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# Neighbour Matrix for Optimal Seismic Design of RC Frames for Minimum Total Life-Cycle Cost

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## ABSTRACT

Structures are subjected to different probable earthquake excitations in their lifetime, which have different destructive effects. Life-cycle cost analysis is an appropriate tool for assessing the structural performance to obtain the best economic scenario over its lifetime. Therefore, it is necessary to define a method for optimal seismic design with life-cycle cost objective. However, the nonlinear behaviour of structures under severe earthquakes and the need to synchronize the various constraints of the seismic code require use of innovative methods instead of optimal classical methods. In this paper, the total life-cycle cost of buildings is the optimization objective for the seismic design of reinforced concrete frames. Therefore, a simple novel optimization algorithm is introduced by defining "Neighbours Matrix". This algorithm reaches a path to minimize the objective throughout the steps, based on changing the objective function in "Neighbour RC frames". The results of optimum seismic design of RC frames including 5-, 8- and 12-story frames indicated that this algorithm reached optimum RC frame with acceptable performance and few numbers of analyses. Also the convergence rate was high because when total life-cycle cost was the objective function, after two steps with a small number of analyses, the TLCC was decreased about an average 25%. The robustness of the algorithm was confirmed by evaluation of the coefficient of variation of structures in the optimal path.

### Keywords:

Life-cycle cost analysis;  
Seismic design;  
Optimization algorithm;  
RC frames; Neighbours matrix

## 1. Introduction

The target of performance-based design is to preserve the desired performance [1]. In this field, Hajirasouliha et al. [2] developed a practical method for performance-based design of RC structures by nonlinear dynamic analysis of RC frames subjected to earthquake excitation. The proposed methodology was very efficient at controlling performance parameters and improving the structural behaviour of RC frames. Bengoa et al. [3] presented a new approach to include the effect of existence of uncertainty in the structural optimization process in several structural parameters combined with the presence of possible damaged configurations. They

demonstrated the advantages of including possible partial collapses that could occur during the life-cycle of a structure. Xu et al. [4] proposed a performance-based structural optimization incorporating back propagation (BP) algorithm. For the RC frames, the section dimensions and corresponding reinforcement ratio of a six-story RC frame were modified. Mokarram and Banan [5] extended the original PSO to achieve a fast converging PSO-based algorithm called FC-MOPSO, which can solve constrained/unconstrained continuous/discrete as well as mixed continuous and discrete MOPs within a few hundreds of function evaluations.

Since earthquake is a probability phenomenon in the lifetime of structures, the hazard probability of earthquake during operation of buildings should be considered. Thus, life-cycle cost analysis (LCCA) has been a methodology introduced to estimate the performance of structures under probable seismic hazards in their life-cycle by the total life-cycle cost (TLCC). Gencturk and Elnashai [6] provided a brief review of the existing literature on life-cycle cost (LCC) optimization of structures. Gencturk [7] applied seismic design optimization with consideration of LCC in three different structural systems to investigate the potential ways to address the objectives of economic and seismic sustainability. Park et al. [8] proposed a performance-based multi-objective optimization seismic retrofit method for steel moment-resisting frames. The method involved determining the position and number of connections to be retrofitted. Müller et al. [9] presented a general framework for the performance-based design optimization of a building under seismic demands for the minimum total cost with minimum reliability levels at each of the three performance levels. Kim and Frangopol [10] proposed a novel approach to establish a multi-objective probabilistic optimum structural health monitoring (SHM) plan of the hull structure of a ship subjected to fatigue. They integrated all the effects into the formulation of the total service life extension and the expected life-cycle cost.

The conclusion of previous studies suggests that recently the life-cycle cost has been considered as a goal of design optimization. In order to achieve this goal, conventional methods cannot be very effective, because using these methods with regard to the large variables and constraints of the problem as well as non-linear behaviour of structures under severe earthquakes may lead to non-convergence in optimization, or increase in the number of analyses. One of the most famous and popular innovative methods to tackle this problem is the genetic algorithm (GA), which can solve most types of discrete variable optimization problems. However, these methods are criticized for being time-consuming [11]. To overcome this problem, methods such as the neighborhood algorithm were presented later. Neighborhood algorithm extracts information from an ensemble of forward solutions

by constructing a multidimensional interplant in the model space [12]. Neighborhood algorithm has somehow problematic relationships complicating achievement of the optimal point, especially for nonlinear problems. Simulated Annealing (SA) is a simple stochastic technique that can be used to find global minima for continuous-discrete-integer variable nonlinear programming problems [11]. The SA has been successfully applied to many engineering fields [13].

In this paper, inspired by the SA algorithm, a novel optimization algorithm is introduced for seismic design of RC frames. In this simple method, the structures are discretely indicated with indicator vectors. The difference with the SA method lies in the conscious categorization of structures in Neighbour Matrix (MN) and use of matrix operations to find the path to reach the optimal structure. The advantages of this method include the flexibility to use it for different purposes and achieve the optimal structure with a small number of analyses. This method is used for optimal seismic design of reinforced concrete (RC) frames with life-cycle cost objective function. Also, drift ratio (DR) is considered as the most important parameter in determining the structural performance.

## 2. Structural Models

To evaluate the method, three sample RC frames of 3, 5 and 8 story with three spans were designed according to Figure (1). It was supposed that they are ordinary office buildings listed in risk category II with intermediate ductility. The design criteria were taken from the ASCE7-16 [14] and ACI 318-14 [15]. Soil type was category *C*, and the short spectral response acceleration ( $S_s$ ) and the spectral response acceleration ( $S_1$ ) at 1-s period are equal to 1.3 g and 0.66 g, respectively. The sections of the structures were designed such that the structures had the ability to withstand gravity loads with minimum reinforcement, and while drift limits met.

The IDARCV7.0 [16] software was used for nonlinear dynamic analysis of structures under earthquake excitations. Natural ground motions were scaled by the design spectrum according to ASCE7-16 [14]. These ground motions are provided in Table (1).

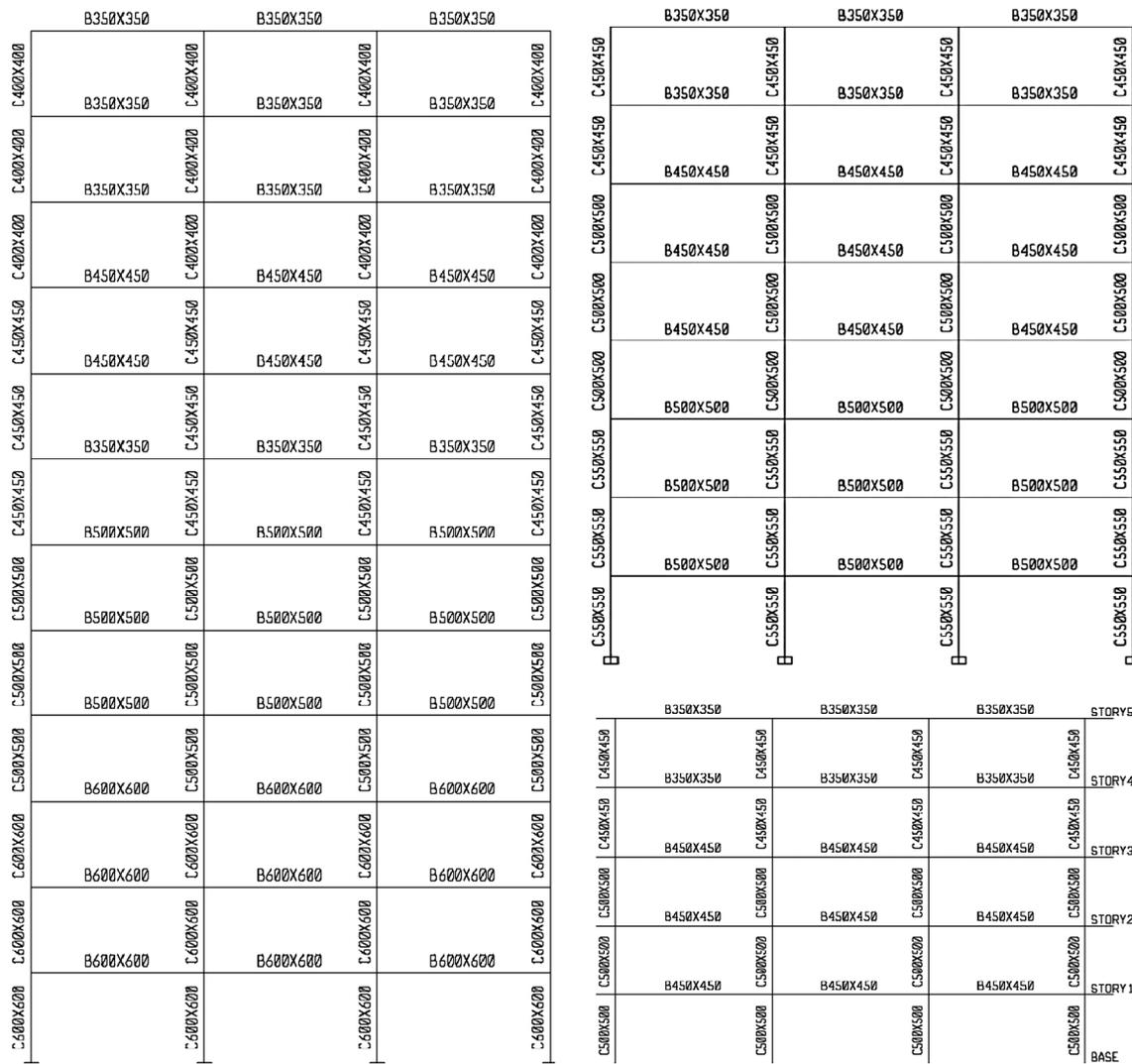


Figure 1. Designed sections of the RC frames.

Table 1. Selected natural ground motions.

Earthquake Name	Location	Year	Magnitude	PGA (g)	Vs(m/s)
Northridge	Littlerock, Brainard Canyon	1994	6.7	0.071	486
Northridge	Castaic Old Ridge Route	1994	6.7	0.56	450
Northridge	Lake Hughes #1	1994	6.7	0.09	425
Northridge	Rancho Paolos Verdes, Hawth	1994	6.7	0.071	580
Imperial Valley	Parachute Test site	1979	6.5	0.2	350
San Fernando	Lake Hughes, #12	1971	6.6	0.35	602
San Fernando	Pasadena, CIT Kresge	1971	6.6	0.1	415
San Fernando	Castaic Old Ridge Route	1971	6.6	0.31	450
Loma Prieta	Gilroy, Gavilon college	1989	6.9	0.35	730
Loma Prieta	Gilroy #6, San Ysidro	1989	6.9	0.167	663
Loma Prieta	Saratoga, Aloha Ave.	1989	6.9	0.50	381
Loma Prieta	Santa Cruz, UCSC	1989	6.9	0.11	713
Loma Prieta	San Francisco, Diamond Heights	1989	6.9	0.1	583
Morgan Hill	Gilroy#6, San Ysidro	1984	6.2	0.22	663
Morgan Hill	Gilroy, Gavilon College	1984	6.2	0.097	730
Kern County	Santa Barbara, Courthouse	1952	7.4	0.052	515
Kern County	Pasadena, CIT Athenaeum	1952	7.4	0.13	415
N. Palm Springs	Fun Valley	1986	6.0	0.13	389
Whittier Narrows	Cataic, Old Ridge Route	1987	6.0	0.067	450
Whittier Narrows	Riverside, Airport	1987	6.0	0.057	390

### 3. Optimization Methodology

In the current novel optimal seismic design methodology, structural reinforcements were determined considering the design objectives and constraints. For this purpose, first of all, the matrices and vectors used were defined.

#### 3.1. Definitions of Utilized Vectors and Matrices

In order to limit the number of possible RC frames, discrete changes in the reinforcement ratio of the elements were taken into account, which were changed into the minimum, the median and the maximum value of the ACI 318-14 [15] limitations. The dimensions of the designed sections were assumed constant. Also, for the 5-story building, all reinforcement and sections of the first and second levels as well as fourth and fifth levels were assumed the same. Therefore, there were  $2^7(3^3)$  types of beams and  $3^3=2^7$  types of columns, were 729(27\*27) different 5-story RC frames could be built. In the same way, for the 8-story building, all reinforcements and sections of the first and second levels as well as third and fourth levels, fifth and sixth levels, and seventh and eighth levels were similar. Thus, there were  $81(3^4)$  types of beams and  $81(3^4)$  types of columns. For the 12-story building, all reinforcements and sections of the first, second, and third levels; fourth, fifth and sixth levels; seventh, eighth and ninth levels; and tenth, eleventh, and twelfth levels were similar. Therefore, there were  $81(3^4)$  types of beams and  $81(3^4)$  types of columns. Accordingly, there were 6561 possible RC frames that could be built for 8- and 12-story buildings. For each 5-story RC frame, an indicator vector consisting of design variables is defined:

$$IV_j = [c_{j6}c_{j5}c_{j4}c_{j3}c_{j2}c_{j1}] \quad (1)$$

where,  $IV_j$  is an indicator vector for  $j^{th}$  RC frame, and  $c_{j6}$  to  $c_{j4}$  and  $c_{j3}$  to  $c_{j1}$  components are the index numbers for the reinforcements of columns and beams, respectively. These numbers are equal to the ratio of the maximum to the minimum of the main reinforcement of the beams (upper face) or the main reinforcements of the columns (longitudinal reinforcements). The components  $c_{j4}$  and  $c_{j1}$  belong to the first and second story levels;  $c_{j5}$  and  $c_{j2}$  are related to the third story level, and  $c_{j6}$  and  $c_{j3}$

represent the fourth and fifth story levels. Column components ( $c_{j6}$  to  $c_{j4}$ ) can be 1.0, 1.7, and 2.4 for the minimum, median, and maximum reinforcements in the columns. Also, beam components ( $c_{j3}$  to  $c_{j1}$ ) can be 1.0, 1.85, and 2.7 for the minimum, median, and maximum reinforcements in the beams.

Each indicator vector of 8- and 12-story RC frames is defined as Equation (2):

$$IV_j = [c_{j8}c_{j7}c_{j6}c_{j5}c_{j4}c_{j3}c_{j2}c_{j1}] \quad (2)$$

Definitions of  $c_{jk}$  for 8- and 12-story RC frames are similar to those of the 5-story RC frames. It means that  $c_{j5}$  and  $c_{j1}$  belong to the first,  $c_{j6}$  and  $c_{j2}$  are related to the second,  $c_{j7}$  and  $c_{j3}$  represent the third, and  $c_{j8}$  and  $c_{j4}$  denote the fourth group. Also, column components ( $c_{j8}$  to  $c_{j5}$ ) can be 1.0, 1.7, and 2.4, and beam coefficients ( $c_{j4}$  to  $c_{j1}$ ) can be 1.0, 1.85, and 2.7.

All possible combinations make a feasible matrix ( $M_{ALL}$ ), including all possible  $IV_j$  vector indicators:

$$M_{ALL} = \begin{bmatrix} IV_1 \\ IV_2 \\ IV_3 \\ \vdots \\ IV_j \\ \vdots \\ IV_N \end{bmatrix} \quad (3)$$

$M_{ALL}$  is a  $N \times m$  matrix; where,  $N$  is the total number of different possible RC frames (729 for 5-story and 6561 for 8- and 12-story RC frames), and  $m$  is the number of components of  $IV_j$  (6 for 5-story and 8 for 8- and 12-story RC frames).

If  $r_j$  is the objective parameter (like DR or TLCC) extracted from the nonlinear analysis of the  $j$ -th RC frame with  $IV_j$  indicator vector, the result vector ( $R$ ) is defined as follows, where each component is  $r_j$ :

$$R = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ \vdots \\ r_j \\ \vdots \\ r_N \end{bmatrix} \quad (4)$$

Unknown transform vector ( $T$ ) is assumed where each component ( $t_k$ ) indicates the average impact factor of all  $c_{jk}$  on the calculated  $r_j$ :

$$T = \begin{bmatrix} t_1 \\ t_2 \\ \vdots \\ t_m \end{bmatrix} \tag{5}$$

Hence, the relationship between  $M_{ALL}$ ,  $T$ , and  $R$  can be written as Equation (6):

$$M_{ALL} \times T = R \tag{6}$$

In Equation (6), the transform vector is unknown and should be estimated via dividing  $R$  by matrix  $M_{ALL}$ . It can yield the best solution for the transform vector as  $T_{best}$  by Equation (7).

$$T_{best} = (M_{ALL}^T \times M_{ALL})^{-1} \times (M_{ALL}^T \times R) \tag{7}$$

To check the accuracy of the solved matrix  $T_{best}$  vector  $S$  is made through multiplying matrix  $M_{ALL}$  by  $T_{best}$ .

$$S = M_{ALL} \times T \tag{8}$$

In Table (2),  $R$  and  $S$  vectors are compared in

two cases, one for the DR results under the  $S_a(T_1)$  and the other for the normalized TLCC to the initial structure. The positive covariance indicates sufficient convergence between the solved  $S$  and  $R$ . When the covariance is +1.0, matrix  $T_{best}$  has perfect precision. The  $T_{best}$  calculated for the 5-, 8-, and 12-story buildings are reported in Table (3).

For each RC frame, a group of Neighbour RC ( $RC_N$ ) frames is defined. An  $RC_N$  frame is an RC frame that except a component, all components of its indicator vector are the same with the main RC frame. This different component is a further amount more or less than the corresponding number of the main RC frame's indicator vector.  $M_N$  is a matrix where the first row represents the indicator vector of the main RC frame, and other rows shows the indicator vectors of the RCN frames. Equation (9) is a  $M_N$  for a 5-story RC frame with  $IV_k$  indicator:

$$M_N = \begin{bmatrix} c_{k6} & c_{k5} & c_{k4} & c_{k3} & c_{k2} & c_{k1} \\ c_{k6} & c_{k5} & c_{k4} & c_{k3} & c_{k2} & c_{k1} + 0.85 \\ c_{k6} & c_{k5} & c_{k4} & c_{k3} & c_{k2} & c_{k1} - 0.85 \\ c_{k6} & c_{k5} & c_{k4} & c_{k3} & c_{k2} & c_{k1} \\ \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix} \tag{9}$$

**Table 2.** Comparison between calculated S and R.

Covariance		Max. Component		Min. Component		Average Components	
		TLCC Results					
		Matrix R	Matrix S	Matrix R	Matrix S	Matrix R	Matrix S
5-Story	+0.428	2.450	1.544	0.452	0.186	0.866	0.844
8-Story	+0.544	2.167	2.778	0.573	0.171	1.238	1.221
12-Story	+0.557	2.150	2.083	0.590	0.388	1.235	1.239
DR Results							
5-Story	+0.511	3.660	1.842	0.500	0.069	0.883	0.847
8-Story	+0.513	4.445	2.099	0.384	0.128	1.012	0.983
12-Story	+0.421	3.289	1.633	0.506	0.267	0.958	0.949

**Table 3.** Calculated matrix  $T_{best}$  in RC frames.

	Values for Beams				Values for Columns			
	$t_1$	$t_2$	$t_3$	$t_4$	$t_5$	$t_6$	$t_7$	$t_8$
TLCC Objectives								
5-Story	-	0.196	0.148	-0.104	-	0.194	0.145	-0.092
8-Story	0.204	0.149	0.116	-0.357	0.193	0.256	0.020	0.089
12-Story	0.136	0.097	0.046	-0.066	0.239	0.322	-0.120	0.032
DR Objectives								
5-Story	-	0.243	0.212	-0.279	-	0.259	0.159	-0.101
8-Story	0.176	0.186	0.141	-0.404	0.230	0.272	-0.034	-0.027
12-Story	0.091	0.086	0.039	-0.122	0.220	0.204	-0.050	0.052

For the component  $c_{ki}$ , which is in the maximum range (2.7 or 2.4), there is no  $c_{ki} + 0.85$  (or 0.70). Also, when it is in the minimum range (1.0), there is no  $c_{ki} - 0.85$  (or 0.70).

For example,  $M_N$  for  $IV_{main} = [2.40 \ 1 \ 1.70 \ 1 \ 1.85 \ 2.70]$  according to Equation (10):

$$M_N = \begin{bmatrix} 2.40 & 1 & 1.70 & 1 & 1.85 & 2.70 \\ 2.40 & 1 & 1.70 & 1 & 1.85 & 1.85 \\ 2.40 & 1 & 1.70 & 1 & 2.70 & 2.70 \\ 2.40 & 1 & 1.70 & 1 & 1 & 2.70 \\ 2.40 & 1 & 1.70 & 1.70 & 1.85 & 2.70 \\ 2.40 & 1 & 2.40 & 1 & 1.85 & 2.70 \\ 2.40 & 1 & 1 & 1 & 1.85 & 2.70 \\ 2.40 & 1.70 & 1 & 1 & 1.85 & 2.70 \\ 1.70 & 1 & 1.70 & 1 & 1.85 & 2.70 \end{bmatrix} \quad (10)$$

By similar definition, a column result matrix ( $R_N$ ) can be built for  $M_N$  where each row of  $R_N$  is the result of the corresponding RC frames in  $M_N$ .

### 3.2. Optimization Algorithm

Positive covariance in Table (2) showed that a path can be found to minimize the goal with the aid of the transform vector. Also, in Hajirasouliha et al. [2] research, it was demonstrated that by increasing reinforcements in the weak element of RC frames,  $D_R$  could be mitigated. Based on these results, inspired by the SA method, a novel optimal seismic design algorithm is presented. The steps of this algorithm are defined as follows:

- Select the appropriate objective function  $f_x$ , where  $x$  is the vector of the design variables, which is the same indicator vector.
- Start the process with an initial RC frame that can bear vertical service loads and have near minimum allowable reinforcements in elements. Therefore, the indicator vector for the first RC frames is as Equation (11).

$$\text{for 5-story RC frame: } IV_{main} = [111111] \quad (11)$$

$$\text{for 8- or 12-story RC frames: } IV_{main} = [11111111]$$

- Build the matrix  $M_N$  and  $R_N$  of the current RC frame.
- Store the  $RC_N$  frames and the current RC frame in the optimum set.

From Equation (12), calculate the  $T_{best}$ :

$$T_{best} = (M_N^T * M_N)^{-1} * (M_N^T * R) \quad (12)$$

where,  $T_{best}$  has  $m$  rows, which is 6 for 5-story RC frames and 8 for 8- and 12-story frames.

- If possible, for the negative value  $t_i$  of matrix  $T_{best}$ , one step increase and for the  $t_i$  greater than 1.0, one step decrease the respective reinforcements of the current RC frame ( $c_{ki}$ ), to create a new RC frame. This process is described as Equation (13). Besides, if possible, create a new RC frame, assign the counter of steps, a further number more ( $k_{new} = k + 1$ ).

$$\text{if } t_i < 0 \rightarrow (c_{ki})_{new} = c_{ki} + 1.85(\text{or } 1.70)(\text{if possible}) \quad (13)$$

$$\text{if } t_i > 1.0 \rightarrow (c_{ki})_{new} = c_{ki} - 1.85(\text{or } 1.70)(\text{if possible})$$

- If the new RC frame cannot be created, this means that all components of the indicator vector of the current RC frame have not changed; then the process stops, and the minimum result in the optimum set is the optimum value, which is for the optimally designed RC frame. This is when all components of the last  $T_{best}$  lie within the range of [0 to 1.0], or the reinforcements corresponding to the negative  $t_i$  are in maximum and there is no possibility for further increase. Also, it stops when reinforcements corresponding to the  $t_i > 1.0$  are in minimum, and there is no potential for further reduction.
- If contrary to Step 7, it is possible to create a new RC frame, the calculation with this new RC frame shall be repeated from Step 3, until finally, in according to the terms of Step 7, the process stops.

The summary flowchart of this optimization algorithm is displayed in Figure (2).

### 4. Life-cycle Cost Analysis

Wen and Kang [17] represented the total cost over a lifetime ( $t$ ) regardless of operation and maintenance costs as a function of the design variable vector as Equation (14).

$$E[C(t, X)] = C_0(X) + E \left[ \sum_{i=1}^{N(t)} \sum_{j=1}^k C_j e^{-\lambda t_i} P_{ij}(X, t_i) \right] \quad (14)$$

where,  $C_0$  is the initial cost for the new or retrofitted

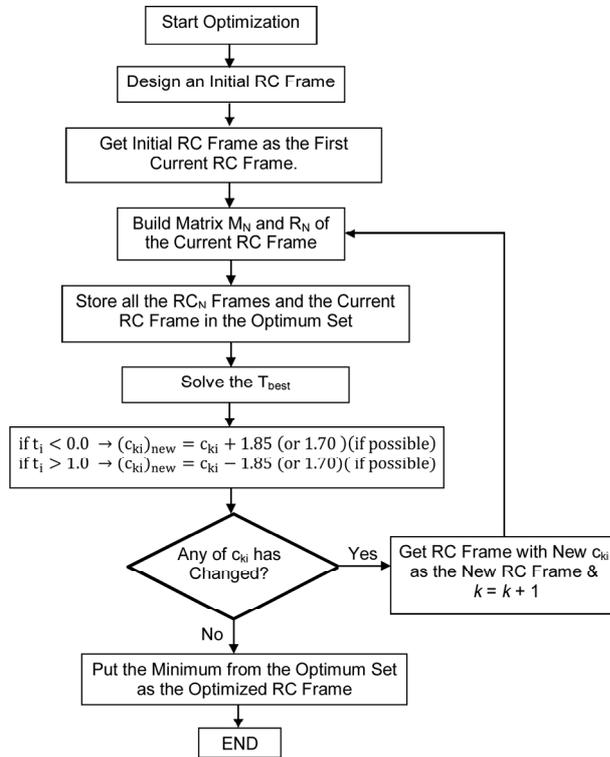


Figure 2. General flowchart of the optimization algorithm.

facility;  $X$  is the design variable vector;  $i$  shows severe loading occurrence number;  $t_i$  denotes the loading occurrence time, a random variable;  $N(t)$  is the total number of severe loading occurrences in  $t$ , a random variable;  $C_j$  represents the cost in present dollar value of  $j^{\text{th}}$  limit state being reached at time of the loading occurrence, including costs of damage, repair, loss of service, as well as deaths and injuries;  $\lambda$  is a constant discount rate/year;  $P_{ij}$  reveals the probability of  $j^{\text{th}}$  limit states being exceeded given the  $i^{\text{th}}$  occurrence of a single hazard or joint occurrence of different hazards; and  $k$  is the total number of limit states under consideration.

Moller et al. [9] included the social costs associated with the occurrence of earthquakes ( $C_s(x_d)$ ), in addition to the initial construction cost

( $C_0(x_d)$ ) and the cost of repairs for damage caused by earthquakes at some time during the life of the structure ( $C_d(x_d)$ ) as Equation (15):

$$C(x_d) = C_0(x_d) + C_d(x_d) + C_s(x_d) \quad (15)$$

Social cost consists of costs of re-insertion into a normal routine, medical and rehabilitation costs for non-fatal injured victims, costs associated with loss of fatality, and costs associated with loss of business or economic activities.

In the current study, the total damage cost ( $C_{LS}$ ) included all the damage cost of structural elements ( $C_{dam}$ ), damage repair cost of non-structural sections ( $C_{nst}$ ), loss of furniture cost ( $C_{fur}$ ), loss of rental cost ( $C_{ren}$ ), commercial loss cost ( $C_{com}$ ), cost of injuries ( $C_{inj}$ ), cost of human fatalities ( $C_{fat}$ ), and social costs ( $C_{soc}$ ).

The calculated value of the maximum  $D_R$  and floor accelerations are used to estimate the total damage cost. The main parameters to estimate  $C_{LS}$  are downtime of full structural damage, lifetime, and discount rate ( $\lambda$ ), which are assumed 18 months, 50 years, and 15%, respectively.

In Table (4), the estimated cost of each of the total damage cost factors is provided for the buildings.

Classification of different levels of loss has been done according to the studies of Elenas and Meskouris [18] as well as FEMA 227 [19] in Table (5).

In order to estimate the maximum inter-story drift ratio index ( $DR_{max}$ ) and floor acceleration ( $a_{floormax}$ ) hazard curves, initially, the  $DR_{max}$  and  $a_{floormax}$  corresponding to each of the PGAs should be calculated. Then, as with the hazard curve of the annual PGA event, the probability of the  $DR_{max}$  and  $a_{floormax}$  was assumed to have a natural normal logarithmic. Figure (3) displays a

Table 4. Estimated cost of the losses.

Loss	Related with	Unit	Full Loss Amount (\$)
1	$C_{dam}$ Damage Index		Full Structural Cost
2	$C_{nst}$ Max Floor Acc. Elevation	Per m <sup>2</sup>	285
3	$C_{fur}$ Max Floor Acc. Elevation	Per m <sup>2</sup>	230
4	$C_{ren}$ Damage Index	Per Each Company	1700
5	$C_{com}$ Damage Index	Per m <sup>2</sup>	5700
7	$C_{inj}$ Damage Index	Per Each Person	143,000
8	$C_{fat}$ Damage Index	Per Each Person	63,000
9	$C_{soc}$ Damage Index	Per Each Person; Each Company; Each Person	1430; 28,500; 5700

**Table 5.** Classification of the levels of damage states.

Performance Level	Damage State	Inter Story Limit Ratio (%)	Loss Depended on Drift (%)	Max Floor Acceleration (g)	Loss Depended on Acc. (%)
MINOR	Slight	$\Delta_{max} \leq 0.2$	0.5	$a_{floor} \leq 0.1$	0.9
IO	Light	$0.2 < \Delta_{max} \leq 1$	20	$0.1 < a_{floor} \leq 0.8$	25
LS	Moderate	$1 < \Delta_{max} \leq 2$	45	$0.8 < a_{floor} \leq 1.0$	35
CP	Major	$2 < \Delta_{max} \leq 3$	80	$1.0 < a_{floor} \leq 1.25$	65
FAIL	Collapse	$3 < \Delta_{max}$	100	$1.25 < a_{floor}$	100



**Figure 3.** The general procedure of TLCC estimations.

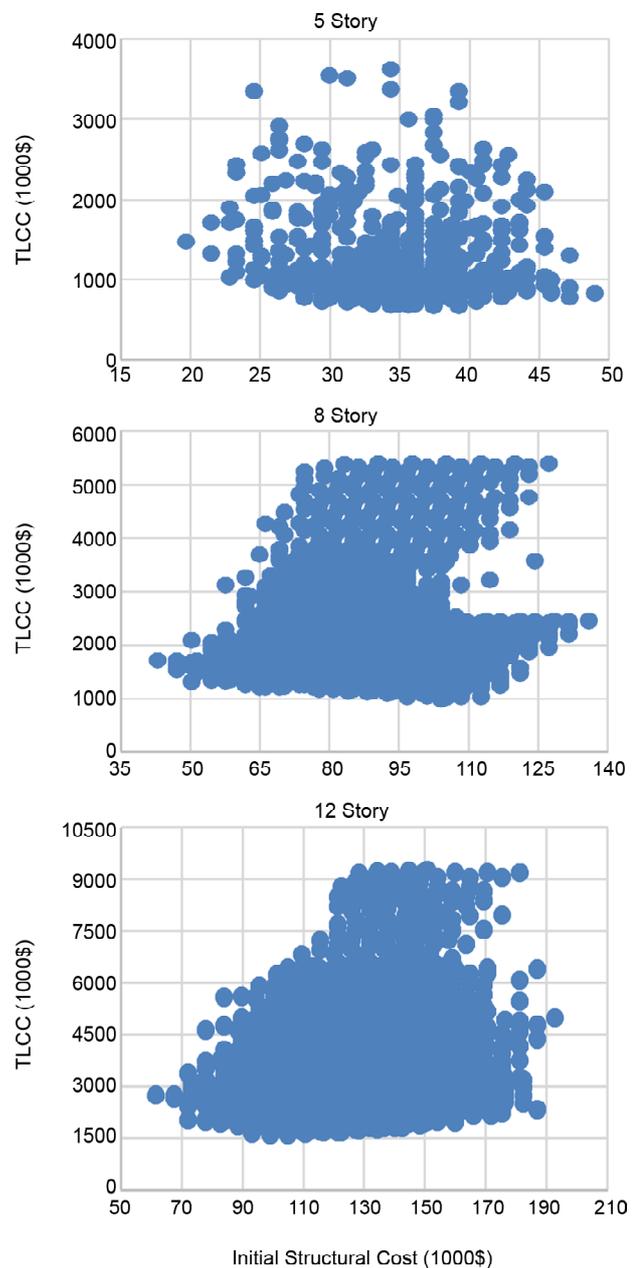
general process for calculating the TLCC of the structures.

### 5. Optimization Problem

In most studies, reduction of initial cost has been optimized, which is desirable for the owners. However, during the life of the structure, the probable damage costs of the structure also incur, which are borne by the operators. On the other hand, the optimal structure in terms of seismic codes is a structure with the lowest damage index under a seismic design. Accordingly, initially *DR* (the supposed damage index in this study), and *LCCA* of the state space, including all *RC* frames, are presented in Figures (4) and (5). Then, optimization objectives are defined with regard to the initial and expected damage costs over the lifetime as along with the damage index.

The results indicated that an optimization algorithm should be used to reach the optimum *RC* frames. In these figures, the dimensions of the elements are constant, and only by changing the reinforcements the initial cost, *DR*, and *TLCC* are altered. In this study, the maximum *DR* of *RC* frames subjected to  $S_a(T_1)$ , and also *TLCC*, as well as, combinations of these factors were used as objectives for the optimal seismic design. The advantage of *TLCC* is combining the initial cost and lifetime. The general optimization problem can be stated as Equation (16):

$$\begin{aligned}
 & \min_{\mathbf{x} \in F} && f(\mathbf{x}) = TLCC \\
 & \text{subject to:} && g_i(\mathbf{x}) \geq 0 \quad i = 1, \dots, I \\
 & && \mathbf{x}_j \in X \quad j = 1, \dots, N
 \end{aligned} \tag{16}$$



**Figure 4.** TLCC of *RC* frames for different initial structural costs.

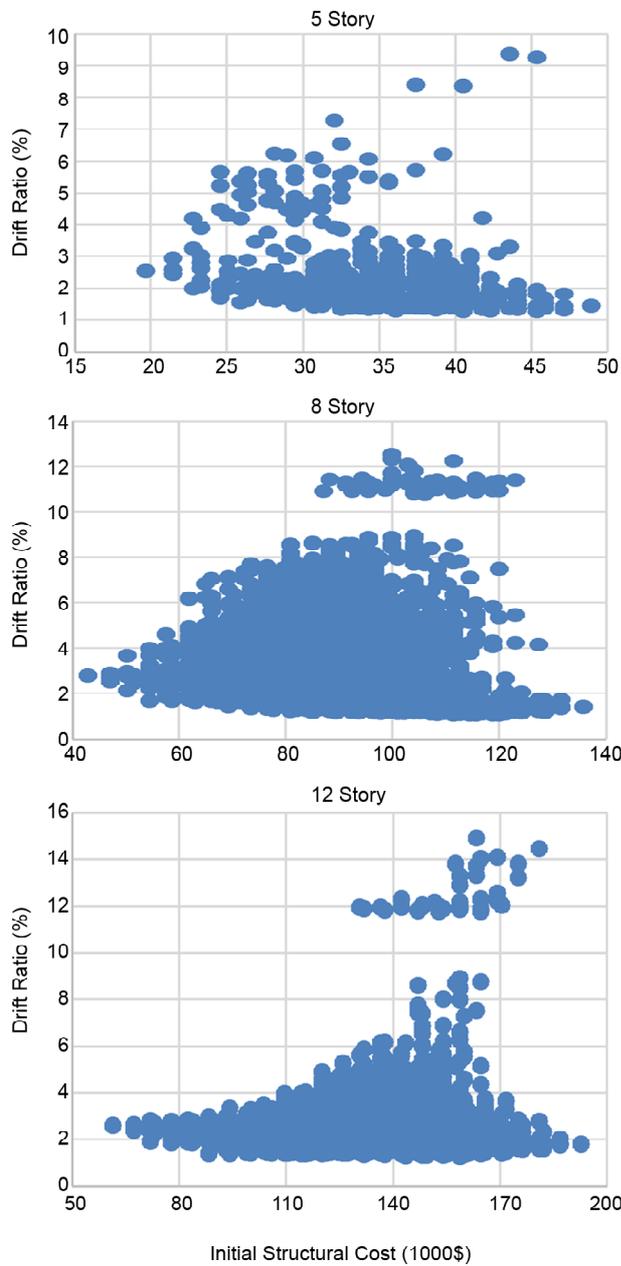


Figure 5. DR of RC frames for different initial structural costs.

where,  $f$  is the objective function to be minimized and  $x$  is the vector of variables. The  $g_i$  functions are the deterministic constraint functions, and  $X$  is a given set of discrete values from which the design variables  $x_j$  take values with  $N$  numbers. The utilized constraints included the ability to withstand under gravity service loads.

### 6. Numerical Results

In Table (6), the process of changing the objective functions is presented for various problems. Note that the built frames in each step has not necessarily a lower objective value than the previous step, as it may cross the structures with a larger objective function value in the path. Also, it is possible to cross the non-optimal structure near an optimal structure.

The efficiency evaluation of the proposed algorithm is presented in Table (7). This table includes the extent of reduction of the objective function in the initial steps, the total number of analysed structures to reach the optimal structure, and the percentage of optimization.

#### 6.1. Sensitivity and Power of Optimization

Robust design optimization (*RDO*) is an additional objective function which is usually taken into account. When an optimization algorithm is robust, it proceeds to convergence in successive steps [20]. Park et al. [21] introduced a complete literature review on robust design optimization. In this part, the robustness of the introduced optimization algorithm was evaluated. Accordingly, the coefficient

Table 6. Summary results for optimal design with the first objective function.

		Step0	Step1	Step2	Step3	Step4	Step5	Step6	Step7
5-Story	$x_j$ Numbers in This Step	0	7	14	22	31	41	52	<b>62</b>
	Minimum TLCC	1480	1033.7	906.1	872.2	757.6	682.8	682.8	<b>672.2</b>
8-Story	$x_j$ numbers in This Step	0	9	18	30	41	53	63	<b>74</b>
	Minimum TLCC	1722.1	1318.9	1318.9	1318.9	1238.2	1109	987.4	<b>987.4</b>
12- Story	$x_j$ Numbers in This Step	0	9	20	30	<b>40</b>	-	-	-
	Minimum TLCC	2762	2052.9	1682.9	1630.3	<b>1630.3</b>	-	-	-

Table 7. The efficiency evaluation of the proposed algorithm.

Reduction in Initial Steps (%)	Reduce Obj. Function after 2 Steps (%)	Total Number of Analysed Frames	Percentage of Optimization (%)
5-Story	39	62	55
8-Story	24	74	43
12-Story	39	40	41

**Table 8.** Comparison between COV. of the RN in each step.

	Initial COV.	Optimum COV.
5 Story	296.7	196.5
8 Story	206.5	159.4
12 Story	353.8	284.4

of variation (COV.) of the RN in each step has been presented in Table (8).

It is demonstrated that in the optimal design stages, all  $RC_N$  frames approached the optimal value. Also, optimum  $RC$  frames stayed in the position where the slope of changes in the  $RC_N$  frames was small. These results proved the accuracy and power of the introduced algorithm, suggesting that the algorithm always follows the convergence process.

## 7. Conclusions

In this paper, a simple novel methodology was introduced to for optimal seismic design of  $RC$  frames, with a strong performance, ease of use, and suitable convergence speed. In this method, the structures were discretely grouped under the category "Neighbours Matrix ( $MN$ )". Then, using matrix operations, a path to reach the optimal structure was found. This method was used for the optimal design of three  $RC$  frames of 5, 8 and 12 stories with  $TLCC$ , or a combination of the  $TLCC$  objective function. The summary of the results is as follows:

- ❖ The convergence rate was high because, after two steps with a small number of analyses (about 2% and 0.3% of all possible  $RC$  frames for the 5-story, and 8- or 12-story frames, respectively), the  $TLCC$  was decreased about an average 25%.
- ❖ For the 5-story  $RC$  frame, with the average analysis numbers of less than 8% of the total number of possible frames, an optimal structure was reached. This for 8-story  $RC$  frames was 1.3%.
- ❖ The number of analyses to reach the optimal structure for the 12-story  $RC$  frame was about 1% of the total number possible structures. Compared to the initial structure, it was 24 to 40% reduction in the objective function.

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