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DESIGN OPTIMIZATION OF REINFORCED CONCRETE BEAMS USING ARTIFICIAL NEURAL NETWORK

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Abstract:— This paper presents an Artificial Neural Networks (ANN) model for the cost optimization of simply supported beams designed according to the requirements of the ACI 318-08 code. The model formulation includes the cost of concrete, the cost of reinforcement and the cost of formwork.
A simply supported beam was designed adopting variable cross sections, in order to demonstrate the model capabilities in optimizing the beam design. Computer models have been developed for the structural design optimization of reinforced concrete simple beams using NEURO SHELL-2 software. The results obtained were compared with the results obtained by using the classical optimization model, developed in the well known Excel software spreadsheet which uses the generalized reduced gradient (GRG). The results obtained using the two modes are in good agreement

Keywords: Reinforced Concrete Beam, Cost Optimization, Artificial Neural Networks, Generalized Reduced Gradient.

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I. INTRODUCTION

A designer's goal is to develop an "optimal solution" for the structural design under consideration. An optimal solution normally implies the most economic structure without impairing the functional purposes the structure is supposed to serve (Rafiq, 1995) [1]. The total cost of the concrete structure is the sum of the costs of its constituent materials; these constituent materials are at least: concrete, reinforcement steel and formwork, (Sarma and Adeli, 1998) [2], [3]. There are some characteristics of reinforced concrete (RC) structures which make their design optimization distinctly different from other structures. The cost of RC structures is influenced by several cost items. In the design optimization of RC structures the cross-sectional dimensions of elements and detailing of reinforcement e.g. size and number of steel bars, need to be determined. Consequently, the number of design parameters, which need to be optimized for a RC structure can be larger than that for a steel structure. Also cracking and durability requirements are two characteristic properties of RC structures; these increase the number of design constraints of the optimization problem of RC structures. (Sahab, 2002) [4]

The existence of optimization methods can be traced to the days of Newton, Lagrange, Bernoulli, Euler, Lagrange and Weirstrass [5]. Despite of these early contributions, very little progress was made until the middle of the twentieth century, when high-speed digital computers made implementation of the optimization procedures possible and stimulated further research on new methods. Spectacular advances followed, producing a massive literature on optimization techniques. This advancement also resulted in the emergence of several well defined new areas in optimization theory. The development of the simplex method by Dantzig in 1963 [6] for linear programming problems and the annunciation of the principle of optimality in 1957 [7] by Bellman for dynamic programming problems paved the way for development of the methods of constrained optimization. Work by Kuhn and Tucker on the necessary and sufficiency conditions for the optimal solution of programming problems laid the foundations for a great deal of later research in nonlinear programming. The contributions of Zoutendijk and Rosen to nonlinear programming during the early 1960 [8] have been significant. Although no single technique has been found to be universally applicable for nonlinear programming problems, work of Carroll and Fiacco and McCormick allowed many difficult problems to be solved by using the well-known techniques of unconstrained optimization. Geometric programming was developed in 1967 [9] by Duffin, Zener, and Peterson. Gomory did pioneering work in integer programming.

An artificial neural network is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system. Why would the implementation of artificial neural networks be necessary? Although computing these days is truly advanced, there are certain tasks that a program made for a common microprocessor is unable to perform; even so a software implementation of a neural network can be made with their advantages and Disadvantages.

Another aspect of the artificial neural networks is that there are different architectures, which consequently require different types of algorithms, but despite being an apparently complex system, a neural network is relatively simple.
Artificial Neural Networks (ANN) is among the newest signal-processing technologies in the engineer's toolbox.. In engineering, neural networks serve two important functions: as pattern classifiers and as nonlinear adaptive filters. An Artificial Neural Network is an adaptive, most often nonlinear system that learns to perform a function (an input/output map) from training data. Adaptive means that the system parameters are changed during operation, normally called the training phase. After the training phase the Artificial Neural Network parameters are fixed and the system is deployed to solve the problem at hand (the testing phase). The Artificial Neural Network is built with a systematic step-by-step procedure to optimize a performance criterion or to follow some implicit internal constraint, which is commonly referred to as the learning rule . The input/output training data are fundamental in neural network technology, because they convey the necessary information to "discover" the optimal operating point. The nonlinear nature of the neural network processing elements (PEs) provides the system with lots of flexibility to achieve practically any desired input/output map, i.e., some Artificial Neural Networks are universal mappers.

An input is presented to the neural network and a corresponding desired or target response set at the output (when this is the case the training is called supervised). An error is composed from the difference between the desired response and the system output. This error information is fed back to the system and adjusts the system parameters in a systematic fashion (the learning rule). The process is repeated until the performance is acceptable. It is clear from this description that the performance hinges heavily on the data. If one does not have data that cover a significant portion of the operating conditions or if they are noisy, then neural network technology is probably not the right solution. On the other hand, if there is plenty of data and the problem is poorly understood to derive an approximate model, then neural network technology is a good choice. This operating procedure should be contrasted with the traditional engineering design, made of exhaustive subsystem specifications and intercommunication protocols. In artificial neural networks, the designer chooses the network topology, the performance function, the learning rule, and the criterion to stop the training phase, but the system automatically adjusts the parameters. So, it is difficult to bring prior information into the design, and when the system does not work properly it is also hard to incrementally refine the solution. But ANN-based solutions are extremely efficient in terms of development time and resources, and in many difficult problems artificial neural networks provide performance that is difficult to match with other technologies. Denker states that "artificial neural networks are the second best way to implement a solution" motivated by the simplicity of their design and because of their universality, only shadowed by the traditional design obtained by studying the physics of the problem. At present, artificial neural networks are emerging as the technology of choice for many applications such as pattern recognition, prediction, system identification, and control.

II. THE MODEL OF OPTIMAL DESIGN

In an optimization problem some of the parameters can be considered as preassigned or fixed parameters and others are considered as design variables. The design variables are determined in such a way that the value of an objective function, which is often the ost of the structure, becomes minimum. Some restrictions, called design constraints, may limit the acceptable values of the design variables. A simply supported rectangular RC beam model is studied in this paper.

Fixed Parameters

The present model is designed to consider all fixed parameters that may have an impact on the cost optimization of simple beams. These include the characteristic strength, modulus of elasticity, unit weight of concrete and reinforcement and the intensity of the dead and live loads. In addition it is assumed that the total cost of concrete and reinforcement is proportional to volume and weight of each material, respectively.

Consequently, the total cost of a structure is calculated using fixed parameters to calculate the cost of unit volume of concrete and unit weight of reinforcement.

The Design Variables

An important first step in the formulation of an optimization problem is to identify the design variables. Design variables should be independent of each other. If one of the design variables can be expressed in terms of others then that variable can be eliminated from the model.

Any structure can described by a set of quantities some of these quantites are pre-assigned because the designer is not free to change them or because it may be known from experience that certain value for these quantites produce a good result this type of quantities is called pre-assigned parameters the other type is the design variables .the design variables represent some or all of the following properties of the structure.
The design variables which were considered in this RC beam model are listed below:

- b = Beam width (integer values)
- d = Effective beam depth (real values)
- n_b = Number of flexural bars (integer values)
- d_b = Diameter of flexural bar (integer values)

The Design Variables' bounds

The variables bounds result from different issues such as the provisions of the code under consideration, the aesthetic of the structural elements in the building, the practical issues and the availability of some sizes of the material at the local market. The following Equations are the bounds considered for the model.
Effective depth:

$d_{min} = h_{min} - d_b/2 - S_c - d_s$, $d_{max} = h_{max} - d_b/2 - S_c - d_s$ (1)

Effective width:

$b \geq b_{min}$, $b \leq b_{max}$ (2)

Wher:e b_{min} and b_{max} are chosen according to architectural and practical considerations.

Bar diameter:

$d_b \geq d_{bmin}$, $d_b \leq d_{bmax}$ (3)

Where: d_{bmin} and d_{bmax} are chosen according to range of reinforcement available at market.

Number of bars:

$n_b \geq n_{bmin}$, $n_b \leq n_{bmax}$ (4)

Where: n_{bmin} and n_{bmax} are chosen according to practical considerations.

Where**:**

- $h_{min} = L/16$ (with refer to the Table 9.5a at the ACI - code)
- h_{max} is chosen according to architectural considerations.
- S_c is the concrete cover.
- d_s is the diameter of stirrups.
- b (in meter) [0.25, 0.35] i.e $0.25 \leq b \leq 0.35$ m
- d (in meter) [0.059 ,1.184]
- n_b [4 ,12]
- d_b (in mm) [12 ,24]

The Constraints

In many practical problems, the design variables cannot be chosen arbitrarily; rather, they have to satisfy certain specified functional and other requirements. The restrictions that must be satisfied to produce an acceptable design which collectively called design constraints. The design constraints which are considered in this optimization model are listed below:

- Design for flexure

$M_u \leq \Phi M_n$ (5)

- Minimum spacing between flexural bars

$S \geq S_{min}$ (6)

S_{min} = max of (d_b, ¾ of max agg. Size, 2.5) cm (7)

- Maximum spacing between bars (cracking control)

$S \leq S_{max}$ (8**)**

$$S\max = \min\left[300 * \left(\frac{280}{0.67} * fy\right), 380 * (280/0.67 * fy) - 2.5 * 50\right](cm)\, ACI\ code \quad (9)$$

- Maximum and minimum reinforcement ratios

$$\left(\frac{Ast}{bd}\right) \leq \rho_{max} \qquad \rho_{min} \leq \left(\frac{Ast}{bd}\right) \quad (10)$$

- Design for shear

$$V_S \leq \frac{2}{3} \sqrt{f'c} * b * d \qquad (kN) ACI - code \tag{11}$$

- Deflection control

$$Md \leq 3Mcr \qquad Ms \leq 3Mcr \tag{12}$$

(Δi) ℓ ≤ limit by ACI-code. as mentioned in table (4.1) in section (4.1.16)
2*(Δi) d + ℓ + (Δi)ℓ ≤ limit by ACI-code, as mentioned in table (4.1) in section (4.1.16)
Where:

- M_d = Bending moment under service dead loads only.
- M_s = Bending moment under service dead and live loads.
- M_{cr} = cracking bending moment.
- (Δi)ℓ = immediate deflection due to live load only.
- 2* (Δi) d + ℓ = long term deflection due to service dead an live loads.

The Objective Function

The objective function aim to finding an acceptable or adequate design that merely satisfies the functional and other requirements of the problem. there will be more than one acceptable design, and the purpose of optimization is to choose the best one of the many acceptable designs available. Thus a criterion has to be chosen for comparing the different alternative acceptable designs and for selecting the best one. The criterion with respect to which the design is optimized,when expressed as a function of the design variables, is known as the criterion or meritor objective function. The choice of objective function is governed by the nature of problem. The objective function for minimization is generally taken as weight in aircraft and aerospace structural design problems. In civil engineering structural designs, the objective is usually taken as the minimization of cost. in structural design,the minimum weight design may not correspond to minimum stress design, and the minimum stress design, again, may not correspond to maximum frequency design. Thus the selection of the objective function can be one of the most important decisions in the whole optimum design process.
The objective function for the simply supported reinforced concrete beam model is:
MIN COST = $C_c[(A_c - A_s) L] + C_c [A_s L)] + C_w [2(b + h)]$ SDG (13)

Where:

- C_c = Cost of concrete per cubic meter.
- C_s = Cost of reinforcement steel per ton.
- C_w = Cost of concrete formwork along the vertical and horizontal surface per square meter.
- A_c = Area of concrete cross section.
- A_s = Area of longitudinal reinforcement.
- L = Span of the beam
- b = width of the beam.
- h = depth of the beam.

The model was run to optimize the design of a rectangular cross section for this beam and loadings while satisfying the provisions of the ACI 318-08 Code.

III. EXAMPLE PROBLEMS

Neural Network For Optimum Design Of Beams

Design a least-cost reinforced concrete of beam simply supported span of 4 m supporting a uniform dead load of 1.5 kN/m and uniform live load of 1 kN/m. The concrete strength (f'c) is 28 MPa and the steel yield strength (f_y) is 420 MPa. The cost of concrete per cubic meter (Cc) is 1200 SDG; the cost of normal steel bars per ton (Cs) is 4750 SDG and the Cost of concrete formwork along the vertical and horizontal surface per meter is 45 SDG.

The developed database for the optimum design of beams according to the requirement of ACI code, which are based on the equations above, were used to train a neural network. The design input to the problem includes the values mentioned above and listed in the Table 1 shown below. With a comprehensive set of examples about 73 examples have been obtained for different values of width (b) ranging between 0.3 m and 0.35 m with increment of 0.0014 m with aided by using spreadsheet for that. For each set, the depth of beam, reinforcement required and cost are obtained. Out of these, the examples have been used for training. The outputs are presented in Figures 1 and 2. Figure 1 presents the relation between the overall depth and the area of steel and Figure 2 presents the relation between the overall depth and the minimum cost. The main output is the optimization cost which it found equal to the amount of 635.81 SDG.

The Classical Optimization Spreadsheet Models

In addition to the developed neural network model, another model is developed for the design optimization of RC simple beams using EXCEL software spreadsheets.

The Generalized Reduced Gradient (GRG) method is considered one of the classical optimization methods. This method was chosen among other classical methods since it is already programmed in the EXCEL SOLVER. Therefore the user builds the design model and then uses the SOLVER toolbox to run the optimization process. According to the user interface and the input data required for the model, the model output the optimization cost value of 633.45 SDG.

Table 1 Part of the developed optimization for the RC simple beam

INPUT				
The Parameter		The value		The unit
Span Length		4		M
Uniform distributed dead load (w_d)		1.5		kN/m
Uniform distributed live load (w_L)		1.0		kN/m
f'_c		28		MPa
f_y		420		MPa
max. agg. Size		25		Mm
cost of concrete per cubic meter(C_c)		1200		SDG
cost of steel per ton (C_s)		4750		SDG
cost of formwork per meter (C_w)		45		SDG
DESIGN VARIABLE				
	Width (b) in m	effective depth in m	Diameter d_b in mm	no of bars
	0.3	0.184	16 x4	6
minimum values of design variables	0.25	0.059	12	4
maximum values of design variables	0.35	1.184	24	12
Optimization Cost (ANN Optimization)			635.81 SDG	
Optimization Cost (Classical Optimization)			633.45 SDG	

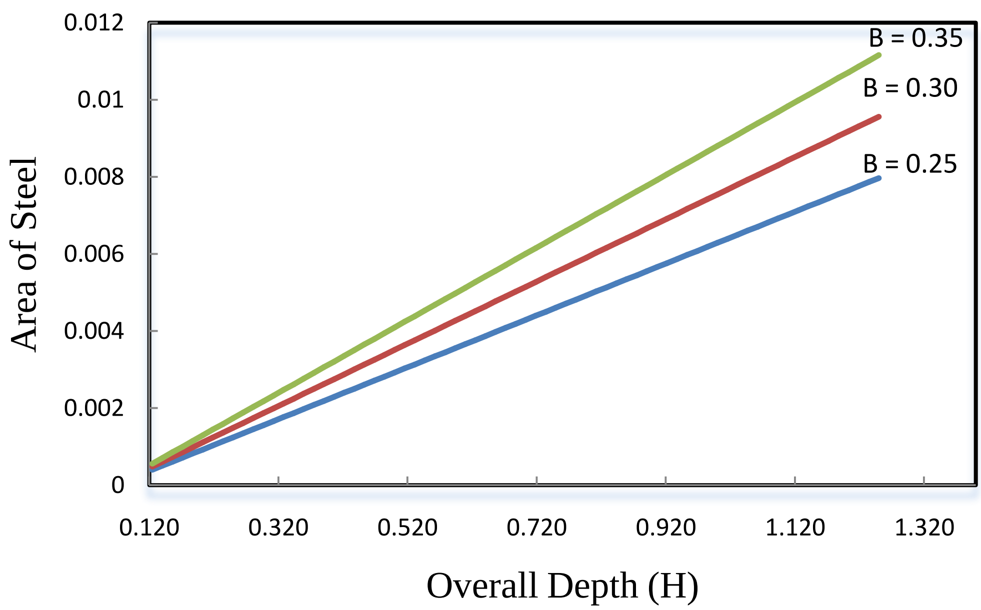

Figure 1 shown the relation between overall depth and area of steel for the RC simple beam

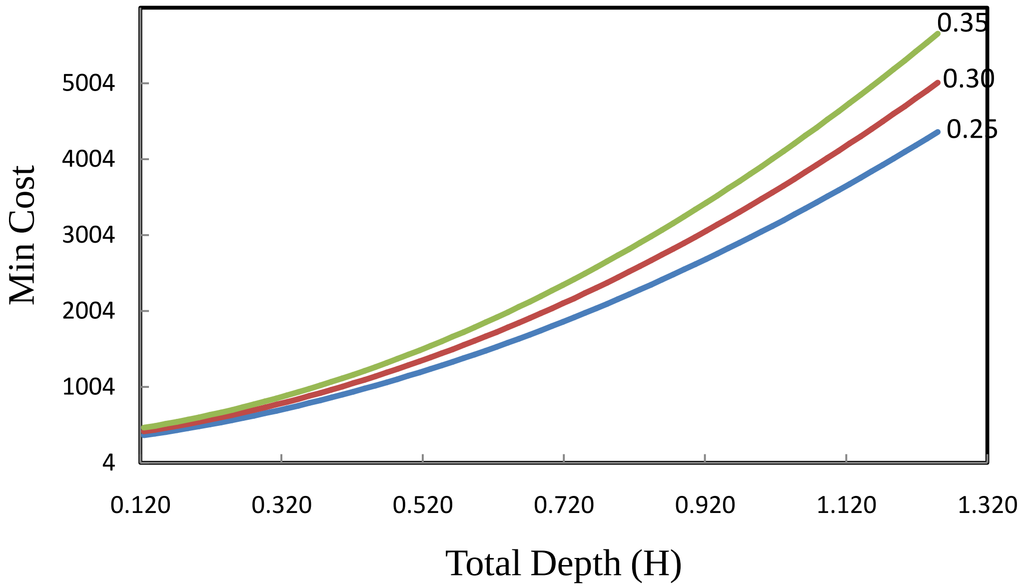

Figure 2 shown the relation between overall depth and min cost for the RC simple beam with variable depth.

Comparison between the Developed ANN and Classical Optimization Models

In order to check the validity of the developed ANN optimization models, the results of these models were compared with those of the classical optimization models. The optimum solution for the cost of RC simple beam according to the data listed in Table (1), and by using the ANN model was found **635.81** SDG and by using the spreadsheet classical model it is **633.45** SDG with percentage difference of **0.37 %** which verified that the results obtained by using ANN model is acceptable**.**

IV. CONCLUSIONS

The paper presents a design optimization model for simply supported concrete beams using Artificial Neural Networks (ANN) as an optimization technique. The main conclusions drawn can be summarized as follows:

- ANN optimization model based on NEURO SHELL 2 software was developed for the design optimization of reinforced concrete simple beams.
- A design optimization model based on EXCEL spreadsheets was developed for the same reason above to verify the work. This model applies the Generalized Reduced Gradient (GRG) optimization method as one of the classical optimization techniques.
- The results obtained from the ANN optimization technique showed good agreement with the one obtained by the GRG technique with a percentage difference of **0.37** %.
- The optimum solution presented satisfies the provisions of the code and minimizes the cost of the structure. This may be of great value to practicing engineers.
- The results presented in Figures 1 and 2, can be used for quickly finding the area of steel and the cost respectively according to the values of overall depth ranging from 0.12 m to 1.3 m coincide with values of width ranging between 0.25 and 0.35 m provided that the design provisions presented are adopted.

REFERENCES

1. RAFIG, M Y, Genetic algorithms in optimum design, capacity check and final detailing of reinforced concrete columns, School of Civil and Engineering University of Plymouth, Plymouth, 1995
2. SARMA A, K C AND ADELI H, Cost optimization of concrete structures, Journal of Structural Engineering, ASCE, Vol. 124, No. 5, 1998, pp. 570-578.
3. SARMA B, K C AND ADELI H Cost optimization of steel structures, Engineering Optimization, Vol. 32, 2000, pp. 777-802.
4. SAHAB A, AND M G, Cost optimization of reinforced concrete flat slab buildings, PhD thesis, University of Bradford, UK., 2002.
5. SAHAB A, AND M G, ASHOUR A F AND TOROPOV V V, Cost optimization of reinforced concrete flat slab buildings, Engineering Structures, Vol. 27, 2004, pp. 313–322
6. CHAKRABARTY A AND B K, Models for optimal design of reinforced concrete beams, Computers and Structures, Vol. 42, No. 3, 1992, pp. 447-451.

7. DAMU A, KARIHALLO A, KARIHALOO, B L AND ROZANY G I N, Minimum cost design of reinforced concrete beams using continuum-type optimality criteria, Structural Optimization, Vol. 7, No. 1/2, 1994, pp. 91-102.

8. Al-SALLOUM Y A AND SIDDQI G H, Cost-optimum design of concrete beams, ACI Structural Journal, Vol. 91, No. 6, 1994, pp. 647-655.

9. SENOUI A B AND ABDUL-SALAM M A, Prediction of Reinforced Concrete Beam Depth Using Neural Networks, Engineering Journal of the University of Qatar, Vol. 11, 1998, pp. 117-132.

10. ACI COMMITTEE 318, BUILING CODE REQUIREMENTS FOR STRUCTURAL CONCRETE, ACI 318-08, American Concrete Institute, 2008.

11. STEPHEN L, NELSON AND DAVID B, MBA's Guide to Microsoft Excel 2002, Maguiness Redmond Technology Press, 2001.