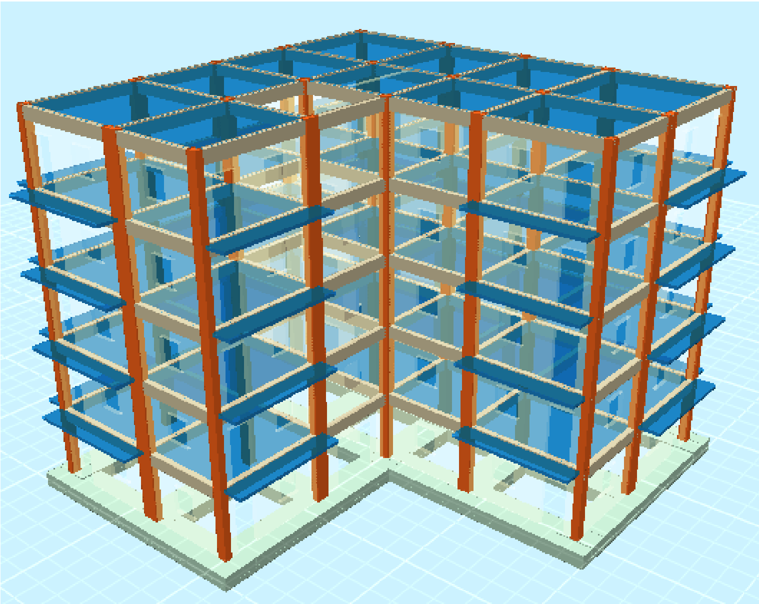

Figure 13: 3D view of the projection in plan irregular building

4.4.5 Building with weak story irregularities (B1)

In accordance with TBEC2018 a building is consider to be irregular along elevation with weak story irregularities when the area of the lateral forces resistant (columns area, shear walls area, 0.15 of walls area) is reduced by 80% or more. This was achieved by removing the walls of the first floor as shown in Figure 14 and Figure 15 for the plan and elevation respectively.

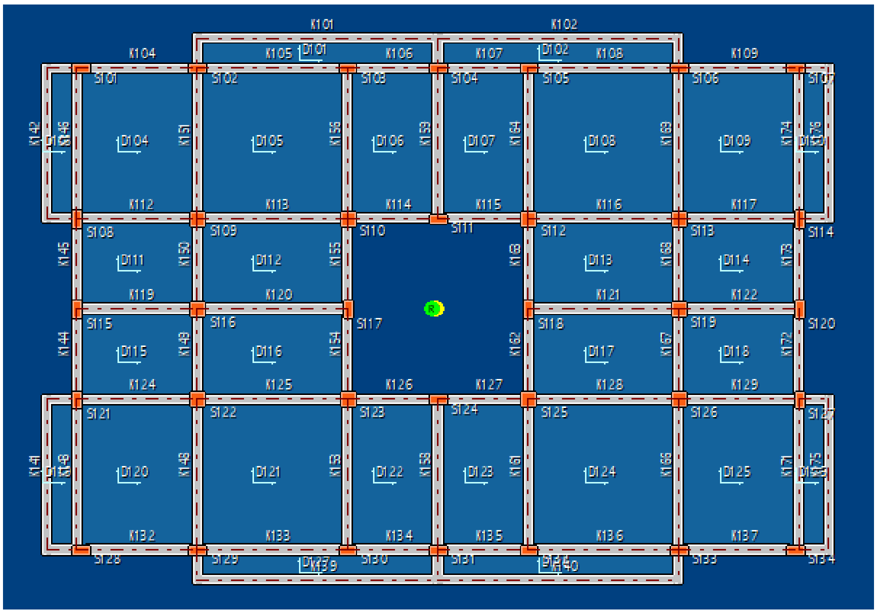

Figure 14: Irregular building weak story geometrical plan

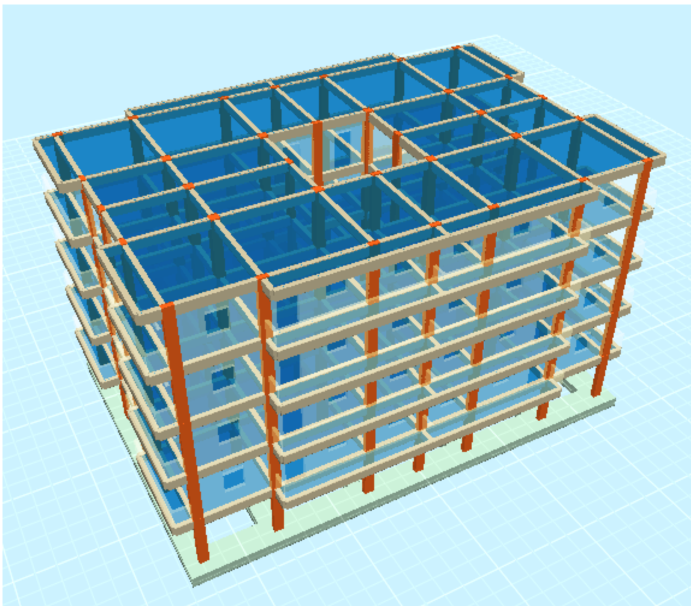

Figure 15: Irregular building weak story 3D view

4.4.6 Building with soft story irregularities (B2)

In accordance with TBEC2018 a building is consider to be irregular along elevation with soft story irregularities when the ratio of the floor drift ratio to either top or bottom ratio is larger than 2. This was achieved by increment of 4^{th} floor height to 3.6 m and decrement of 5^{th} floor height to 2.7m, while keeping other floors height as 3 meters. In Figure 16 and Figure 17, the proposed three-dimensional view is illustrated.

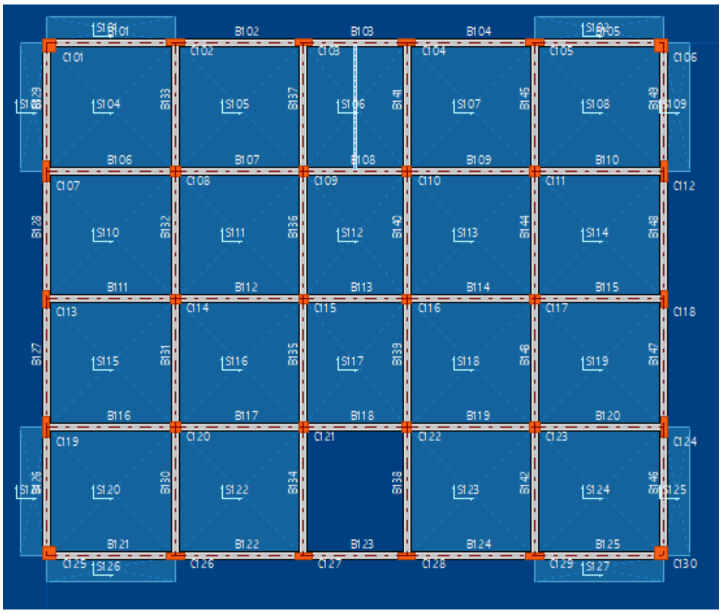

Figure 16: Geometric plan of the soft story irregular building

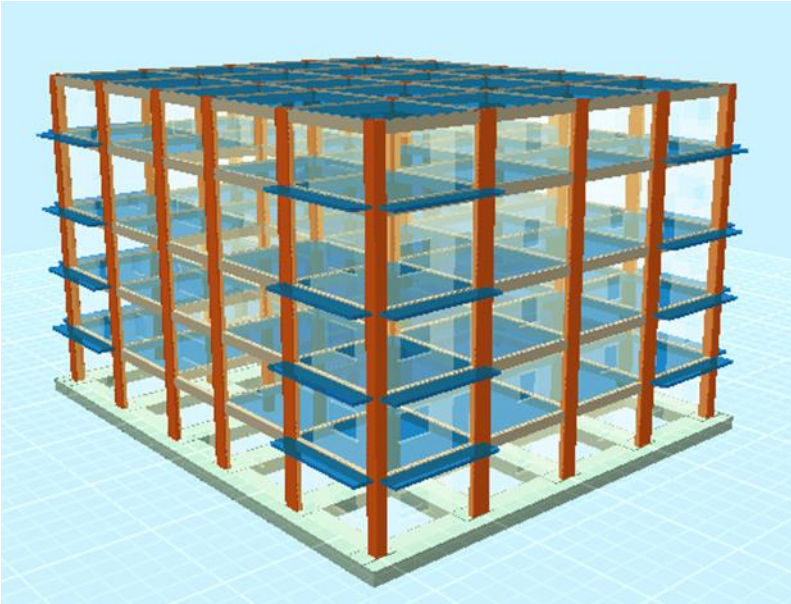

Figure 17: 3D view of the soft story irregular building

4.5 Structural Models

The structures with geometry identified in section 4.4 are modeled, analyzed, and designed using STA4CAD software. Where buildings initially are designed (sections capacity and reinforcement) with respect to gravity loads and lateral loads of the considered earthquake code (TEC1975, TEC1997 and TEC2007). Then nonlinear static pushover analysis is initiated to identify the building performance in accordance with TBEC2018.

4.6 Buildings Category with Respect to TBEC2018

Before calculating the earthquake forces that will act on the selected structure multiple parameters are need to be identified which are listed as follow;

4.6.1 Buildings usage category (BKS)

This parameter scales the earthquake forces to accommodate the function of the considered buildings. Since all the building considered in this research are assumed to be for residential use the buildings are from category BKS=3 (i.e. I=1) as shown in Table 1.

Table 1: Building importance factor (TS2018)

Building usage category	Purpose of the considered building	Importance factor (I)
BKS=1	Buildings which are necessary after the occurrence of earthquake, buildings which are intensively used by people, and buildings which are used as storage for precious or dangerous material.	1.5
BKS=2	Buildings which are used intensively by people for limited time.	1.2
BKS=3	Other buildings	1.0

4.6.2 Building design category (DTS)

This parameter is linked to short period acceleration for Spectral acceleration with 10% exceedance within 50 years. For this reason, the building design category is DTS=1 since S_{DS}> 0.75 for all the considered cases as mentioned in TBEC2018 Table 3.2.

4.6.3 Building height category (BYS)

This parameter is thoroughly linked to the building net height above the ground level. For this purpose, the building height category for all considered structure is BYS=6 since all building height is less than 17.5 meters and larger than 10.5 meters as mentioned in TBEC2018 Table 3.3.

4.6.4 Building performance target

Based on the above parameters the building performance target should be controlled damage (KH) as mentioned in TBEC2018 Table 3.4, Part C.

4.7 Pushover Analysis

In this study the nonlinear static pushover analysis is conducted in accordance with TBEC2018. This analysis is selected since it is widely used in the literature for the performance-based design. In this analysis method, step by step increment of lateral forces are analyzed by taking into consideration the domain of the structure modal vibration shape amplitude and the mass sources in both orthogonal directions. In addition, the secondary moment resulted from the P-Delta effect is also considered.

4.8 Artificial Neural Network

In this research, MATLAB 2018 neural network module is used in this study to construct and train the network. Feed forward artificial neural network composed of three layers structure is adopted. The general structure of the network is composed of multiple input cells followed by multiple hidden layer defined by the user and an output layer, where all of which are interconnected. The input layers are determined to be the variety of considered parameters which are listed as follow;

1- Designed earthquake standard (TEC1975, TEC1997, TEC2007, or TBEC2018)
2- Type of the building (regular, A1, A2, A3, B1, B2, or week column strong beam)
3- Designed peak ground acceleration (0.1, 0.2, 0.3, or 0.4)
4- Performance check peak ground acceleration (0.2, 0.3, 0.4, or 0.55)
5- Designed soil type (Za, Zb, Zc, or Zd)
6- Performance check soil type (Za, Zb, Zc, Zd, or Ze)
7- Designed concrete grade (C16, C20, or C25)
8- Designed reinforcing steel grade (S220, or S420)

Meanwhile, the output layer is composed of 4 main results which are listed as follow;

1- Immediate occupancy (KK)
2- Controlled damage (KH)
3- Collapse prevention (GO)
4- Collapse case (GD)

Since there are no guidance on the number of the hidden layer that should be used it will be determined through trail and errors technique which will be discussed thoroughly in the results and discussion chapter.

Back propagation technique is adopted to train the network which is derived through the chain rule presented in calculus theory. Multiple back propagation algorithm methods will be used and the optimum method will be presented later on the results and discussion chapter. The considered back propagation method are listed as follow;

1- BFGS Quasi-Newton Backpropagation.
2- Bayesian regularization backpropagation.
3- Conjugate Gradient Backpropagation with Powell-Beale Restarts.
4- Conjugate gradient backpropagation with Fletcher-Reeves updates.
5- Conjugate gradient backpropagation with Polak-Ribiére updates.
6- Gradient descent backpropagation.
7- Gradient descent with momentum backpropagation.
8- Gradient descent with adaptive learning rate backpropagation.
9- Levenberg-Marquardt backpropagation.
10- One-step secant backpropagation.
11- Resilient backpropagation.
12- Scaled conjugate gradient backpropagation.

4.9 Multiple Linear Regression Analysis

The data of the input parameters and the performance analysis results as output parameter are used to construct a prediction model through multiple variable linear regression analysis. This is achieved by converting the input and output parameters to numerical values instead of their string values. Then, these numerical data are fed into EViews 10 software which evaluated the coefficients of the linear model.

Chapter 5

RESULTS AND DISCUSSIONS

5.1 Introduction

This chapter represents the construction and results of the created ANN and MVLRA models. In addition, this chapter compares between the two approaches. Also, it involves identification of the superior variables that significantly influences the prediction model by several methods.

5.2 Artificial Neural Network (ANN) Results

The selected input parameters of the case study are fed into an ANN model that uses the feed-forward back propagation method where multiple training algorithms and multiple number of hidden layers are applied. In this part of the thesis, the performance of the training algorithms and the optimum number of hidden layers for each and every training algorithm is presented.

5.2.1 BFGS quasi-newton backpropagation

The results of the BFGS Quasi-Newton Backpropagation training algorithms with respect to the various number of hidden layers are presented in Figure 18. As observed, the confidence of the training range is fluctuating with increasing the number of hidden layers where the optimum performance for this training algorithm is achieved by using four hidden layers which yields an accuracy rate of 86%. In addition, increasing the number of hidden layers beyond 32 shows a stable performance with confidence range of 81%.

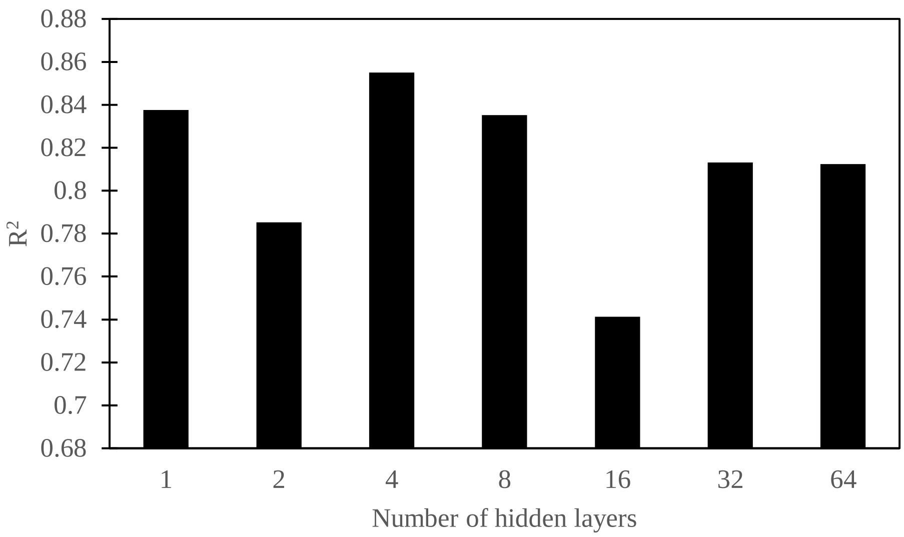

Figure 18: BFGS Quasi-Newton Backpropagation training confidence with respect to the number of hidden layers

5.2.2 Bayesian regularization backpropagation

The influence of the number of hidden layers on the performance of Bayesian regularization backpropagation training algorithm is presented in Figure 19. Results indicate that, the best performance is governed by using one hidden layer which it yield a confidence range of 88%. Ultimately, increasing the number of hidden layers by no means enhanced the performance of the neural network where the performance of the neural network degrade gradually with increasing number of hidden layers.

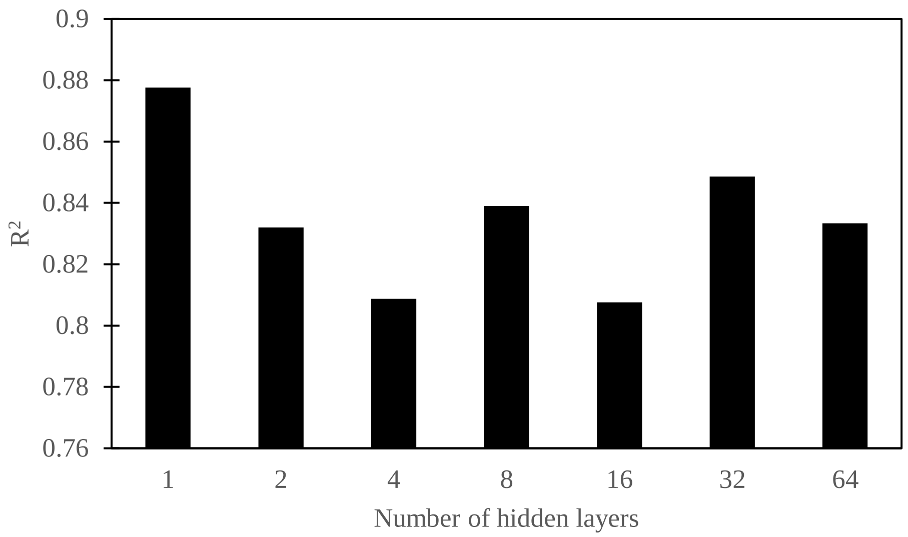

Figure 19: Bayesian regularization backpropagation training confidence with respect to the number of hidden layers

5.2.3 Conjugate gradient backpropagation with Powell-Beale restarts

The performance of Conjugate Gradient Backpropagation with Powell-Beale Restarts method with respect to the number of hidden layers are shown in Figure 20. The performance is increased by increasing the number of hidden layers until thirty-two number of hidden layers where it give an accuracy of 83%. However, the model with sixty-four number of hidden layer drops back in terms of performance.

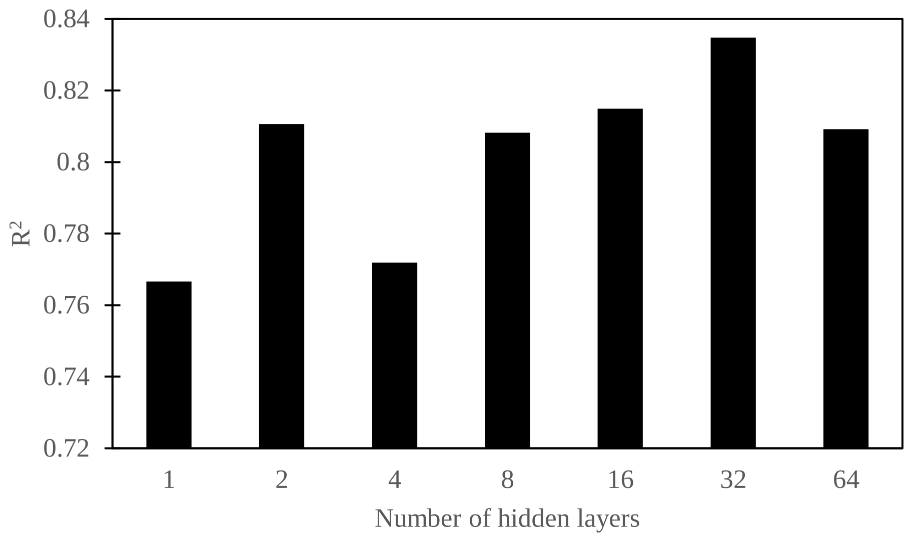

Figure 20: The performance of Conjugate Gradient Backpropagation with Powell-Beale Restarts method with respect to the number of hidden layers

5.2.4 Conjugate gradient backpropagation with Fletcher-Reeves updates

The results of Conjugate gradient backpropagation with Fletcher-Reeves updates training algorithm with respect to the various number of hidden layers are presented in Figure 21. As seen, the best performance for this training algorithm is obtained by using either sixteen or thirty-two hidden layers which yields an accuracy rate of 84% where it drops significantly afterwards using more hidden layers.

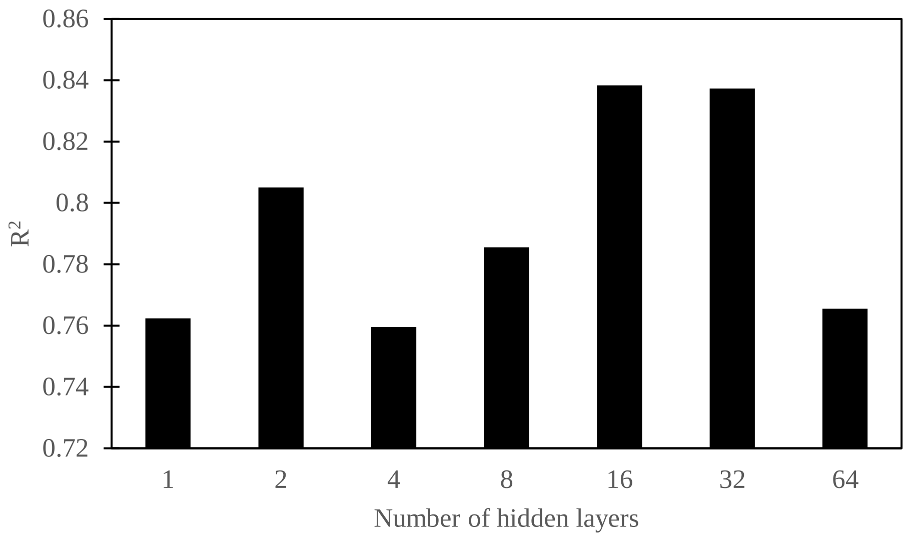

Figure 21: The results of the Conjugate gradient backpropagation with Fletcher-Reeves updates training algorithm with respect to the various number of hidden layers

5.2.5 Conjugate gradient backpropagation with Polak-Ribiére updates

The influence of the number of hidden layers on the performance of Conjugate gradient backpropagation with Polak-Ribiére updates training algorithm is presented in Figure 22. Variation of the hidden layers number in this method is not significant. However, sixteen number of hidden layer resulted very low accuracy with only 28%. The best performance is observed in this model with sixty-four hidden layer as 84%.

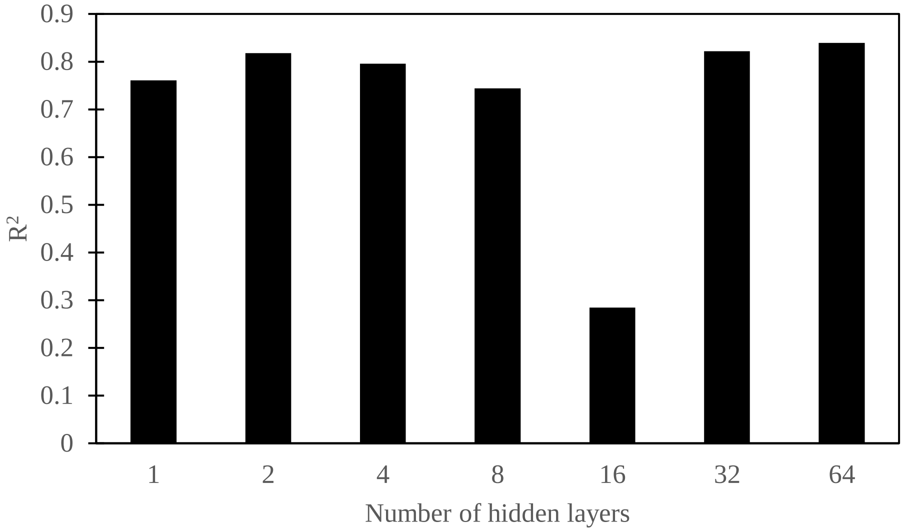

Figure 22: The influence of the number of hidden layers on the performance of Conjugate gradient backpropagation with Polak-Ribiére updates training algorithm

5.2.6 Gradient descent backpropagation

The Gradient descent backpropagation method confidence with respect to the number of hidden layers are displayed in Figure 23. The best performance of the model is achieved using four number of hidden layers with an accuracy of 80%. Increasing the number of hidden layer did not enhance the performance of the model.

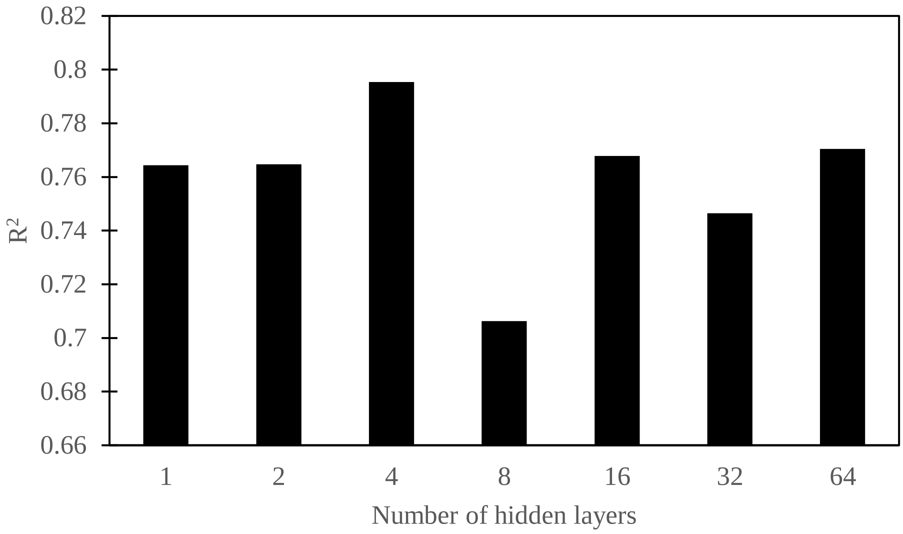

Figure 23: The performance of Gradient descent backpropagation method with respect to the number of hidden layers

5.2.7 Gradient descent with momentum backpropagation

The performance of Gradient descent with momentum backpropagation method with respect to the number of hidden layers are shown in Figure 24. The performance is observed to fluctuate by changing number of hidden layers. The model with four number of hidden layers gives the best accuracy which is 79%.

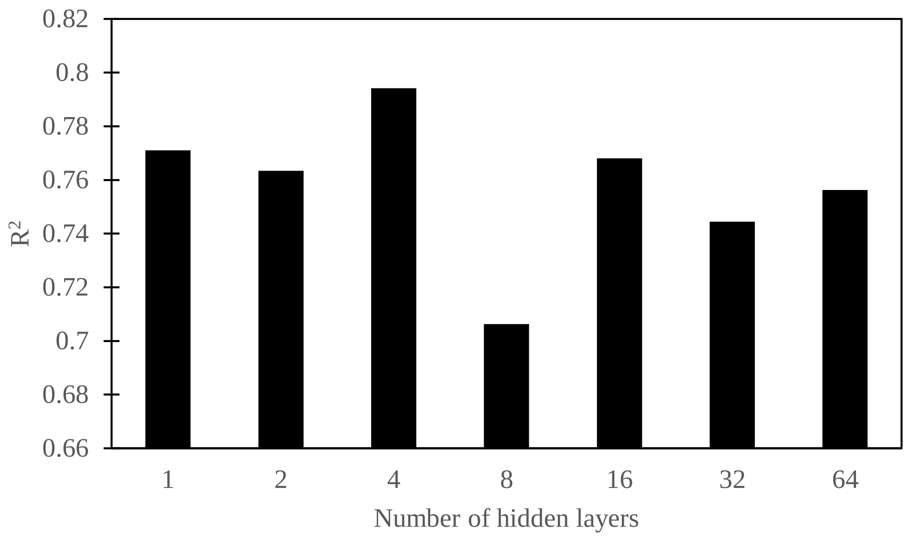

Figure 24: The performance of Gradient descent with momentum backpropagation method with respect to the number of hidden layers

5.2.8 Gradient descent with adaptive learning rate backpropagation

The results of Gradient descent with adaptive learning rate backpropagation training algorithm with respect to the various number of hidden layers are presented in Figure 25. As seen, the best performance for this training algorithm is obtained by using a number of sixteen hidden layers which yields an accuracy rate of 88% where it drops significantly afterwards using more hidden layers.

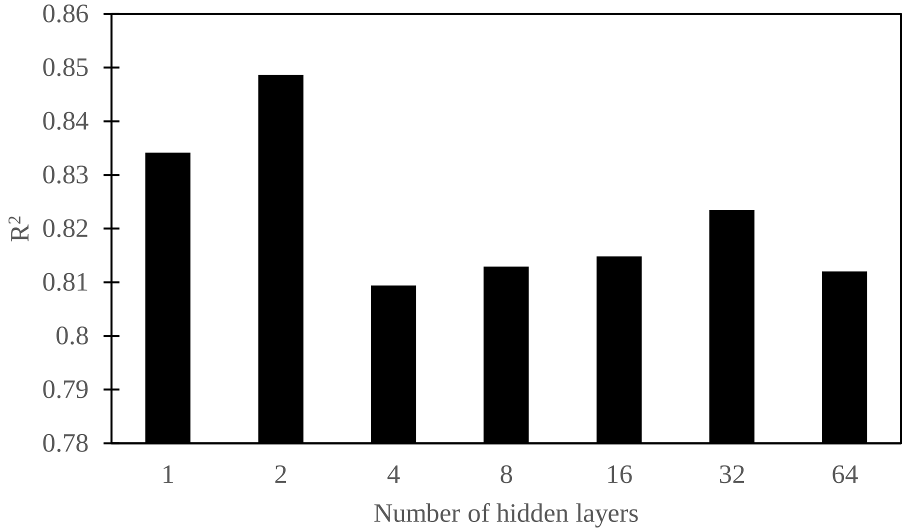

Figure 25: The performance of Levenberg-Marquardt backpropagation method with respect to the number of hidden layers

5.2.9 Levenberg-Marquardt backpropagation

The Levenberg-Marquardt backpropagation method confidence with respect to the number of hidden layers are displayed in Figure 26. The best performance of the model is achieved using eight number of hidden layers with an accuracy of 85%. Increasing the number of hidden layers did not enhance the performance of the model where at sixty-four hidden layers it reaches 73%.

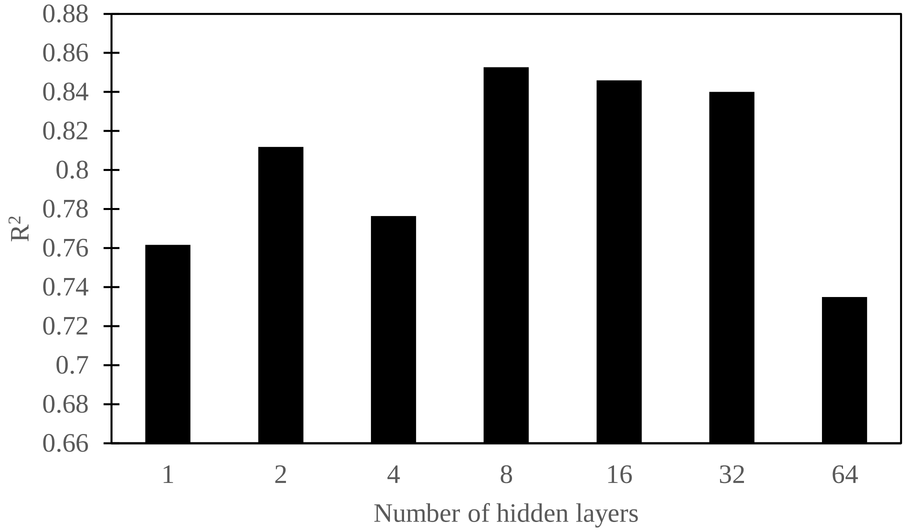

Figure 26: The performance of Levenberg-Marquardt backpropagation method with respect to the number of hidden layers

5.2.10 One-step secant backpropagation

The results of the One-step secant backpropagation training algorithm with respect to the various number of hidden layers are presented in Figure 27. As observed, the confidence of the training range is fluctuating with increasing the number of hidden layers where the optimum performance for this training algorithm is achieved by using four hidden layers which yields an accuracy rate of 86%. In addition, increasing the number of hidden layers beyond 32 shows a stable performance with confidence range of 81%.

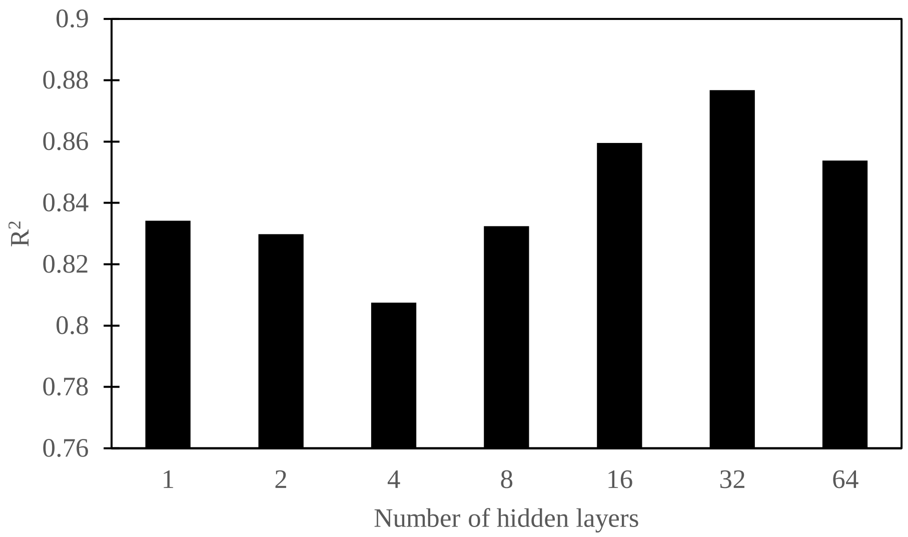

Figure 27: One-step secant backpropagation training confidence with respect to the number of hidden layers

5.2.11 Resilient backpropagation

The performance of resilient backpropagation with respect to the number of hidden layers are shown in Figure 28. From Figure 28, stability in performance is observed and increment in number of layers does not affects the outcomes where it gives an accuracy of 88% using 2 hidden layers.

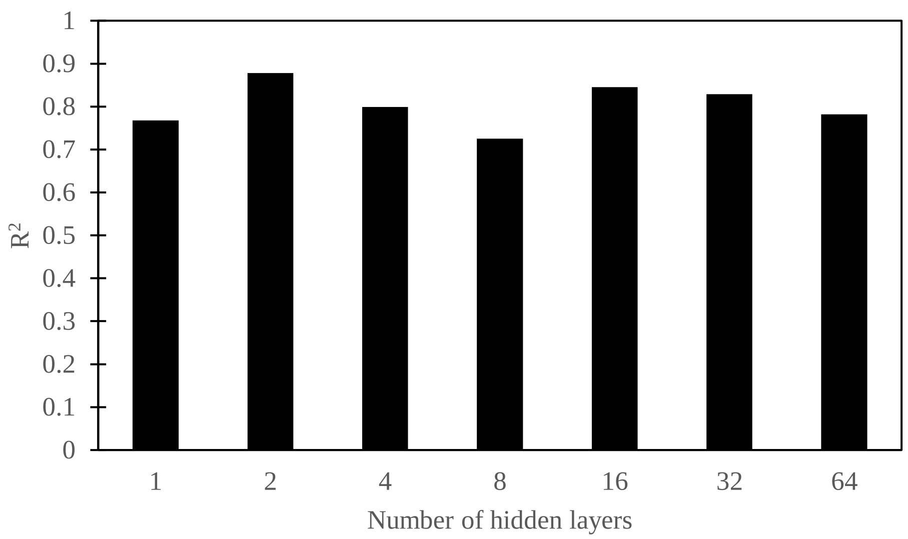

Figure 28: The performance of resilient backpropagation method with respect to the number of hidden layers

5.2.12 Scaled conjugate gradient backpropagation

The influence of the number of hidden layers on the performance of Scaled conjugate gradient backpropagation training algorithm is presented in Figure 29. Results indicate that, the performance increases with increasing the number of the hidden layers where the optimum performance is achieved by using sixty-four layers which yields a confidence range of 88%.

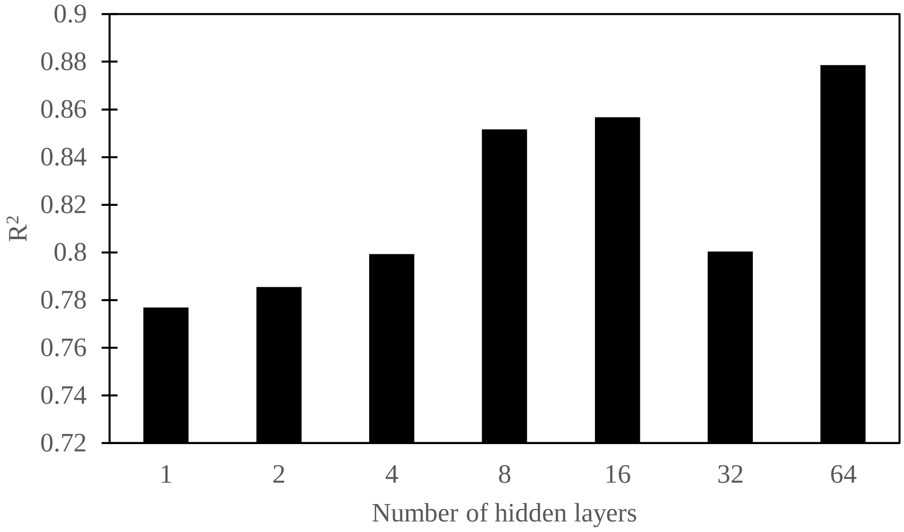

Figure 29: The performance of Scaled conjugate gradient backpropagation method with respect to the number of hidden layers

5.2.13 Optimum training algorithm

The results of the training algorithms using their optimum number of hidden layers is presented in Figure 30. As observed, the optimum training algorithm is Scaled conjugate gradient backpropagation method with an accuracy of 0.8786. On the other hand, the least accurate training algorithm is Gradient descent with momentum and adaptive learning rate backpropagation where it has an accuracy of 0.7941.

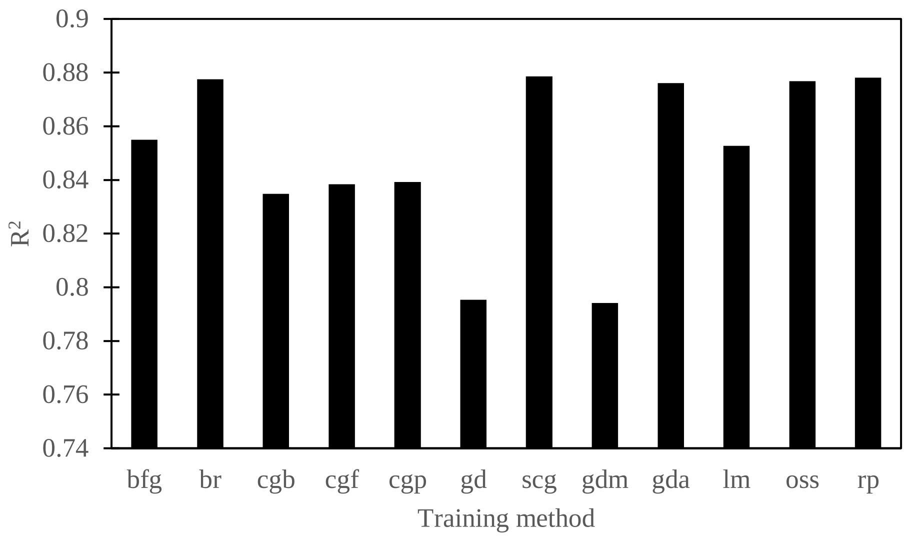

Figure 30: Accuracy of training algorithms at their optimum number of hidden layers

5.3 Application of the Artificial Neural Network Model

Table 2: Application of the created ANN model to a case study

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
EQ	TEC 1997	TEC 1975	TEC 2007	TEC 2007	TBEC 2018	TEC 1997	TEC 1975	TEC 2007	TEC 2007	TBEC 2018
IR	Reg	A1	A3	B1	B2	Reg	A1	A3	B1	B2
AD	0.4	0.3	0.2	0.1	0.55	0.4	0.3	0.2	0.1	0.55
AC	0.55	0.4	0.3	0.2	0.55	0.55	0.4	0.3	0.2	0.55
SD	Zc	Za	Zb	Za	Zd	Zd	Za	Zc	Zb	Ze
SC	Zd	Za	Zc	Zb	Zd	Ze	Zb	Zd	Zc	Ze
CG	C20	C16	C25	C25	C25	C20	C16	C25	C25	C25
SG	S220	S220	S420	S420	S420	S220	S220	S420	S420	S420
Act. Per.	GO	KH	KH	KK	KH	GO	KH	KH	KK	KH
Pred. Per.	GO	KH	KK	KK	KH	GO	KH	KH	KK	KH

Table 2 shows the predicted performance level of a case study as an application of the existing buildings with various parameters. Since the created ANN model with the optimum method of training algorithm has the accuracy of prediction of 88%, it is clearly seen from the application as well that nine out of ten building performance levels are predicted in a way correctly by using the created ANN model when compared to the actual performance levels.

5.4 Multiple Variable Linear Regression Analysis

Linear regression analysis is conducted using multiple variables. The fitting function is developed on the basis of the sum of square root error method. The obtained results are displayed in Figure 30 where 1, 2, 3, and 4 represents KK, KH, GO, and GD performance levels respectively. The fitting function is presented in Equation (5.1).

$$PER = \alpha_1 + \alpha_2 EQ + \alpha_3 IR + \alpha_4 AD + \alpha_5 AC + \alpha_6 SD + \alpha_7 SC + \alpha_8 CG + \alpha_9 SG \tag{5.1}$$

where:

PER: Performance level (KK, KH, GO, and GD),

EQ: Earthquake standard (TS1975, TS1997, TS2007, and TS2018),

IR: Irregularity type (Regular, A1, A2, A3, B1, and B2),

AD: Designed peak ground acceleration (0.1g, 0.2g, 0.3g, and 0.4g),

AC: Checked peak ground acceleration (0.2g, 0.3g, 0.4g, and 0.55g),

SD: Designed soil type (Za, Zb, Zc, and Zd),

SC: Checked soil type (Za, Zb, Zc, Zd, and Ze),

CG: Grade of concrete (C16, C20, and C25),

SG: Grade of steel, (S220 and S420).

α_{1-9}: Fitting coefficient which are presented in Table 2.

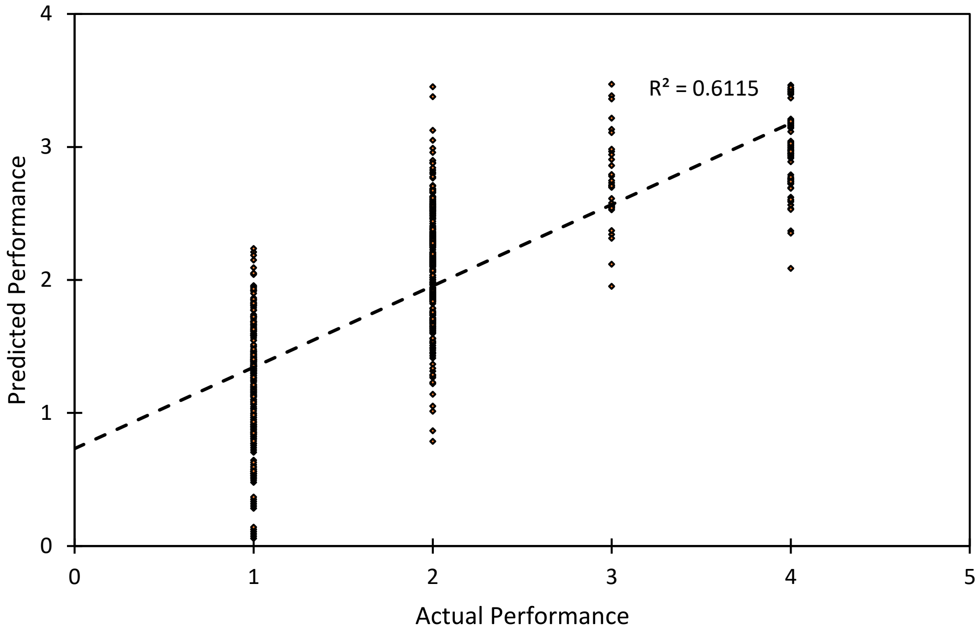

Figure 31: Predicted performance using the linear regression analysis verses the actual performance

Table 3: Fitting coefficients of the multiple linear regression analysis

Name	coefficient	Standard Error	P-value
α_1	0.045442413	0.030840533	0.141218519
α_2	-0.658243257	0.246379722	0.00777942
α_3	0.033990148	0.026330666	0.197301523
α_4	0.258251794	0.297339034	0.385489416
α_5	0.063013699	0.207331263	0.761302088
α_6	0.207070707	0.123416684	0.093971111
α_7	0.353535354	0.106961126	0.00101293
α_8	0.434066933	0.170918332	0.011381438
α_9	-0.192857143	0.040932684	3.14336E-06

5.5 Comparison between ANN and MVLRA

The obtained performance from the optimum trained Artificial Neural Network model and the Multiple Variable Linear Regression Analysis are presented in Figure 32 where 1, 2, 3, and 4 represents KK, KH, GO, and GD performance levels respectively. Results show that artificial neural network is more accurate in predicting the actual performance than the multiple variable linear regression analysis. However, it is worth to mention that both methods predict the building performances with KH level in extreme high accuracy. On the other hand, MVLRA accuracy is dramatically reduced for the GO and GD performance levels.

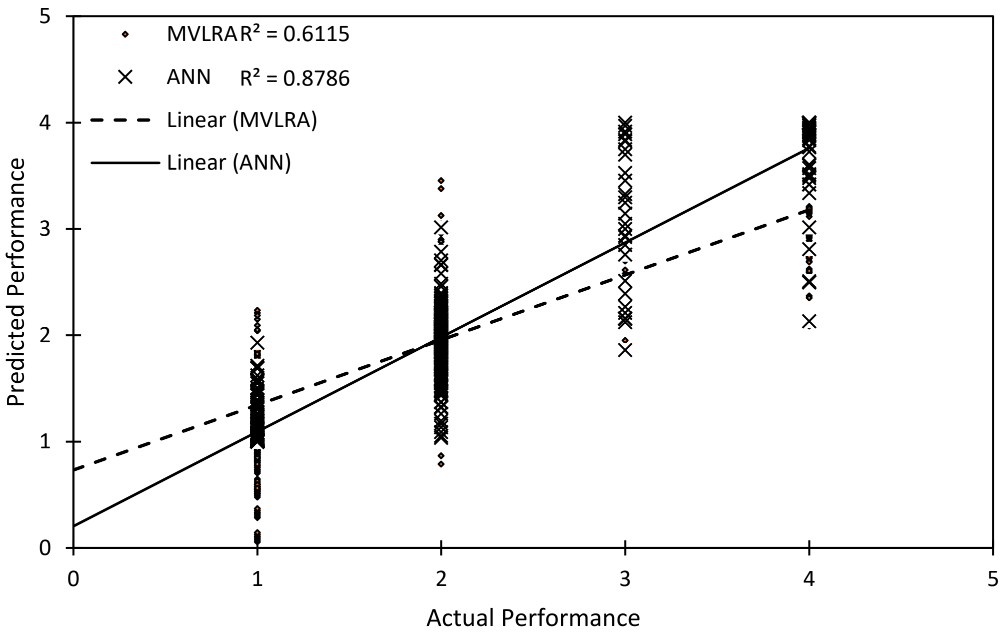

Figure 32: Comparison between performances obtained by ANN model and MVLRA

Table 4: Prediction accuracy comparison of ANN and MVLRA regarding TEC

	ANN	MVLRA
TEC 1975	0.8648	0.6321
TEC 1997	0.9147	0.6704
TEC 2007	0.6518	0.5247
TBEC 2018	0.7660	0.4630

Table 4 shows the accuracy of prediction of the created artificial neural network model and multiple linear regression analysis regarding the data obtained from the case study which are the existing buildings that are designed in accordance with several earthquake codes, respectively. It is clear that artificial neural network model has higher prediction accuracy than multiple linear regression analysis. In addition, highest accuracy of prediction among the data observed as 91% with the existing buildings which are designed with TEC 1997.

Also, Table 5 below shows the accuracy of prediction of the artificial neural network model and the multiple linear regression analysis regarding the data obtained with respect to the buildings designed earthquake codes and actual performance levels. As seen from Table 5, the accuracy of prediction for the collapse prevention and collapse case performance levels is higher than the controlled damage performance level. Although the prediction accuracy decreased for the existing classified data compared to the overall data used in creation of quick performance assessment methods, the highest accuracy of prediction is observed in determination of collapse prevention performance level of buildings which are designed according to TEC 2007 with 92% for the artificial neural network model and 79% for the multiple linear regression analysis.

Table 5: Performance level prediction accuracy comparison of the ANN and MVLRA

	KK		KH		GO		GD	
	ANN	**MVLRA**	**ANN**	**MVLRA**	**ANN**	**MVLRA**	**ANN**	**MVLRA**
TEC 1975	0.6226	0.2014	0.3193	0.1359	0.6476	0.7288	0.7762	0.7692
TEC 1997	0.3259	0.1665	0.3534	0.2189	0.7248	0.8800	0.7904	0.5950
TEC 2007	0.2762	0.0243	0.3300	0.0906	0.9213	0.7881	-	-
TBEC 2018	0.2498	0.0034	0.5207	0.1905	-	-	-	-

5.6 Predictor Variable Importance

5.6.1 Standardized coefficient method

Multiple linear regression analysis coefficients are standardized to assess the importance and order of the input variables on the prediction results. Results of the standardized regression coefficients are presented in Figure 33. It can be clearly noted that the most important predictor variable is the earthquake standard that intensely dominated the standardized coefficients. On the other hand, irregularities by no means seams to contribute or influence the prediction results since it has very minimal standardized coefficient. The order of the used predictor variable is presented as follow;

1- Earthquake standard of which the building is designed.

2- Concrete grade of the building.

3- Site class at which the performance analysis is conducted.

4- Steel grade of the building.

5- Designed peak ground acceleration.

6- Used soil type in the design process.

7- Peak ground acceleration at which the performance analysis is conducted.

8- Irregularities of the building.

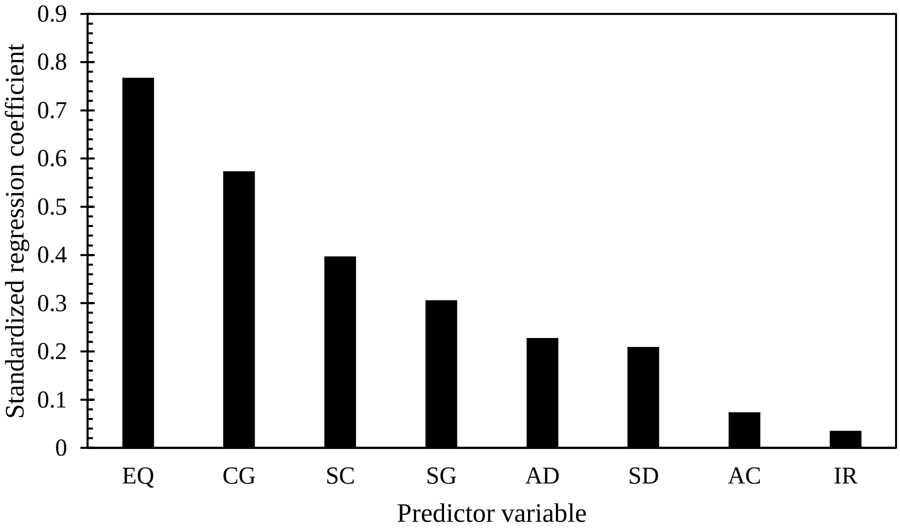

Figure 33: Order of the variable importance with respect to the standardized regression coefficients

5.6.2 Zero-order correlations method

The raw data obtained from the performance analysis results are used to evaluate the zero-order correlation method for each and every predictor variable. Results which are presented in Figure 34 indicate that there is no significance variation among the used parameters. However, the least parameters which might influence the prediction model are found to be irregularities and the earthquake standard which is used in the design of buildings.

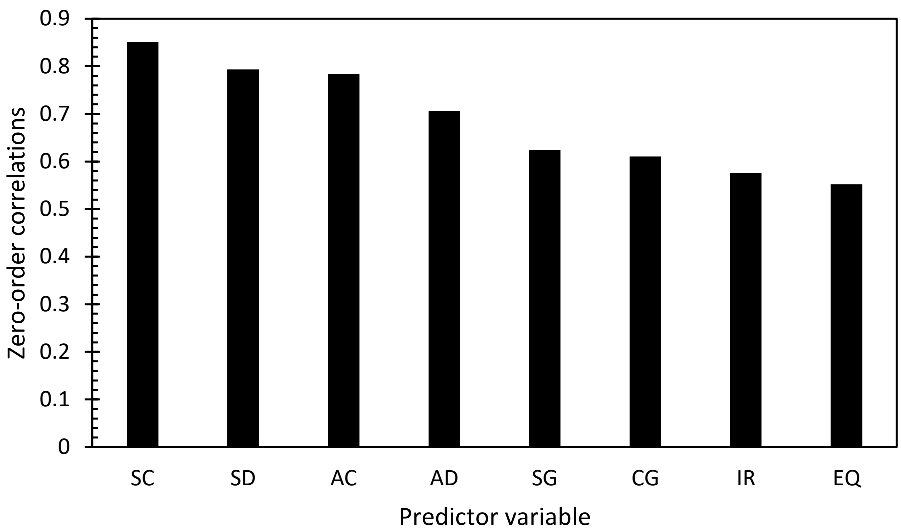

Figure 34: Variable importance order by zero-order correlations method

5.6.3 Product measure of standardized regression coefficient and zero-order correlation

As seen from the Figure 35 below, almost similar order of the predictor variables according to the importance obtained by product measure method as in standardized regression coefficient which is highly related with each other.

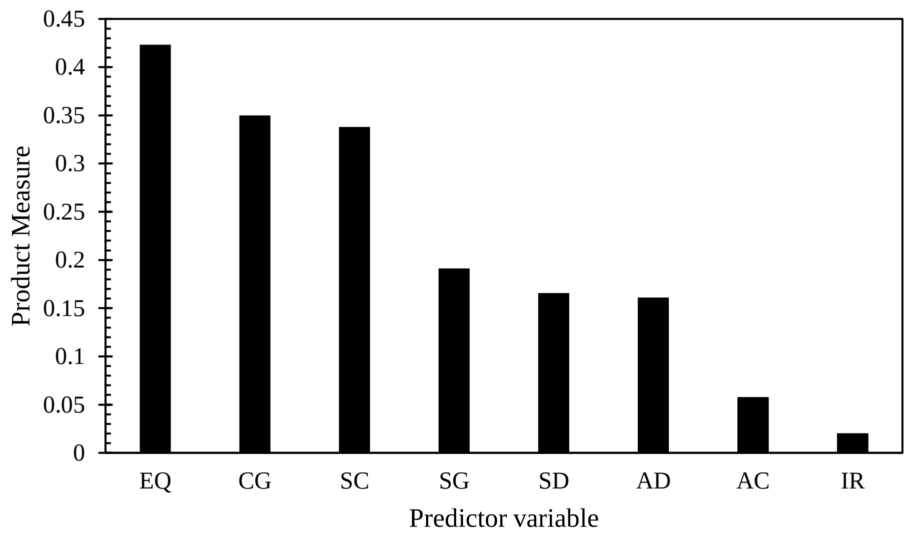

Figure 35: Order of the variable importance in accordance with product measure

5.6.4 Determination of predicting variable importance using P-value

The data obtained from the performance analysis results is used to generate multiple linear regression analysis and the p-values are determined in order to evaluate the predictor variable importance. As seen from the results shown in Figure 35 that the lower the p-value is the higher the significant predictor variable. Also, since the p-values are less than 0.05, steel grade, soil type at which performance analysis conducted, earthquake standards which the building is designed and grade of concrete predictor variables are found to be statistically significant which is playing important role in identification of performance assessment compared to the other predictor variables.

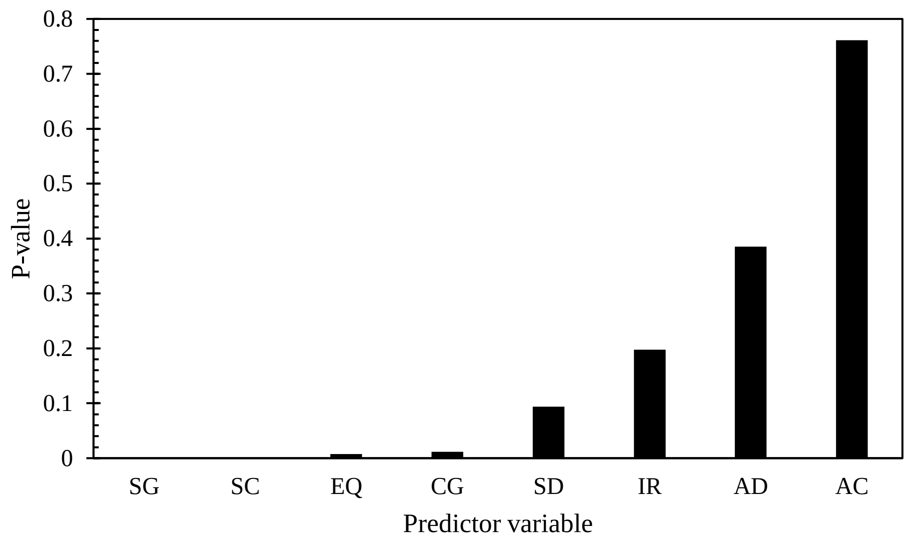

Figure 36: Variable importance order with respect to the P-value

5.6.5 Variable elimination method

Regarding the difference between the R^2 determined by the multiple linear regression analysis and R^2 obtained by removing one predictor variable, the significance of each and every predictor variable is detected as seen in Figure 37. As seen from the Figure 37 above, it is observed that the grade of steel, soil type to be used when the performance analysis conducted, designed earthquake standards of the building and concrete grade are the most significant predictor variables similarly to the other approaches.

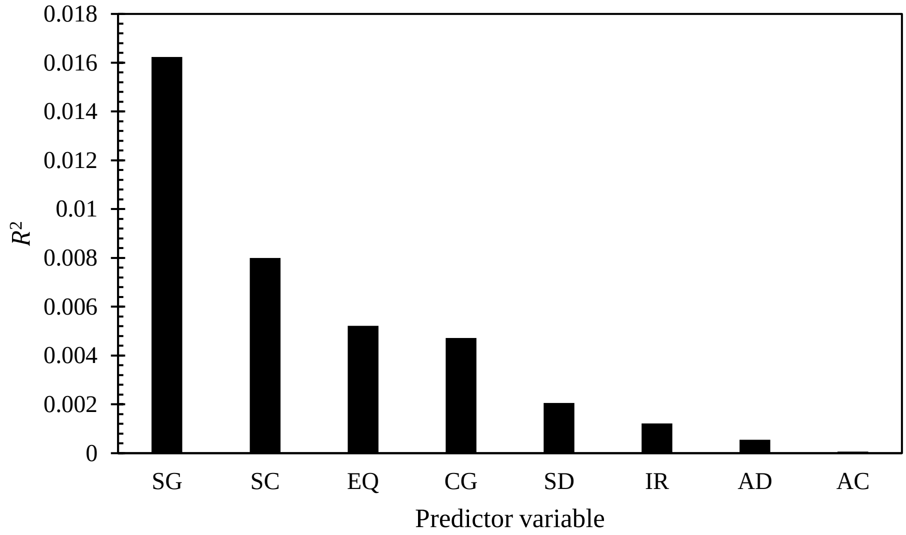

Figure 37: Order of the variables with respect to the significance which is obtained from variable elimination method

5.6.6 Comparison of different approaches regarding determination of predictor variable importance

When it is looked through the P-value and variable elimination method, it is clear that similar order of predictor variable importance. On the other hand, although in literature it is recommended to use zero-order correlation method, it gives different order instead of the all other methods that have been discussed in the existing study. Standardized regression coefficient gives almost similar results as the statistical p-value and variable elimination method as well. In general, it is clear to comment that, earthquake standard of which the building is designed, concrete grade of the building, soil type at which the performance analysis is conducted and steel grade of the building are more effective in terms of predictor variable importance on the model compared to the other predictor variables such as designed peak ground acceleration, used soil type in the design process, peak ground acceleration at which the performance analysis is conducted and irregularities of the building.

Chapter 6

CONCLUSION AND RECOMMENDATIONS FOR FUTURE STUDIES

6.1 Conclusion

In this research, quick estimation methods of buildings seismic performance under different properties and conditions are created by developing an artificial neural network model and by linear regression analysis as an alternative method as well in accordance with the latest Turkish earthquake code (TBEC2018). Hence, 540 analysis have been done regarding reinforced concrete buildings with various plan geometries, material grades, irregularities, seismic design codes, peak ground accelerations and site classes. Following are the conclusive remarks based on the statements given above:

- Number of hidden layers used in the structure of the constructed neural network influences the results of the predicted performance dramatically and every training method has its unique optimal number of hidden layers.
- Scaled conjugate gradient backpropagation training method resulted the highest accuracy (R^2 = 0.8786) compared with the other training methods at their optimal number of hidden layers.
- It can be seen from the application that nine out of ten building performance levels are predicted correctly by using the created ANN model when compared

to the actual performance levels since the created ANN model with the optimum method of training algorithm has the accuracy of prediction of 88%.

- Multivariable linear regression analysis prediction of accuracy for the building performances levels obtained as ($R^2 = 0.6115$).
- Both of ANN and MVLRA gives higher accuracy for predicting buildings performance with controlled damage. However, the accuracy is reduced for prediction the other types of performance levels.
- The predictor variables are sorted according to their significance by using standardized coefficient regression, zero-order correlation methods, product measure of these two methods, P-value and variable elimination method which are widely used in literature. Both methods agree that the least important predictor variable is the geometrical irregularities of the structure which concludes that it does not influence the seismic performance of buildings.

Finally, it can be concluded that artificial neural network performs better than multiple linear regression analysis in terms of prediction of the building seismic performance in accordance with TBEC2018.

6.2 Recommendations for Future Studies

- Fixed number of floors is used in this study where buildings that has various number of floors can be implemented as well.
- Since the building performance is evaluated for residential buildings only spectral acceleration with 10% exceedance within 50 years probability is considered. Additional studies can be done by considering other structural building types with various spectral accelerations as well.
- Only spectral acceleration data from Istanbul province are used where other provinces can be included for further research.

REFERENCES

Arslan, M. H. (2010). An evaluation of effective design parameters on earthquake performance of RC buildings using neural networks. *Engineering Structures, 32*(7), 1888-1898.

Arslan, M. H., Ceylan, M., & Koyuncu, T. (2015). Determining earthquake performances of existing reinforced concrete buildings by using ANN. *World Acad Sci Eng Technol Int J Civ Environ Struct Constr Archit Eng*, 9(8), 921-925.

Burden, F. & Winkler, D., 2008. Bayesian regularization of neural networks. In: *Artificial neural networks*. s.l.:Humana Press, pp. 23-42.

Charalambous, C. (1992). Conjugate gradient algorithm for efficient training of artificial neural networks. *IEE Proceedings G (Circuits, Devices and Systems)*, 139(3), 301-310.

Chatterjee, A. (2009). A fletcher–reeves conjugate gradient neural-network-based localization algorithm for wireless sensor networks. *IEEE transactions on vehicular technology*, 59(2), 823-830.

Chatterjee, S., Sarkar, S., Hore, S., Dey, N., Ashour, A. S., & Balas, V. E. (2017). Particle swarm optimization trained neural network for structural failure prediction of multistoried RC buildings. *Neural Computing and Applications*, 28(8), 2005-2016.

Curtis, Frank E., and Xiaocun Que. "A quasi-Newton algorithm for nonconvex, nonsmooth optimization with global convergence guarantees." *Mathematical Programming Computation* 7.4 (2015): 399-428.

Elhag, T. M. S. & Boussabaine, A. H., 1998. *An artificial neural system for cost estimation of construction projects*. s.l., In Proceedings of the 14th ARCOM annual conference, pp. 219-245.

Estêvão, J. (2018). Feasibility of using neural networks to obtain simplified capacity curves for seismic assessment. *Buildings*, 8(11), 151.

Fletcher, R., 2013. *Practical methods of optimization*. s.l.:John Wiley & Sons.

Gill, P. E., and W. Murray. "M. n. WRIGHT, Practical Optimization." (1981).

Hakan Arslan, M. (2009). Application of ANN to evaluate effective parameters affecting failure load and displacement of RC buildings. *Natural Hazards and Earth System Sciences*, 9(3), 967-977.

Hassan, A. F., & Sozen, M. A. (1997). Seismic vulnerability assessment of low-rise buildings in regions with infrequent earthquakes. *ACI Structural Journal*, 94(1), 31-39.

Hecht-Nielsen, R., 1990. *Neurocomputing*. s.l.:Addison-Wesley.

JICA, 2004. *Japan International Cooperation Agency*, Country Strategy Paper for Natural Disasters in Turkey, Ankara.

Kameli, I., Miri, M., & Raji, A. (2011). Prediction of target displacement of reinforced concrete frames using artificial neural networks. *Advanced Materials Research* (Vol. 255, pp. 2345-2349). Trans Tech Publications.

Kvalheim, O. M., Arneberg, R., Bleie, O., Rajalahti, T., Smilde, A. K., & Westerhuis, J. A. (2014). Variable importance in latent variable regression models. *Journal of Chemometrics*, 28(8), 615–622. doi: 10.1002/cem.2626

Morfidis, K., & Kostinakis, K. (2018). Approaches to the rapid seismic damage prediction of r/c buildings using artificial neural networks. *Engineering Structures*, 165, 120-141.

Naoum, R. S., Abid, N. A., & Al-Sultani, Z. N. (2012). An enhanced resilient backpropagation artificial neural network for intrusion detection system. *International Journal of Computer Science and Network Security (IJCSNS)*, 12(3), 11.

Nathans, L. L., Oswald, F. L., & Nimon, K. (2012). Interpreting multiple linear regression: A guidebook of variable importance. *Practical Assessment, Research & Evaluation*, 17(9).

Ozcebe, G., Yucemen, M. S., & Aydogan, V. (2004). Statistical seismic vulnerability assessment of existing reinforced concrete buildings in Turkey on a regional scale. *Journal of earthquake engineering*, 8(05), 749-773.

Rafiq, M. Y., Bugmann, G. & Easterbrook, D. J., 2001. Neural network design for engineering applications. *Computers & Structures*, 79(17), pp. 1541-1552.

Raftery, J., 1994. *Principles of building economics*. s.l.:Oxford, Blackwell.

Riedmiller, M. (1994). Advanced supervised learning in multi-layer perceptrons—from backpropagation to adaptive learning algorithms. *Computer Standards & Interfaces*, 16(3), 265-278.

Saini, L. M., & Soni, M. K. (2002). Artificial neural network-based peak load forecasting using conjugate gradient methods. *IEEE Transactions on Power Systems*, 17(3), 907-912.

Sapna, S., Tamilarasi, A., & Kumar, M. P. (2012). Backpropagation learning algorithm based on Levenberg Marquardt Algorithm. *Comp Sci Inform Technol (CS and IT)*, 2, 393-398.

Seely, I., 1996. *Building economics*. 4th ed ed. London: Macmillan.

Setyawati, B. R., Sahirman, S. & Creese, R. C., 2002. Neural networks for cost estimation. *AACE International Transactions*.

Silva, F. M., & Almeida, L. B. (1990, February). Acceleration techniques for the backpropagation algorithm. *European Association for Signal Processing Workshop* (pp. 110-119). Springer, Berlin, Heidelberg.

Soyluk, A. & Harmankaya, Z., 2012. The history of development in Turkish seismic design codes. *International Journal of Civil & Environmental Engineering*, 12(1), pp. 25-29.

TEC, 1975. *Specification for Structures to be Built in Disaster Areas*. Turkey: Ministry of Public Works and Settlement Government of Republic of Turkey.

TEC, 1997. *Specification for Structures to be Built in Disaster Areas*. Turkey: Ministry of Public Works and Settlement Government of Republic of Turkey.

Upadhyay, D. (2013). Classification of eeg signals under different mental tasks using wavelet transform and neural network with one step secant algorithm. *International Journal of Scientific Engineering and Technology*, 2(4), 256-259.

Uyanık, G. K., & Güler, N. (2013). A study on multiple linear regression analysis. *Procedia-Social and Behavioral Sciences*, 106, 234-240.

Yakut, A. (2004). Preliminary seismic performance assessment procedure for existing RC buildings. *Engineering Structures*, 26(10), 1447-1461.