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Mustafa koçer
Selcuk University

Musa Hakan Arslan
Selcuk University

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Determination of moment, shear and ductility capacities of spiral columns using an artificial neural network

Mustafa Koçer[a,*], Murat Öztürk[a], M. Hakan Arslan[a]

[a] Department of Civil Engineering, Faculty of Engineering and Natural Sciences, Konya Technical University, Konya, 42130, Turkey

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ABSTRACT

Intelligent systems are frequently used to solve difficult and complex problems in today's world. Especially in the discipline of civil engineering, much research has been conducted with the help of intelligent systems. The objective of this study is to identify the moment and shear force capacities of reinforced concrete spiral columns and their displacement ductility values by using an algorithm based on an Artificial Neural Network (ANN). In the study, 86 different spiral column experiments tested in the literature were compiled, and the moment and shear force capacities obtained through the experiments were arranged at a certain level. In addition, the ductility values of the tested columns were calculated using graphical experimental data. The output layer consists of four neural network models, which are ANN_1 (with three output neurons), ANN_2, ANN_3, and ANN_4 (with one output neuron), and moment, shear force capacity, and displacement ductility parameters were obtained, respectively. According to results of this study, it was observed that moment and shear force capacities of spiral columns could be particularly well estimated using ANN. However, it was found that the estimation success of ANN for displacement ductility was not sufficient.

1. Introduction

Columns are known as the most important load-bearing elements of reinforced concrete buildings. The damage inflicted by an earthquake on one of these elements affects the whole structure and the building collapses when the damage increases. These bearing elements cannot be exposed to only axial load due to a casting feature of reinforced concrete constructions. Therefore, the columns reach their load-bearing capacity under section effect while bearing moment and shear force capacity in addition to axial load under vertical and horizontal loads. When one of these section impacts exceeds the ultimate capacity, the column reaches ultimate capacity and the behavior of the column is determined with respect to this parameter.

The failure as a result of exceeding the moment capacity of columns due to increased horizontal load during an earthquake is a desired behavioral model. It is because while a rotation occurs in the section under a fixed normal force value in critical section areas where plastic hinges are formed due to the force of the earthquake, ductile section behavior is formed without a significant change in achieved moment value.

The shear force has critical effect on reinforced concrete columns which are exposed to horizontal load during an earthquake. Shear force in reinforced concrete columns reduces the horizontal resistance of buildings and leads to a rapid loss of capacity [1]. Most of the reinforced concrete columns in the past earthquakes have collapsed due to insufficient shear resistance. Therefore, estimating the shear capacity of reinforced concrete columns is of great importance [2].

In terms of seismic performance, it is crucial to provide sufficient ductility in load-bearing systems of buildings or in elements constituting the load-bearing system. It has been widely accepted that in all earthquake regulations it is necessary to provide sufficient ductility level of the elements that form the load-bearing system and particularly the columns. Ductility is a sectional feature that can be measured [3]. The ratios of transverse and longitudinal reinforcement, the presence of confinement, the strength of concrete and reinforcement, and axial forces on the section have a one-to-one impact on ductility values. In order to determine the ductility value of load-bearing system element, displacement and curvature values at yielding and ultimate strength (depletion of power) are needed. In compliance with the capacity design, the ductility of elements should not decrease below certain limit values.

Intelligent systems are frequently used to solve difficult and complex problems in today's world. Especially in the discipline of civil engineering, much research has been conducted with the help of intelligent systems [4–8]. The principal reason for an ANN to be the subject of studies conducted in the field of civil engineering and other

* Corresponding author.
E-mail addresses: mkocer@ktun.edu.tr (M. Koçer), mozturk@ktun.edu.tr (M. Öztürk), mharslan@ktun.edu.tr (M. Hakan Arslan).

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Abbreviation list

γ	coefficient reflecting impact of the axial load on the cracking
A_{cc}	cross-sectional area of the column
A_{si}	sum of cross-section areas of longitudinal reinforcement
f_c	compressive strength of the concrete
M_r	moment capacity
N_r	axial force capacity
x_i	distance of column reinforcement to center
x_p	distance of column center
σ_{si}	reinforcement stress
A_c	cross-sectional area of the column
A_g	a gross cross-sectional area of the column
A_{sw}	sum of cross-section areas of confinement reinforcement
A_v	transverse reinforcement area
b	column width
b_w	column width
d	effective depth of column
f_c'	compressive strength of the concrete
f_{ct}	tensile strength of the concrete
f_y	yield strength of circular stirrup or spiral reinforcement
f_{yw}	yield strength of confinement reinforcement
m	number of test data
n	number of elements in the output layer of ANN
N_d	the design axial load of the column
O	estimated value
P	number of test data
P	axial load
s	the spacing of transverse reinforcement
$T_{estimate}$	estimated values
t_i	target value
T_{real}	real values
V_r	shear force capacity
x'	normalized value
x_i	input value
x_{max}	highest values in the input set
x_{min}	lowest values in the input set
$y_{(t)}$	error term
L	column effective length
ρ_s	volumetric reinforcement ratio (%)

disciplines is the fact that it offer an alternative solution model for problems which are hard to solve with traditional techniques thanks to its success in approaching and defining the data in different structures and forms.

The objective of this study is to identify moment and shear force capacities and displacement ductility of spiral columns with different engineering features by using an ANN technique, comparing the obtained results with results of laboratory studies and testing the effectiveness of ANN in this field based on the analyses. There was no implementation of smart systems that determine shear, flexural and ductility of spiral columns simultaneously and separately in the literature. The dataset used within the scope of the study was composed of results of 86 spiral column tests obtained from the data bank that includes tests conducted by different researchers at the Pacific Earthquake Engineering Research Center (PEER) and in the literature. 50 of these data sets are used for training, 29 for testing, and 7 for verification. Moment and shear force capacities of columns contained in verification set were compared with theoretical results obtained from current reinforced concrete regulations [9,10] and effectiveness of convergence of the ANN and theoretical approaches to experimental results were evaluated.

2. General characteristics of columns

2.1. Moment capacities of columns

Capacities of columns exposed to combine bending (N + M) are determined by writing equations of compliance amounting reinforcement sequence and two equations of equilibrium. A typical circular column section exposed to axial load N and strain diagram is shown in Fig. 1. Moment capacity of this element M_r, is calculated by the generalized formula in Eq. (1), after the height of the compression area, c, is identified. Strength recovery that occurs in the concrete core is ignored in this formulation. Even though it is possible to derive equations to determine the capacity of columns, using these equations for each and every N or M is rather troublesome. Therefore, calculations of load-bearing capacity of columns are made more easily via design tables and computer programs. Strength values given in Eqs. (1) and (2) should be considered as characteristic values for design and current (measured) strength for verification.

$$M_r = N_r \times e = 0.85 f_c A_{cc}(x_p - \bar{x}) + \sum_{i=1}^{n} A_{si}\sigma_{si}x_i \tag{1}$$

$$N_r = 0.85 f_c A_{cc} + \sum_{i=1}^{n} A_{si}\sigma_{si} \tag{2}$$

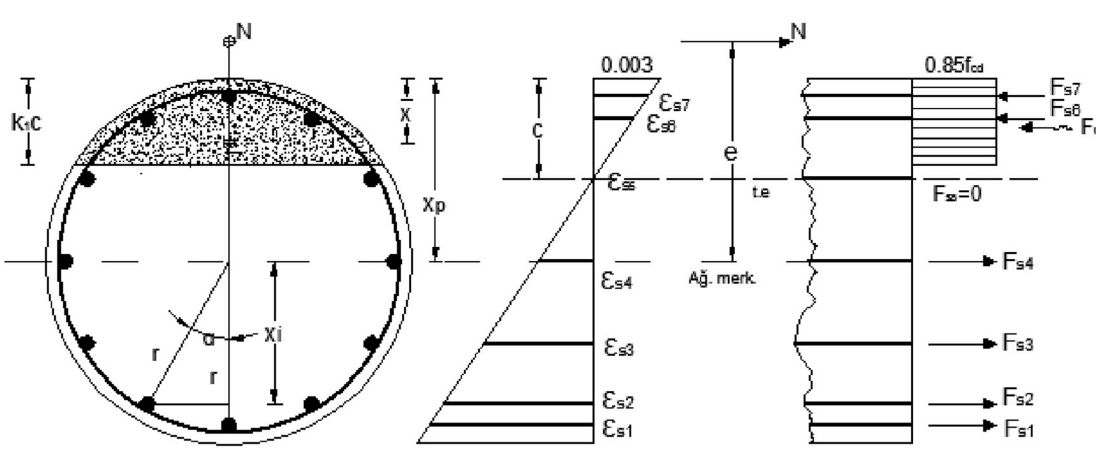

Fig. 1. Circular column under combined bending.

2.2. Shear force capacities of columns

Analytic formulas to calculate the shear strength of circular columns are present in many reinforced concrete building regulations such as the American Concrete Institute (ACI 318-08) [9], Design of Concrete Structures (CSA) [11], The Shear Strength of Reinforced Concrete Members (ASCE-ACI) [12], Specification for Design and Construction of Concrete Structure (JSCE) [13], Reinforced Concrete Structures Design and Construction Rules (TBC 500-2000) [14], and shear strength of circular columns in the empirical expressions contained in these regulations is calculated by taking the contribution of concrete and confinement reinforcement. Therefore, it is accepted that a portion of the design shear force is carried by concrete (V_c) and the remaining portion is carried by transverse reinforcement (V_s).

$$V_r = V_s + V_c \tag{3}$$

The equation below is given in ACI 318-08 [9] earthquake regulation in order to calculate the contribution of concrete (V_c) to the shear strength of elements exposed to shear, bending, and axial pressure [9].

$$V_c = 0.166\left(1 + \frac{P}{13.80A_g}\right)\sqrt{f_c'}\ b\,d\,(\text{Units: MPa}) \tag{4}$$

Here, P is the axial load that the column is exposed to; A_g is a gross cross-sectional area of the column; f_c' is the compressive strength of the concrete; b is column width, and d is the effective depth of the column. The contribution of transverse reinforcement, V_s:

$$V_s = \frac{A_v f_y d}{s} \tag{5}$$

is calculated with Eq. (5). Here, A_v is transverse reinforcement area, f_y is yield strength of circular stirrup or spiral reinforcement and s is the spacing of transverse reinforcement.

According to TBC 500-2000 [14], the contribution of concrete to shear strength V_c is calculated by taking 80% of the cracking strength (V_{cr}) of the reinforced concrete section at shearing [10]. Cracking strength of concrete at shearing (diagonal cracking strength), V_{cr} is calculated with the following equation:

$$V_{cr} = 0.65 \times f_{ct} \times b_w \times d \times \left(1 + \gamma\frac{N_d}{A_c}\right) \tag{6}$$

$$V_c = 0.\ 80\,V_{cr} \tag{7}$$

Here, N_d is the design axial load of the column; A_c, is the cross-sectional area of the column; f_{ct} is the tensile strength of the concrete; b_w is the column width; d is the effective depth of the column and γ is the coefficient reflecting impact of the axial load on the cracking strength (in case of axial pressure, $\gamma = 0.07$ in case of axial tension, $\gamma = -0.3$). The contribution of transverse reinforcement, V_s is calculated with Eq. (8):

$$V_s = \left(\frac{A_{sw}}{s}\right)f_{yw}\,d \tag{8}$$

Here, A_{sw} is the sum of cross-section areas of confinement reinforcement, s is the confinement reinforcement spacing, f_{yw} is the yield strength of confinement reinforcement, and d is the effective depth of column.

2.3. Displacement ductility

Ductility is the plastic deformation ability of structure and constituting elements without any significant loss of strength and rigidity [15]. Among the ductility parameters, displacement is the most appropriate to evaluate the behavior of the structure and columns. The ductility of a cantilever column is determined by the ratio of ultimate displacement to yield displacement.

When calculating displacement ductility, various alternative methods have been offered to identify yield and ultimate displacement on the load-displacement curve as a result of experimental studies conducted by various researchers [15–17]. In this study, yield displacement is obtained by idealizing load-displacement envelope curve according to the two-line elasto-plastic behavior model (Fig. 2). In addition, ultimate displacement is determined by taking into account a certain amount of strength loss following the maximum load.

3. Artificial intelligence

The Artificial Neural Network (ANN) has been widely used to forecast difficult engineering problems. In the literature, the comparison between the ANN and other nonlinear regression model using error analysis showed that the ANN has good forecasting value for estimation capacity. Also in the literature it is well known that the percentage of error analysis using Mean Absolute Percentage Error (MAPE) for ANN produced less error than the linear and nonlinear regression. On the other hand, it is still discussed that some combined ANN and new generation soft computing methods can give a better results than conventional ANN.

3.1. Artificial neural networks (ANNs)

ANN might be considered as a logically programmed mechanism which was developed with the inspiration from the biological nervous system and which aims to generate the basic operations of the human brain with a certain software. A basic ANN cell in engineering has a simpler structure than a biological nerve cell and is defined as a processing element which connects the data obtained from the external environment to neurons via weights and produces an output by

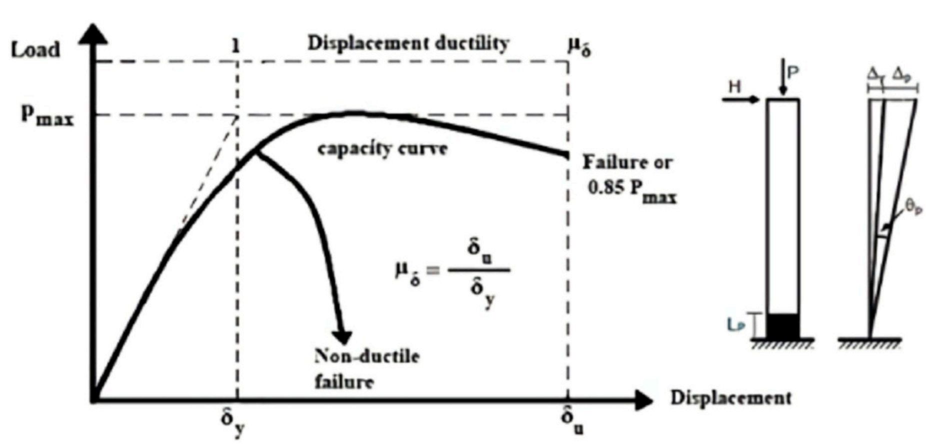

Fig. 2. Determination of yield and ultimate displacements of columns.

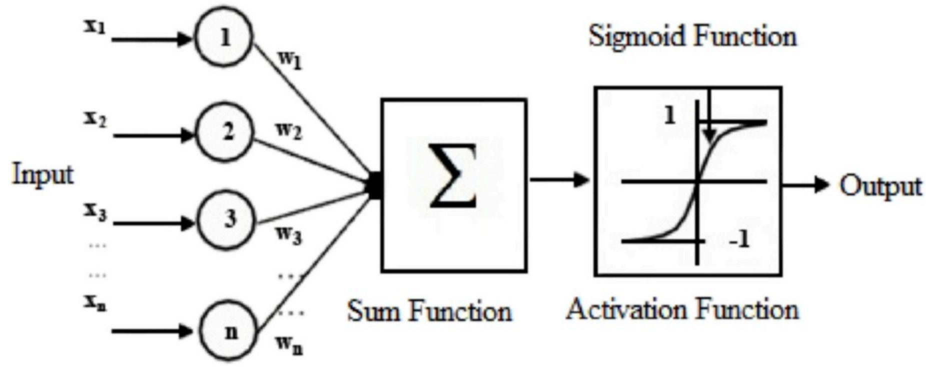

Fig. 3. A basic ANN cell [7].

determining the impact of these weights on the input when the sum of inputs exceeds the internal threshold value. The weights here are updated for all new data and the connection to neuron means the result of the multiplication of inputs with weights corresponding to these inputs with the help of sum function [18]. The result obtained passes through the activation function, calculates the net output during the operation and also generates the neuron output of this operation. The activation function is generally a non-linear function. A mathematical model of a simple neuron cell is shown in Fig. 3.

4. Composing a data set and selection of parameters

In this section, moment and shear force capacities and ductility values of spiral columns having different features are attempted to be estimated with four different ANNs. The dataset is obtained from the data bank comprising tests conducted by different researchers at the Pacific Earthquake Engineering Research Center (PEER) and in the literature. The experimental features of 79 spiral column test elements in this set, such as column section and height, mechanical features and ratios of longitudinal and transverse reinforcement, mechanical feature of concrete, axial load ratio and concrete cover, are taken into consideration to obtain moment and load-bearing capacities of columns, and continuity value of displacement ductility obtained via displacement sizes between yield and ultimate strength are arranged as shown in APPENDIX-1. Randomly selected 50 test elements among 79 test elements constituted the training set of the ANN algorithm while 29 test elements formed the test group. The test data are stated in terms of intended use (training or test) in the table in APPENDIX-1. It is observed in the experiments that columns are generally broken under the impact of bending or flexure + shear (shear flexural) and only a few reached its capacity due to shearing. In the study, a verification set involving 7 spiral columns compiled from literature was formed and it was tested.

In order for the accuracy of the study, it is crucial to determine ANN architecture that will be used to determine moment and shear force capacities of reinforced concrete spiral columns under vertical and horizontal loads and their displacement ductility and to obtain the results within the optimum period. Therefore, 9 parameters to represent the input layer of the training algorithm, variables of problem and value of a column in the output layer are specified. These nine parameters are the parameters found in the empirical formulas used to calculate the moment and shear force carrying capacities of the reinforced concrete columns. In order to minimize the selection of input data in this layer and to ensure homogeneity of inter-column values, input parameters are composed by using processes such as column diameter and concrete cover instead of column area, axial load ratio instead of axial load, and longitudinal and transverse ratios instead of reinforcements. Since the column diameter D and length L are selected as parameters in the input layer, the slenderness ratio that are related to H/L are not considered as a parameter. Input parameters and numerical change ranges of training and test set are shown in Table 1.

The number of processing elements in the output layer is formed by the definition of the problem. Four different network architectures are created in this study. These network architectures are named ANN_1, ANN_2, ANN_3, and ANN_4. Model ANN_1 has three neurons in output layer and moment and shear force capacities of spiral columns and their ductility are estimated simultaneously. ANN_2, ANN_3, and ANN_4 network architectures have one output neuron; moment capacity, shear force capacity and section ductility are estimated respectively. The input layers of the four network structures are the same. However, while the output layer of the ANN_1 model has three neurons, the ANN_2, ANN_3 and ANN_4 network architectures have a single output neuron. The outputs in the ANN_1 model cover the outputs of the other three ANN's. Moment and shear force capacities of spiral columns are obtained from the test results. Ductility capacities are also calculated by load-displacement graphics obtained from the tests. For example, how the yield and failure displacement values calculated based on horizontal load (shear force) that cantilever column would bear by using

Table 1
Input parameters and change ranges of training and test set.

No	Symbol	Input Parameters	Minimum Value	Maximum Value
1	D	Diameter (mm)	152	1520
2	d'	Concrete cover (mm)	9,7	60,3
3	L	Column effective length (mm)	570	9140
4	f_c	Concrete compressive strength (MPa)	23,1	90
5	f_y	Yield strength of longitudinal reinforcement MPa)	296	507,5
6	ρ_t	Longitudinal reinforcement ratio (%)	0,52	5,57
7	f_{yw}	Yield strength of transverse reinforcement (MPa)	300	1000
8	ρ_s	Volumetric reinforcement ratio (%)	0,13	3,43
9	N/N_o	Axial load ratio (%)	0,08	0,42

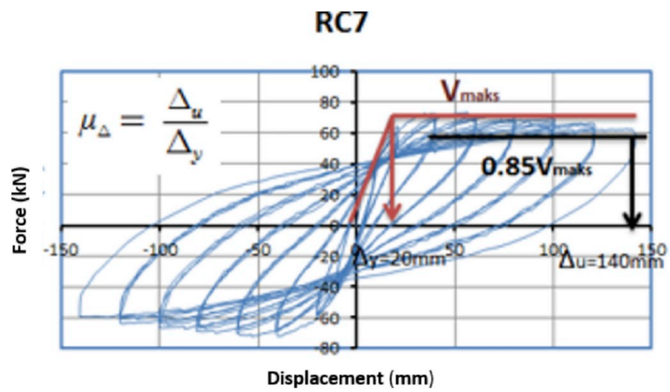

Fig. 4. Saatcioglu and Baingo (1999) lateral load-displacement curve belonging to RC7 test element [19].

Table 2
Output parameters and change ranges of training and test set.

No	Symbol	Output Parameters	Minimum Value (kN-m)	Maximum Value (kN-m)
1	M	Moment	22	14500
2	V	Shear	14	2968
3	μ	Ductility	1,23	14,04

load-displacement graph obtained from Saatcioglu and Bingo [20], RC7 test is shown in Fig. 4.

Input parameters and numerical change ranges of training and test set are shown in Table 2.

The input and output data in ANN are subjected to normalization process to provide homogeneity between columns before getting trained in the network. There are numerous data normalization techniques in the literature. Some of them are Median, Rule of Minimum, Rule of Maximum, Sigmoid, and Z-Score [20]. The data set used in this study is subjected to a scaling procedure between [0, 1]. In order to achieve this, min-max normalization technique is preferred as in studies of Pu [21], Arslan [3], and Koroglu [22], and scaling is made by using the formula given in Eq. (9) The values of training and test data after normalization procedure are given in the table in APPENDIX-2.

$$x' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

In Eq. (9) x' is the normalized value of x_i input value and, x_{max} and x_{min} respectively represent the highest and lowest values in the input set.

There are numerous criteria values in the literature which are used to evaluate the accuracy of estimation of established ANN models. The simplest error term among these values is calculated by means of finding the error value between real values and estimated values (y (t) = T_{real}-$T_{estimate}$) [23]. In this study, the most commonly used performance criteria values in literature shown in Table 3 are examined [24–26].

Here, P is the number of test data, o_i is the estimated value, t_i is the target value, m is the number of test data and n is the number of elements in the output layer of ANN. The accuracy of classification is obtained from Eq. (10) [27].

$$\text{Classification accuracy}\,(\%) = 100 - \text{Test Error} \tag{10}$$

Table 3
Performance criteria values.

The coefficient of determination (R^2), $R^2 = 1 - \left(\frac{SS_{err}}{SS_{tot}}\right)$, $R^2 = 1 - \left(\frac{\sum_{i=1}^{P}(t_i - o_i)^2}{\sum o_i^2 - \frac{(\sum o_i)^2}{P}}\right)$
Root Mean Square Error (RMSE), $RMSE = \sqrt{\frac{\sum_{i=1}^{P}(t_i - o_i)^2}{P}}$
Mean Absolute Error (MAE), $MAE = \frac{1}{P}\sum_{i=1}^{P}\lvert t_i - o_i\rvert$
Mean Absolute Percentage Error (MAPE), $MAPE = \frac{1}{P}\sum_{i=1}^{P}\frac{\lvert t_i - o_i\rvert}{o_i} \times 100$
Test Error (TE), $Test\ Error\,(\%) = \left(\frac{\sum_{i=1}^{P}\lvert t_i - o_i\rvert}{m \times n}\right) \times 100$

Table 4
Training algorithms used in ANN.

BFG	Broyden- Fletcher- Goldfarb-Shanno
BR	Bayesian Regularization
CGB	Conjugate Gradient with Powell/Beale Restarts
CGF	Fletcher-Powell Conjugate Gradient
CGP	Polak-Ribiere Conjugate Gradient
GD	Gradient Descent
GDM	Gradient Descent with Momentum
GDA	Variable Learning Rate Gradient Descent
GDX	Gradient Descent with Adaptive Learning
LM	Levenberg-Marquardt
OSS	One Step Secent
SCG	Scaled Conjugate Gradient

5. ANN training and results

The number of hidden layers of ANN model and the number of processing elements in the hidden layer is determined by means of the trial-and-error method as in similar studies [1–28]. During trial-and-error method learning, momentum and iteration values are fixed and firstly, numbers of hidden layers and processing elements of hidden layers are determined. By raising the number of hidden layers of ANN models incrementally from 1 to 3 and the number of neurons in the hidden layer from 2 to 50, numbers of optimum hidden nodes and hidden nodes cells are obtained in values where the training and test errors are the lowest. When performing these operations, the values of momentum, learning coefficient and iteration are kept fixed. Later on, the number of iterations is changed and the network architecture with the lowest training and test error is established. Performances of ANN models are evaluated with R^2 (determination coefficient). Feed-forward networks are the most commonly used network model in ANN and since they do not have a loop within themselves, they produce output data quickly without any delay. The feed-forward neural network has drawn great interest in many applications due to its universal approximation capability [29]. In this study 12 different feed-forward back propagation algorithms were used. These feed-forward back-propagation algorithms which can update weight and bias values of network parameters and back-propagate the error are used to train ANN models created in MATLAB program (Table 4).

The quadratic mean of error between the expected value and the estimated value (MSE) is used as a performance function during the training of the ANN model; a sigmoid function which can address wide input range in hidden layers and provide a smooth transition between values is used as a transfer function and purelin function is used in the output layer. Delta rule which adapts itself by intending to minimize quadratic mean of error between expected output and output produced by the network is used as adaptive learning function. Training

Table 5
Optimum ANN parameters.

ANN Models	Target	Number of H.L[a]	H.L[a] Number of Nodes	Number of Iterations	Learning Duration (sec)	Learning Ratio	Momentum Coefficient
ANN_1	M_r-V_r-μ	2	17–5	100000	288	10	0,01
ANN_2	M_r	1	3	5000	10	10	0,01
ANN_3	V_r	2	13–3	38000	70	10	0,01
ANN_4	μ	3	13-3-17	5000	15	10	0,01

[a] H.L = Hidden Layer.

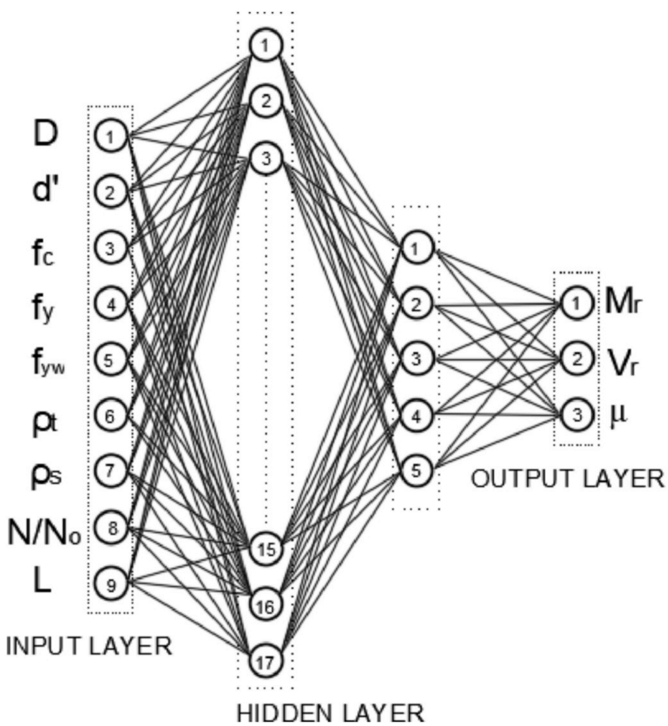

Fig. 5. Network architecture of ANN_1 model.

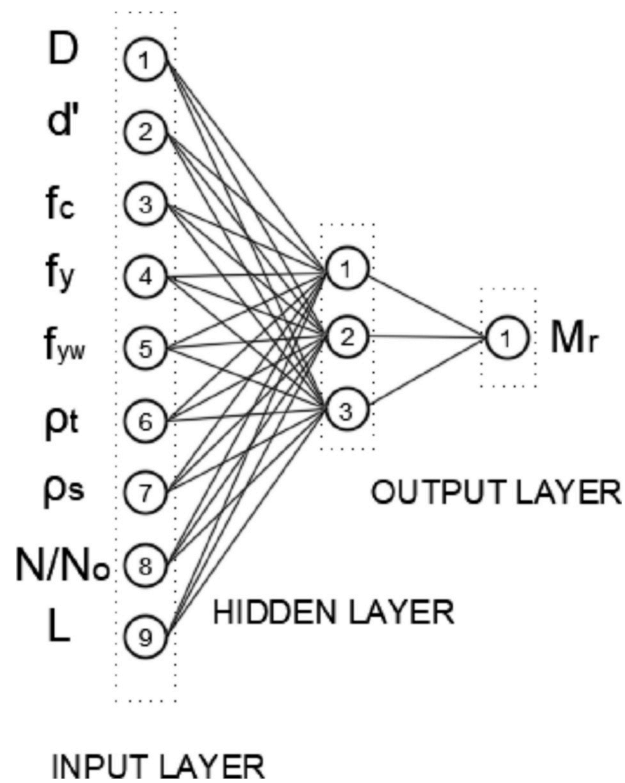

Fig. 6. Network architecture of ANN_2 model.

parameters belonging to ANN models are shown in Table 5 and network structures are shown in Figs. 5–8.

At the end of training, the values of moment, shear and ductility are normalized. To compare these values with actual values, conversion is applied with a correlation of Eq. (11).

$$x_i = x' \times (x_{\max} - x_{\min}) + x_{\min} \tag{11}$$

5.1. Results of ANN_1 model

R^2, RMSE, MAE, MAPE, Test Error results used to evaluate performances of ANN models are shown in Table 6 for ANN_1 model. According to the results, for ANN_1 model's 12 different training algorithms, R^2 values were obtained between 0.9499 and 0.16. It is determined that the network model created with the SCG algorithm which has the highest R^2 value and the lowest RMSE, MAE, MAPE and Test Error values is the most appropriate model among the models created to obtain a moment, shear and section ductility capacities of spiral columns. The resulting value of 94.99% R^2 value of sensitivity analysis shows that 94.99% of the total change is determined by the established model, that is, by independent or dependent variables, 5.01% occurs accidently or by other disregarded variables. The data obtained by the test results of moment, shear and ductility capacities of spiral columns are compared with the estimation results obtained from ANN_1 model in Fig. 9 and it is observed that ANN_1 is successful with a sufficient sensitivity ratio of 94.99%.

The impacts of output parameters on network performance of ANN_1 model are separately shown in Fig. 10. As seen from distribution diagrams moment capacity was R^2= 96.49%, shear force capacity was R^2= 87.34%, section ductility capacity was R^2=75.05%. It is normal that the estimated values of ANN's moment capacity were more convenient than the estimated value of shear force capacity since no classification is made in terms of failure type of columns when test data set is organized and damage is caused by bending in most of the columns during tests. It is observed that the ductility value could not reach the convergence level of the other two output parameters.

5.2. ANN_2 model results

Performance criteria values for ANN_2 model are shown in Table 7. According to the results, for 12 different training algorithms of ANN_2 model, R^2 values change between 0.5033 and 0.9762. It is determined that the network model created with the SCG algorithm which has the highest R^2 value and the lowest RMSE, MAE, MAPE and Test Error values is the most appropriate model among the models created to obtain a moment, shear and section ductility capacities of spiral columns. Sensitivity analysis result shows that ANN_2 model is quite successful in estimating moment capacity with R^2 sensitivity ratio of 97.62%. Fig. 11 shows the distribution diagram of monitored and predicted values of the SCG algorithm while Fig. 12 shows a graphical presentation of the estimated values and actual values.

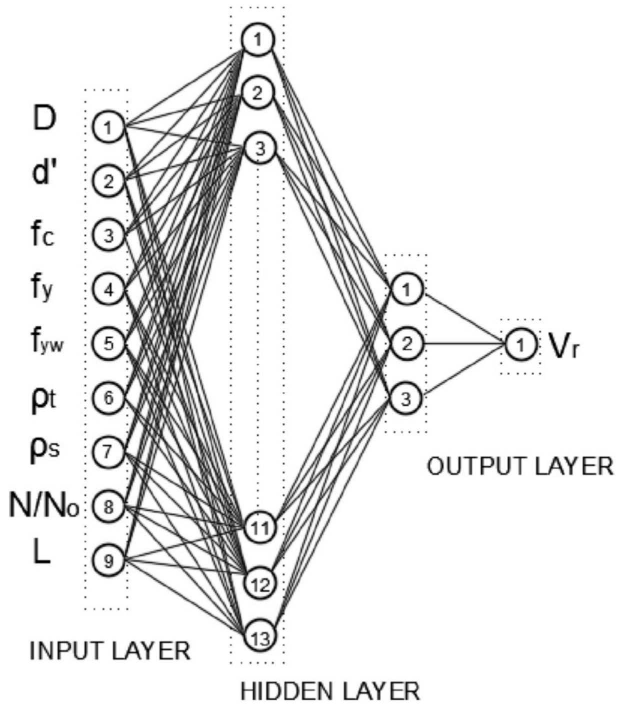

Fig. 7. Network architecture of ANN_3 model.

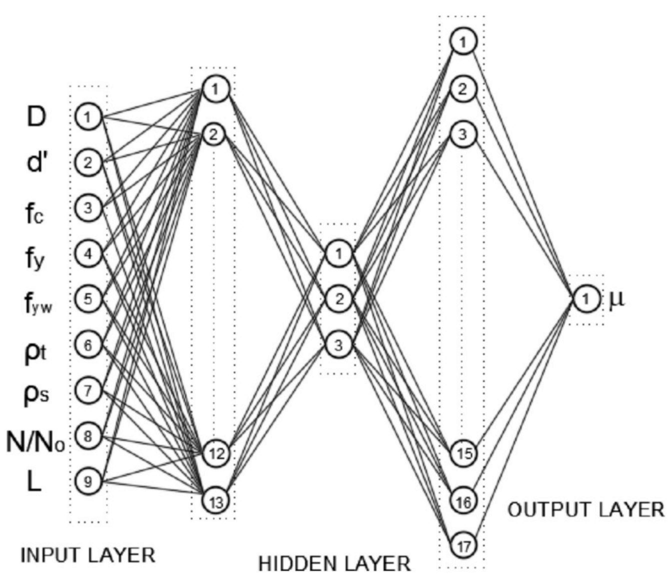

Fig. 8. Network architecture of ANN_4 model.

5.3. ANN_3 model results

Criteria parameters such as R^2, RMSE, MAE, MAPE, Test Error used to evaluate performances of ANN models are shown in Table 8 for ANN_3 model. According to the results, for 12 different training algorithms of ANN_3 model, R^2 values change between 0.2336 and 0.9621. It is determined that the network model created with the SCG algorithm which has the highest R^2 value and the lowest RMSE, MAE, MAPE and Test Error values is the most appropriate model among the models created to obtain shear capacities of spiral columns. Sensitivity analysis result shows that ANN_3 model is quite successful in estimating shear force capacity with R^2 sensitivity ratio of 96.21%. Fig. 13 shows the distribution diagram of the observed and predicted values of the SCG algorithm while Fig. 14 shows a graphical presentation of the estimated values and actual values.

5.4. ANN_4 model results

Performance criteria parameters such as R^2, RMSE, MAE, MAPE, and Test Error are shown in Table 9 for ANN_4 model. According to the results, R^2 values for 12 different training algorithms of ANN_4 model changes between 0.2338 and 0.7760. It is determined that the network model created with the SCG algorithm which has the highest R^2 value and the lowest RMSE, MAE, MAPE and Test Error values is the most appropriate model among the models created to obtain section ductility capacities of spiral columns.

Sensitivity analysis result shows that ANN_4 model is not quite successful in estimating section ductility with R^2 sensitivity ratio of 77.60%. Fig. 15 shows the distribution diagram of the observed and predicted values of the SCG algorithm while Fig. 16 shows a graphical presentation of the estimated values and actual values.

6. Verification set

In this section of the study, a verification set involving 7 spiral columns used as test elements which are compiled from literature independent of test and training set is formed to measure the performance accuracy of ANN_1 network model (Table 10). The verification set shown in Table 10 is tested with the network model ANN_1 which has the most complex structure proposed and the moment and shear force capacities along with ductility values of circular spiral columns are estimated. The estimation results of verification set show that the estimation result values of ANN1 model and test results are rather close to each other and the proposed model is successful with a classification accuracy of 80.78% (Table 11).

As a result of the sensitivity analysis, R^2 values for the moment, shear and ductility parameters and convergence successes were obtained with 88.87%, 98.75%, and 16.69% precision respectively. It is seen that the success of predicting moment and shear force capacities of spiral columns in network model ANN_1 is better than the success of predicting displacement ductility. The main reason for this is considered to be the fact that the displacement ductility values are rather low in comparison to the values of moment and shear. Fig. 17 shows the distribution diagram of observed and predicted values of verification set.

The shear force capacities of spiral column test elements included in the verification set are compared with the theoretical approaches specified in reinforced concrete construction regulations [9,14] in Table 12. When the contribution of concrete is calculated in the

Table 6
Criteria results of ANN_1 model obtained by analysis.

ANN training algorithms		BFG	BR	CGB	CGF	CGP	GD	GDM	GDA	GDX	LM	OSS	SCG
Results of ANN_1 Model	R^2	0,56	0,62	0,76	0,7355	0,8339	0,8232	0,8235	0,9076	0,8393	0,1664	0,4804	0,9499
	RMSE	0,1634	0,1646	0,1279	0,1316	0,0971	0,1109	0,1139	0,081	0,0971	0,3967	0,2789	**0,0776**
	Test Error	6,8755	6,1362	6,0782	5,2706	4,5147	6,7409	6,735	4,7145	4,8004	12,357	8,4137	**4,0562**
	MAE	0,0688	0,0614	0,0608	0,0527	0,0451	0,0674	0,0673	0,0471	0,048	0,1236	0,0841	**0,0406**
	MAPE	0,4448	0,397	0,3932	0,341	0,2921	0,4361	0,4357	0,305	0,3106	0,7995	0,5443	**0,2624**

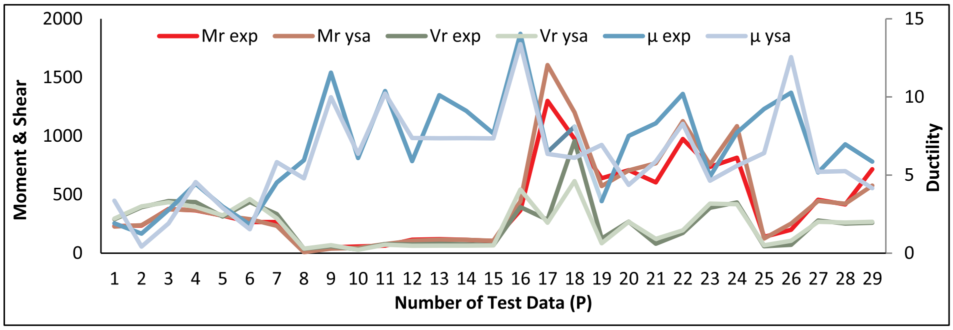

Fig. 9. Graphic presentation of estimated values and actual values of SCG training function of ANN_1 model.

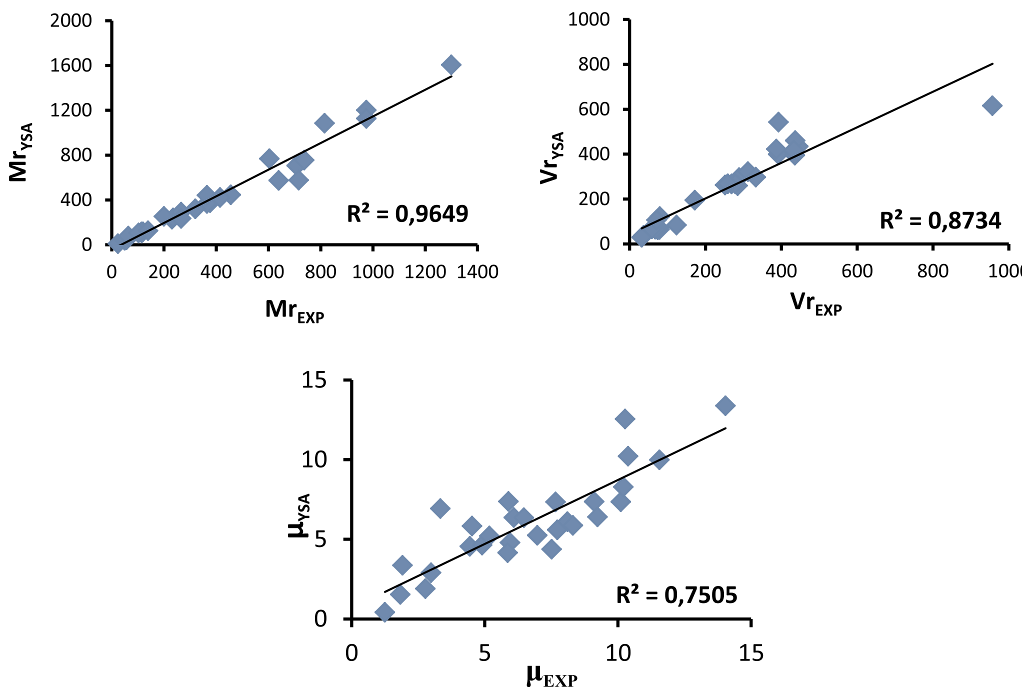

Fig. 10. Comparison of the estimated moment, shearing and ductility values of ANN_1 model with test results.

Table 7
Criteria results of ANN_2 model obtained by analysis.

ANN training algorithms		BFG	BR	CGB	CGF	CGP	GD	GDM	GDA	GDX	LM	OSS	SCG
Results of ANN2 Model	R^2	0,9585	0,9295	0,5033	0,7449	0,8465	0,7355	0,6706	0,8494	0,8469	0,9576	0,8091	**0,9762**
	RMSE	0,0046	0,0071	0,0163	0,013	0,0089	0,0132	0,0199	0,0088	0,009	0,0047	0,0099	**0,0035**
	Test Error	0,301	0,3765	1,1232	1,0191	0,6544	0,9261	1,3473	0,7283	0,5523	0,2762	0,5685	**0,2268**
	MAE	0,003	0,0038	0,0112	0,0102	0,0065	0,0093	0,0135	0,0073	0,0055	0,0028	0,0057	**0,0023**
	MAPE	0,3922	0,4905	1,4633	1,3276	0,8525	1,2066	1,7552	0,9489	0,7195	0,3598	0,7406	**0,2954**

calculation of shear force capacity, axial load levels on columns are also taken into consideration. The types of failure occurred in columns when the column reaches load-bearing capacity during tests are specified in tables for each test element. Among the test elements, only the test element no. 2 reached failure state due to shear capacity and the experimental shear force capacity value of this column is obtained with a ratio of 1.072 to the closest result by TBC 500-2000 regulation. But when the mean of shear force capacity rates of all test elements are taken into consideration, the worst result is obtained from TBC 500-2000 with the rate of 0.55 and a rather successful result is obtained with the rate of 1.002 with the recommended ANN_1 model. The calculated shear force capacities of test elements 3/4/5/7 in accordance with theoretical approaches stated in reinforced concrete construction regulations and their experimental shear force capacity values are quite different as shown in Table 12. The reason for this difference is that these test elements reach their horizontal load bearing capacities due to bending before they reach their shear force capacities calculated in accordance with theoretical approaches. Fig. 18 shows the load-displacement curves of sample columns which reach their horizontal load bearing capacities due to bending and shear force. As shown in these curves, there is no increase of horizontal load in the ductile section due to bending and it continues to bear the load by increasing displacement under a fixed horizontal strength.

A comparison is made between experimental moment capacities of

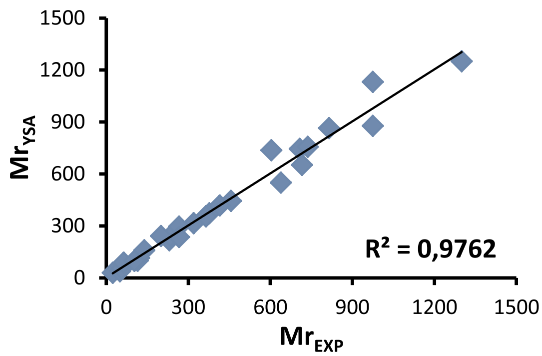

Fig. 11. Moment distribution diagram of the SCG training algorithm of ANN_2 model.

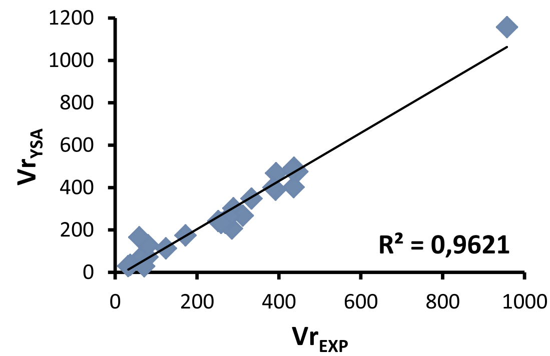

Fig. 13. Distribution diagram of shear values SCG training algorithm of ANN_3 model.

spiral column test elements included in the verification set and theoretical approaches specified in the reinforced concrete construction regulations in Table 13. As a result of this comparison, among the ratio means of experimental moment capacities of spiral columns in the verification set and the ratio means of moment capacities obtained by using equations in regulations: the worst result is obtained with ACI 318-08 regulation as 1.29 and the closest result is obtained in the recommended ANN model with TBC 500-2000 with the rate of 0.9942 and rate of 1.13, respectively. It is seen in the light of results that the network model created in this study provides more appropriate results which are fairly close to the actual data than the reinforced concrete regulations.

7. Conclusions

In this study, an ANN based algorithm is developed to estimate the moment and shear force capacities and the displacement ductility of a reinforced concrete spiral column by means of the data obtained from 86 spiral column tests carried out experimentally in literature. It is found in the study that the moment and shear force capacities and the displacement ductility of spiral columns are more precisely estimated in comparison to the empirical approaches specified in the reinforced concrete regulations. The Network performance of the recommended and developed ANN network model has tested again by means of the verification set which is particularly independent of the selected data set and it is observed that the ANN model would be reliably used due to its success to estimate the moment and shear force capacities and the displacement ductility of spiral columns simultaneously.

The moment and shear force capacities and the displacement ductility of the network structures named ANN_1, ANN_2, ANN_3, ANN_4 led to encouraging results of 94.49%, 97.62%, 96.21%, 77.60% respectively and this proved that ANN has a potential use in this field. In addition, the success of the verification set shows that it could be used as an alternative method to overcome the difficulties in estimating the moment and shear force capacities and displacement ductility of a spiral column.

It is seen that the SCG algorithm is more successful than other feed-forward back-propagation training algorithms. The closest result to the SCG algorithm is obtained with the GDA algorithm as 90.76% in network architecture named ANN_1.

The results of ANN_1 and ANN_4 showed that they are far off the estimation results of the moment and shear force capacities in predicting displacement ductility of spiral columns. It is considered that the main reason for this finding is the acceptances made in the determination of displacement values in yield and collapse positions. Moreover, as the ductility values are numerically lower than the values

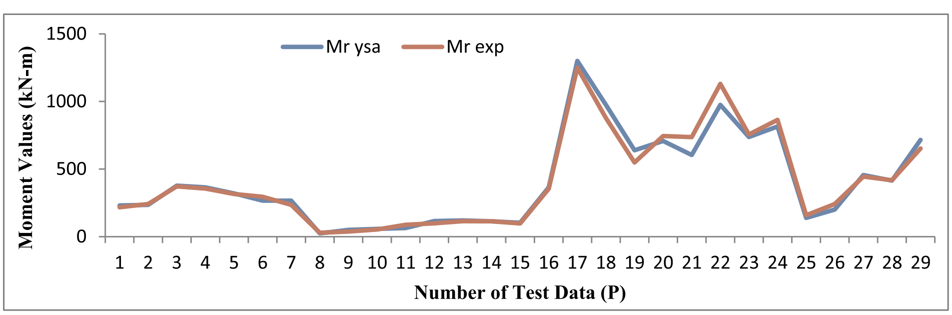

Fig. 12. Graphic presentation of estimated values and actual values of SCG training function of ANN_2 model.

Table 8
Criteria results of ANN_3 model obtained by analysis.

ANN training algorithms		BFG	BR	CGB	CGF	CGP	GD	GDM	GDA	GDX	LM	OSS	SCG
Results of ANN_3 Model	R^2	0,2336	0,5614	0,7381	0,9403	0,9557	0,5603	0,545	0,504	0,4567	0,7011	0,8551	**0,9621**
	RMSE	0,0658	0,0505	0,035	0,0171	0,0143	0,0444	0,0452	0,0469	0,0492	0,0473	0,0285	**0,0178**
	Test Error	2,7932	2,0629	1,3454	1,0106	0,8838	3,4828	3,52	2,055	1,9289	2,5542	1,3489	**1,0791**
	MAE	0,0279	0,0206	0,0135	0,0101	0,0088	0,0348	0,0352	0,0205	0,0193	0,0255	0,0135	**0,011**
	MAPE	1,2208	0,9016	0,5884	0,4417	0,3863	1,5222	1,5384	0,8981	0,843	1,1163	0,5895	**0,4795**

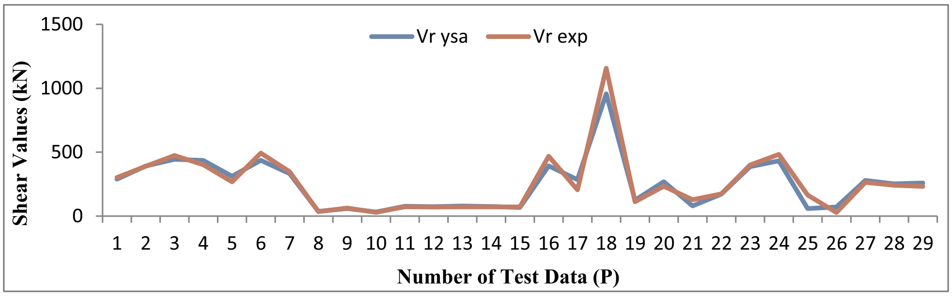

Fig. 14. Graphic presentation of estimated values and actual values of SCG training function of ANN_3 model.

Table 9
Criteria results of ANN_4 model obtained by analysis.

ANN training algorithms		BFG	BR	CGB	CGF	CGP	GD	GDM	GDA	GDX	LM	OSS	SCG
Results of ANN_4 Model	R^2	0,4302	0,6032	0,3551	0,2338	0,6467	0,3932	0,0811	0,4802	0,4739	0,5123	0,5688	**0,776**
	RMSE	0,2418	0,1822	0,274	0,2765	0,1591	0,2043	0,2521	0,1928	0,1911	0,1791	0,1649	**0,1365**
	Test Error	17,287	13,169	16,954	16,082	12,336	14,968	19,972	13,475	13,47	13,729	13,334	**10,977**
	MAE	0,1729	0,1317	0,1695	0,1608	0,1234	0,1497	0,1997	0,1348	0,1347	0,1373	0,1333	**10,98**
	MAPE	1,394	1,0619	1,3672	1,2968	0,9947	1,207	1,6104	1,0866	1,0862	1,1071	1,0752	**0,8851**

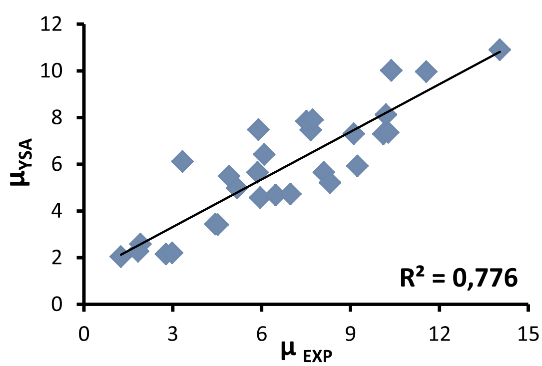

Fig. 15. Distribution diagram of ductility values of SCG training algorithm of ANN_4 model.

of moment and shear force values, it is assumed that the little differences between the predicted and estimated values increase the error percentage and consequently, increase the test error. On the other hand, when calculating displacement ductility, various alternative methods have been offered to identify yield and ultimate displacement on the load-displacement curve. In this study, yield displacement is obtained by idealizing load-displacement envelope curve according to the two-line elasto-plastic behavior model. Ductility capacity is not an experimental result such as moment and shear force capacity and is determined according to the acceptances. Therefore, it varies according to the assumptions made. The effect of the input parameters was compared with IBM SPSS analysis program [30]. It is seen that the parameters effective in ductility capacity are effective in artificial neural networks. However, the estimation of the ductility capacity of artificial neural networks is not sufficiently successful. Therefore, it is considered that the effect on ductility capacity of approximate assumptions such as determination of yield displacement has a great effect, thus affecting the result to a great extent.

The effect of the nine parameters selected for the input layer on the parameters in the output layer was evaluated by correlation analysis using the IBM SPSS statistic program (Table 14). According to the results of correlation analysis, it was seen that column diameter D, cover thickness d’ and column length L were effective for moment capacity (M_r). For the shear force capacity (V_r), the column diameter D, the cover thickness d, the volumetric ratio of the confinement reinforcement ρ_s along with the column length and the yield strength of reinforcement steel f_y were effective parameters. Also for the capacity of ductility (μ), the longitudinal reinforcement ratio ρ_t is determined as the most effective parameter. Other effective parameters for ductility are volumetric ratio of reinforcement ρ_s, yield strength f_y and also the axial load ratio N/N_o. In contrast to the reinforced concrete behavior, it is seen from the correlation distribution given in Table 14 that the concrete type (or concrete compressive strength f_c) and the yield strength

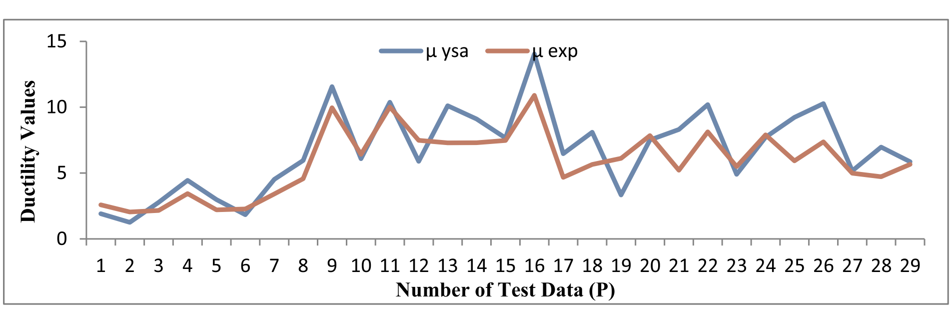

Fig. 16. Graphic presentation of estimated values and actual values of SCG training function of ANN_4 model.

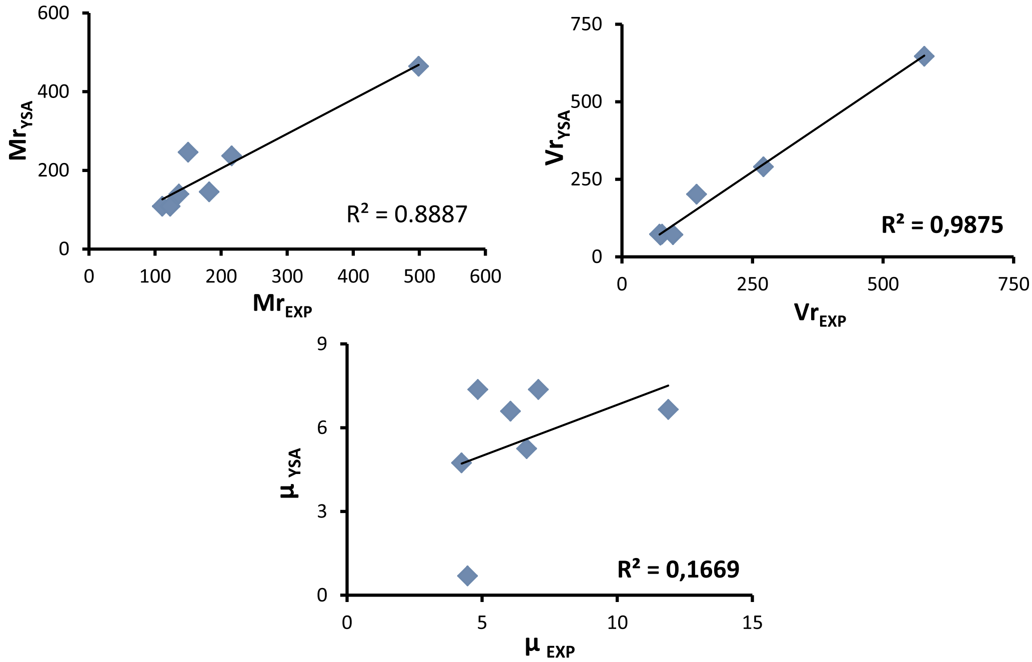

Fig. 17. Distribution diagram of verification set.

Table 10
Input parameter values of verification set.

Specimen Name	D (mm)	d' (mm)	L (mm)	f_c (MPa)	f_y (MPa)	ρ_l (%)	f_{yw} (MPa)	ρ_s (%)	$P_e/(f_c*A_g)$
Wong et al., 1990, No. 3	400	20	800	37	475	3,2	300	1,42	0,39
Ang et al., 1985, No. 21	400	18	800	33,2	436	3,2	326	0,38	0
Kunnath et al., 1997, A4	305	14,5	1372	35,5	448	2,04	434	0,94	0,09
Kunnath et al., 1997, A5	305	14,5	1372	35,5	448	2,04	434	0,94	0,09
Hamilton, 2002, UCI2	406,4	15	1854,2	36,5	458,5	1,17	691,5	0,53	0
Hamilton, 2002, UCI3	406,4	10,5	1047,7	34,7	458,5	1,37	691,5	0,1	0
Hamilton, 2002, UCI6	406,4	15	1854,2	35,6	458,5	1,17	691,5	0,53	0

Table 11
Comparison of test results of verification set with estimated results of ANN_1 model.

Specimen Name	Experimental Result			ANN_1			Test Error (%)		
	M (kN-m)	V (kN)	μ	M (kN-m)	V (kN)	μ	M	V	μ
Wong et al., 1990, No. 3	499	579	6,65	464,32	646,52	5,25	6,95	11,66	21,04
Ang et al., 1985, No. 21	216	271	4,46	236,56	290,29	0,69	9,52	7,12	84,47
Kunnath et al., 1997, A4	111	72	7,08	108,64	72,81	7,37	2,13	1,13	4,09
Kunnath et al., 1997, A5	123	77	4,84	108,64	72,81	7,37	11,67	5,44	52,26
Hamilton, 2002, UCI2	136	74	6,05	139,49	69,73	6,59	2,57	5,77	8,92
Hamilton, 2002, UCI3	150	143	4,24	246,18	201,68	4,74	64,12	41,04	11,76
Hamilton, 2002, UCI6	182	98	11,89	145,38	71,45	6,65	20,12	27,09	44,05
Mean Percentage Error							**16,724**	**14,177**	**32,369**
Test Error							**19,22**		
Classification Accuracy (100-Test Error)							**80,78**		

of longitudinal reinforcement f_y are not effective in the ductility values along with the moment and shear force capacity. This can be explained by the fact that the reinforcement and concrete strength are not changed in a very wide range in the selected data set.

The moment and shear force capacities of test elements involved in the verification set are compared by means of experimental, ANN, and regulatory approaches. The results of the empirical formula contained in regulation are far from the results of the experimental and ANN results. This is because the samples in the verification set reach to collapse mechanisms with different failure modes. When the result of the sample showing shear failure (failure type 2) is examined for the shear force capacity and the result of the samples having bending damage (failure type 1) for the moment capacity are examined, it is true that results of theoretical approaches might be evaluated more accurately. When the theoretical results are examined in this respect, it is seen that they are parallel to ANN and experimental results and ACI

Table 12
Comparison of shear force capacities of spiral columns included in verification set with traditional methods.

No	Specimen Name	Failure Type	V_r (TS 500–2000)	V_r (ACI)	V_{ANN1} (ANN)	V_{EXP} (Experi-mental)	V_{EXP}/V_{TS}	V_{EXP}/V_{ACI}	V_{EXP}/V_{ANN1}
1	Wong et al., 1990, No. 3	3	472,284	522,54	646,516	579	1,2259	1,10804	0,89556
2	**Ang et al. 1985, No. 21**	**2**	**252,623**	**195,26**	**290,290**	**271**	**1,0727**	**1,38789**	**0,93354**
3	Kunnath et al., 1997, A4	1	265,693	228,98	72,8130	72	0,2709	0,31443	0,98883
4	Kunnath et al., 1997, A5	1	265,693	228,98	72,8130	77	0,2898	0,33627	1,05750
5	Hamilton, 2002, UCI2	1	449,241	358,89	69,7267	74	0,1647	0,20619	1,06128
6	Hamilton, 2002, UCI3	3	224,522	170,36	201,680	143	0,6369	0,83939	0,70904
7	Hamilton, 2002, UCI6	1	447,030	357,35	71,4548	98	0,2192	0,27424	1,37149
	Average						**0,5543**	**0,63806**	**1,00246**

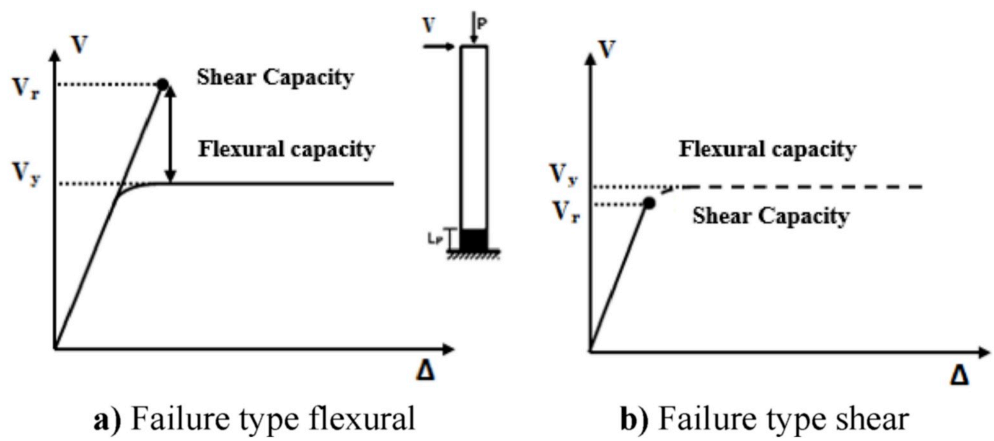

Fig. 18. Load-displacement curves of columns under horizontal load. **a)** Failure type flexural **b)** Failure type shear.

Table 13
Comparison of moment capacities of spiral columns included in verification set with traditional methods.

No	Specimen Name	[a]Failure Type	M_r (TS 500–2000)	M_r (ACI)	M_{ANN1} (ANN_1)	M_{EXP} (Experi-mental)	M_{EXP}/M_{TS}	M_{EXP}/M_{ACI}	M_{EXP}/M_{ANN1}
1	Wong et al., 1990, No. 3	3	348,5	313,84	464,32	499	1,43	1,59	1,07
2	Ang et al., 1985, No. 21	2	250,2	240	236,56	216	0,86	0,90	0,91
3	Kunnath et al., 1997, A4	**1**	**98,8**	**91,74**	**108,64**	**111**	**1,12**	**1,21**	**1,02**
4	Kunnath et al., 1997, A5	**1**	**98,8**	**91,79**	**108,64**	**123**	**1,24**	**1,34**	**1,13**
5	Hamilton, 2002, UCI2	**1**	**134,6**	**113,33**	**139,49**	**136**	**1,01**	**1,20**	**0,97**
6	Hamilton, 2002, UCI3	3	159,1	131,58	246,18	150	0,94	1,14	0,61
7	Hamilton, 2002, UCI6	**1**	**138,8**	**112,35**	**145,38**	**182**	**1,31**	**1,62**	**1,25**
	Average						**1,13**	**1,29**	**0.9942**

[a] Failure Type = 1: Flexure, 2: Shear, 3: Flexure-Shear.

Table 14
Correlation distribution of the values in the input layer on the parameters in the output layer.

Correlations	D Diameter (mm)	d' Concrete cover (mm)	L (mm)	fc (MPa)	fy (MPa)	ρ_t (%)	fyw (MPa)	ρ_s (%)	N/N_o
Mmax (kN-m)	**,863**[b]	**,814**[b]	**,605**[b]	-,050	,192	-,102	-,008	-,008	,032
Vmax (kN)	**,774**[b]	**,760**[b]	**,237**[a]	-,146	,210	,013	**-,226**[a]	**-,226**[a]	,084
μ	-,007	-,079	,173	,001	,088	**,348**[b]	**,296**[b]	**,296**[b]	**,298**[b]

[a] Correlation is significant at the 0.05 level (2-tailed).
[b] Correlation is significant at the 0.01 level (2-tailed).

318-08 regulation is more reliable than TS 500–2000. No classification is made in terms of failure types of column samples when the current data set is prepared. It is assumed that having a sufficient number of data for each and every failure type in data set would lead to more appropriate results.

When the architecture of the network model is generated in the study, no tangible generalization is obtained with regard to the most appropriate number of hidden layers and of processing elements in hidden layers. Therefore, determination of the number of hidden layers and of the neurons in these layers is only possible with a trial-and-error method for now. Even though the problems requested to be solved in the network are non-linear, appropriate results are obtained.

Increasing the number of test data used for training of network would facilitate learning and thus, more appropriate results might be obtained. Because test data are used to verify, caliber or improve the ANN network models. Estimation of moment and shear force capacities and displacement ductility of ANN network model is dependent on the experimental test data set on which the model is based.

Appendix 1

Selected Data Set for Training and Testing

No	Specimen Name	D (Diameter) (mm)	d' (Concrete cover) (mm)	L (mm)	fc (MPa)	fy (MPa)	ρ_l (%)	fyw (MPa)	ρ_s (%)	P_e/(f'c*Ag)	M_{max} (kN-m)	V_{max} (kN)	μ
1	Ang et al., 1985, No. 1	400	18,00	800	37,5	436	3,20	328	0,51	0,00	256	321	1,81
2	Ang et al., 1985, No. 2	400	18,00	800	37,2	296	3,20	328	0,51	0,00	175	219	5,79
3	Ang et al., 1985, No. 4	400	20,00	800	30,6	436	3,20	316	0,51	0,00	231	289	1,91
4	Ang et al., 1985, No. 5	400	18,00	800	31,1	436	3,20	328	0,76	0,00	265	331	1,55
5	Ang et al., 1985, No. 6	400	18,00	600	30,1	436	3,20	328	0,51	0,00	235	392	1,25
6	Ang et al., 1985, No. 7	400	18,00	800	29,5	448	3,20	372	0,38	0,00	225	281	1,23
7	Ang et al., 1985, No. 8	400	18,00	800	28,7	448	3,20	372	1,02	0,20	377	445	2,77
8	Ang et al., 1985, No. 9	400	18,00	1000	29,9	448	3,20	372	1,02	0,20	401	364	3,34
9	Ang et al., 1985, No. 10	400	21,00	800	31,2	448	3,20	332	1,02	0,20	371	437	2,28
10	Ang et al., 1985, No. 12	400	18,00	600	28,6	436	3,20	328	1,02	0,10	321	526	1,23
11	Ang et al., 1985, No. 13	400	18,00	800	36,2	436	3,20	326	1,02	0,10	365	436	4,44
12	Ang et al., 1985, No. 14	400	18,00	800	33,7	424	3,24	326	0,51	0,00	253	316	3,49
13	Ang et al., 1985, No. 15	400	18,00	800	34,8	436	1,92	326	0,51	0,00	184	230	6,10
14	Ang et al., 1985, No. 16	400	18,00	800	33,4	436	3,20	326	0,51	0,10	287	352	2,03
15	Ang et al., 1985, No. 17	400	18,00	1000	34,3	436	3,20	326	0,51	0,10	320	312	2,98
16	Ang et al., 1985, No. 18	400	18,00	600	35,0	436	3,20	326	0,51	0,10	309	505	2,29
17	Ang et al., 1985, No. 19	400	18,00	600	34,4	436	3,20	326	0,38	0,10	266	437	1,83
18	Ang et al., 1985, No. 22	400	20,00	800	30,9	436	3,20	310	0,39	0,00	228	285	2,91
19	Ang et al., 1985, No. 23	400	21,00	800	32,3	436	3,20	332	0,76	0,00	266	333	4,52
20	Ang et al., 1985, No. 24	400	20,00	800	33,1	436	3,20	310	0,77	0,00	272	341	4,58
21	Wong et al., 1990, No. 1	400	20,00	800	38,0	423	3,20	300	1,42	0,19	394	461	6,61
22	Wong et al., 1990, No. 2	400	18,00	800	37,0	475	3,20	340	0,47	0,39	412	489	3,96
23	Lim et al., 1990, Con1	152	10,20	1140	34,5	448	5,57	620	1,45	0,24	22	14	4,63
24	Lim et al., 1990, Con1	152	10,20	570	34,5	448	5,57	620	1,45	0,24	24	37	5,95
25	Lim et al., 1990, Con1	152	10,20	570	34,5	448	5,57	620	1,45	0,35	24	36	5,23
26	NIST, Full Scale Flexure	1520	58,70	9140	35,8	475	1,99	493	0,63	0,07	13300	1289	5,41
27	NIST, Full Scale Shear	1520	60,30	4570	34,3	475	1,99	435	1,49	0,07	14500	2968	5,67
28	NIST, Model N1	250	9,90	750	24,1	446	1,98	441	1,41	0,10	50	59	11,5
29	NIST, Model N2	250	9,90	750	23,1	446	1,98	441	1,41	0,21	63	73	10,1
30	NIST, Model N3	250	9,70	1500	25,4	446	1,98	476	0,68	0,10	57	32	6,09
31	NIST, Model N4	250	9,90	750	24,4	446	1,98	441	1,41	0,10	51	63	9,98
32	NIST, Model N5	250	9,90	750	24,3	446	1,98	441	1,41	0,20	64	77	10,3
33	NIST, Model N6	250	9,70	1500	23,3	446	1,98	476	0,68	0,11	52	30	6,61
34	Kunnath et al., 1997, A2	305	14,50	1372	29,0	448	2,04	434	0,94	0,09	115	74	5,89
35	Kunnath et al., 1997, A6	305	14,50	1372	35,5	448	2,04	434	0,94	0,09	119	77	7,37
36	Kunnath et al., 1997, A7	305	14,50	1372	32,8	448	2,04	434	0,94	0,09	120	79	10,1
37	Kunnath et al., 1997, A8	305	14,50	1372	32,8	448	2,04	434	0,94	0,09	107	68	7,28
38	Kunnath et al., 1997, A9	305	14,50	1372	32,5	448	2,04	434	0,94	0,09	114	75	9,11
39	Kunnath et al., 1997, A10	305	14,50	1372	27,0	448	2,04	434	0,94	0,10	113	74	7,64
40	Kunnath et al., 1997, A11	305	14,50	1372	27,0	448	2,04	434	0,94	0,10	103	68	7,66
41	Kunnath et al., 1997, A12	305	14,50	1372	27,0	448	2,04	434	0,94	0,10	109	72	7,07
42	Benzoni & Priestley 1994, NR1	610	15,88	914,5	30,0	462	0,52	361	0,28	0,06	365	393	14
43	Benzoni & Priestley 1994, NR2	610	15,88	914,5	30,0	462	1,04	361	0,17	0,06	537	579	5,43
44	Hose et al., 1997, SRPH1	610	27,76	3660	41,1	455	2,66	414	0,89	0,15	1300	285	6,47
45	Vu et al., 1998, NH1	457	24,76	910	38,3	427,5	2,41	430,2	1,14	0,31	530	535	5,92
46	Vu et al., 1998, NH3	457	24,76	910	39,4	427,5	2,41	430,2	1,14	0,15	501	510	7,49
47	Vu et al., 1998, NH4	457	26,35	910	35,0	468,2	5,21	434,4	2,70	0,15	870	905	6,03
48	Vu et al., 1998, NH5	457	24,76	910	35,2	507,5	2,41	448,2	0,85	−0,08	344	403	7,00
49	Vu et al., 1998, NH6	457	26,35	910	35,0	486,2	5,21	434,4	3,04	0,33	975	957	8,10
50	Kowalsky et al., 1996, FL1	457	30,16	3656	36,6	477	3,62	445	0,92	0,30	544	101	6,95
51	Kowalsky et al., 1996, FL2	457	30,16	3656	40,0	477	3,62	437	0,60	0,27	639	124	3,33
52	Kowalsky et al., 1996, FL3	457	30,16	3656	38,6	477	3,62	445	0,92	0,28	611	117	5,84
53	Lehman et al., 1998, 415	609,6	22,23	2438	31,0	461,96	1,49	606,76	0,70	0,07	708	269	7,51
54	Lehman et al., 1998, 815	609,6	22,23	4876	31,0	461,96	1,49	606,76	0,70	0,07	745	130	5,62
55	Lehman et al., 1998, 1015	609,6	22,23	6096	31,0	461,96	1,49	606,76	0,70	0,07	604	80	8,31
56	Lehman et al., 1998, 407	609,6	22,23	2438	31,0	461,96	0,75	606,76	0,70	0,07	443	172	10,1
57	Lehman et al., 1998, 430	609,6	22,23	2438	31,0	461,96	2,98	606,76	0,70	0,07	1180	448	5,70
58	Calderone et al., 2000, 328	609,6	28,58	1828	34,5	441,28	2,73	606,76	0,89	0,09	1030	525	9,83
59	Calderone et al., 2000, 828	609,6	28,58	4876	34,5	441,28	2,73	606,76	0,89	0,09	975	172	10,2
60	Calderone et al., 2000,1028	609,6	28,58	6096	34,5	441,28	2,73	606,76	0,89	0,09	1160	157	7,70
61	Sritharan et al., 1996, IC1	600	30,16	1800	31,4	448	1,92	431	0,54	0,05	737	387	4,90
62	Sritharan et al., 1996, IC2	600	30,16	1800	34,6	448	1,92	431	0,54	0,04	775	411	6,10
63	Sritharan et al., 1996, IC3	600	30,16	1800	33,0	461	1,92	434	0,81	0,04	815	433	7,72

64	Saatcioglu & Baingo 1999, RC1	250	13,75	1645	65,0	419	3,28	1000	1,54	0,31	138	55	9,29
65	Saatcioglu & Baingo 1999, RC3	250	13,75	1645	90,0	419	3,28	1000	1,54	0,42	163	56	5,25
66	Saatcioglu & Baingo 1999, RC4	250	14,00	1645	90,0	419	3,28	580	1,75	0,42	162	55	3,66
67	Saatcioglu & Baingo 1999, RC6	250	15,65	1645	90,0	419	3,28	420	1,74	0,42	154	57	5,51
68	Saatcioglu & Baingo 1999, RC7	250	13,75	1645	90,0	419	3,28	1000	1,54	0,21	139	59	9,23
69	Saatcioglu & Baingo 1999, RC8	250	13,75	1645	90,0	419	3,28	1000	1,54	0,42	158	55	3,68
70	Saatcioglu & Baingo 1999, RC9	250	13,75	1645	90,0	419	3,28	420	3,43	0,42	200	71	10,2
71	Nelson & Price 2000, Col 1	508	21,31	1524	56,2	470	0,99	455	0,13	0,13	488	283	4,50
72	Nelson & Price 2000, Col 2	508	21,31	1524	56,3	470	0,99	455	0,13	0,11	456	279	5,17
73	Nelson & Price 2000, Col 3	508	21,31	1524	57,0	470	0,99	455	0,13	0,10	423	260	5,51
74	Nelson & Price 2000, Col 4	508	21,31	1524	52,7	470	0,99	455	0,13	0,11	415	252	6,97
75	Henry 1998, 415p	609,6	22,23	2438	37,2	462	1,49	606,76	0,70	0,12	831	277	4,41
76	Henry 1998, 415s	609,6	22,23	2438	37,2	462	1,49	606,76	0,35	0,06	716	259	5,86
77	Chai, Priestley 1991, Test 3	609,6	20,00	3657	32,6	315,1	2,54	351,6	0,17	0,19	889	207	5,81
78	Hamilton, 2002, UCI1	406,4	14,9606	1854	36,5	458,5	1,17	691,5	0,53	0,00	130	70	6,59
79	Hamilton, 2002, UCI5	406,4	10,4394	1047	35,4	458,5	1,17	691,5	0,26	0,00	178	170	5,97

Appendix 2

Normalization of Data Set

No	D	d'	L	f_c	f_y	ρ_l	f_{yw}	ρ_s	N/N_o	M_{max}	V_{max}	μ	Purpose of use
1	0,1813	0,1640	0,0268	0,2152	0,6619	0,5307	0,0400	0,1152	0,1600	0,016162	0,103927	0,045277	Training
2	0,1813	0,1640	0,0268	0,2108	0,0000	0,5307	0,0400	0,1152	0,1600	0,010568	0,069397	0,355972	Training
3	0,1813	0,2036	0,0268	0,1121	0,6619	0,5307	0,0229	0,1152	0,1600	0,014436	0,093094	0,053084	Test
4	0,1813	0,1640	0,0268	0,1196	0,6619	0,5307	0,0400	0,1909	0,1600	0,016784	0,107312	0,02498	Training
5	0,1813	0,1640	0,0035	0,1046	0,6619	0,5307	0,0400	0,1152	0,1600	0,014712	0,127962	0,001561	Test
6	0,1813	0,1640	0,0268	0,0957	0,7187	0,5307	0,1029	0,0758	0,1600	0,014021	0,090386	0	Training
7	0,1813	0,1640	0,0268	0,0837	0,7187	0,5307	0,1029	0,2697	0,5600	0,02452	0,145904	0,120219	Test
8	0,1813	0,1640	0,0502	0,1016	0,7187	0,5307	0,1029	0,2697	0,5600	0,026178	0,118483	0,164715	Training
9	0,1813	0,2233	0,0268	0,1211	0,7187	0,5307	0,0457	0,2697	0,5600	0,024106	0,143196	0,081967	Training
10	0,1813	0,1640	0,0035	0,0822	0,6619	0,5307	0,0400	0,2697	0,3600	0,020652	0,173324	0	Training
11	0,1813	0,1640	0,0268	0,1958	0,6619	0,5307	0,0371	0,2697	0,3600	0,023691	0,142857	0,250585	Test
12	0,1813	0,1640	0,0268	0,1584	0,6052	0,5386	0,0371	0,1152	0,1600	0,015955	0,102234	0,176425	Training
13	0,1813	0,1640	0,0268	0,1749	0,6619	0,2772	0,0371	0,1152	0,1600	0,011189	0,073121	0,380172	Training
14	0,1813	0,1640	0,0268	0,1540	0,6619	0,5307	0,0371	0,1152	0,3600	0,018304	0,114421	0,062451	Training
15	0,1813	0,1640	0,0502	0,1674	0,6619	0,5307	0,0371	0,1152	0,3600	0,020583	0,10088	0,136612	Test
16	0,1813	0,1640	0,0035	0,1779	0,6619	0,5307	0,0371	0,1152	0,3600	0,019823	0,166215	0,082748	Training
17	0,1813	0,1640	0,0035	0,1689	0,6619	0,5307	0,0371	0,0758	0,3600	0,016853	0,143196	0,046838	Test
19	0,1813	0,2233	0,0268	0,1375	0,6619	0,5307	0,0457	0,1909	0,1600	0,014228	0,09174	0,131148	Training
20	0,1813	0,2036	0,0268	0,1495	0,6619	0,5307	0,0143	0,1939	0,1600	0,016853	0,107989	0,256831	Test
21	0,1813	0,2036	0,0268	0,2227	0,6005	0,5307	0,0000	0,3909	0,5400	0,017268	0,110697	0,261514	Training
22	0,1813	0,1640	0,0268	0,2078	0,8463	0,5307	0,0571	0,1030	0,9400	0,025694	0,15132	0,419984	Training
23	0,0000	0,0099	0,0665	0,1704	0,7187	1,0000	0,4571	0,4000	0,6400	0,026937	0,160799	0,213115	Training
24	0,0000	0,0099	0,0000	0,1704	0,7187	1,0000	0,4571	0,4000	0,6400	0	0	0,265418	Training
25	0,0000	0,0099	0,0000	0,1704	0,7187	1,0000	0,4571	0,4000	0,8600	0,000138	0,007786	0,368462	Test
26	1,0000	0,9684	1,0000	0,1898	0,8463	0,2911	0,2757	0,1515	0,3000	0,000138	0,007448	0,312256	Training
27	1,0000	1,0000	0,4667	0,1674	0,8463	0,2911	0,1929	0,4121	0,3000	0,917116	0,431618	0,326308	Training
28	0,0716	0,0040	0,0210	0,0149	0,7092	0,2891	0,2014	0,3879	0,3600	1	1	0,346604	Training
29	0,0716	0,0040	0,0210	0,0000	0,7092	0,2891	0,2014	0,3879	0,5800	0,001934	0,015234	0,806401	Test
30	0,0716	0,0000	0,1085	0,0344	0,7092	0,2891	0,2514	0,1667	0,3600	0,002832	0,019973	0,692428	Training
31	0,0716	0,0040	0,0210	0,0194	0,7092	0,2891	0,2014	0,3879	0,3600	0,002417	0,006093	0,379391	Test
32	0,0716	0,0040	0,0210	0,0179	0,7092	0,2891	0,2014	0,3879	0,5600	0,002003	0,016588	0,68306	Training
33	0,0716	0,0000	0,1085	0,0030	0,7092	0,2891	0,2514	0,1667	0,3800	0,002901	0,021327	0,714286	Test
34	0,1118	0,0949	0,0936	0,0882	0,7187	0,3010	0,1914	0,2455	0,3400	0,002072	0,005416	0,419984	Training
35	0,1118	0,0949	0,0936	0,1854	0,7187	0,3010	0,1914	0,2455	0,3400	0,006424	0,020311	0,363778	Test
36	0,1118	0,0949	0,0936	0,1450	0,7187	0,3010	0,1914	0,2455	0,3400	0,0067	0,021327	0,479313	Training
37	0,1118	0,0949	0,0936	0,1450	0,7187	0,3010	0,1914	0,2455	0,3400	0,006769	0,022004	0,693208	Test
38	0,1118	0,0949	0,0936	0,1405	0,7187	0,3010	0,1914	0,2455	0,3400	0,005871	0,01828	0,472287	Training
39	0,1118	0,0949	0,0936	0,0583	0,7187	0,3010	0,1914	0,2455	0,3600	0,006354	0,02065	0,615144	Test
40	0,1118	0,0949	0,0936	0,0583	0,7187	0,3010	0,1914	0,2455	0,3600	0,006285	0,020311	0,50039	Training
41	0,1118	0,0949	0,0936	0,0583	0,7187	0,3010	0,1914	0,2455	0,3600	0,005595	0,01828	0,501952	Test
42	0,3348	0,1221	0,0402	0,1031	0,7849	0,0000	0,0871	0,0455	0,2800	0,006009	0,019634	0,455894	Training
43	0,3348	0,1221	0,0402	0,1031	0,7849	0,1030	0,0871	0,0121	0,2800	0,023691	0,128301	1	Test
44	0,3348	0,3569	0,3606	0,2691	0,7518	0,4238	0,1629	0,2303	0,4600	0,035571	0,191266	0,327869	Training
45	0,2230	0,2976	0,0397	0,2272	0,6217	0,3743	0,1860	0,3061	0,7800	0,088272	0,09174	0,409055	Test
46	0,2230	0,2976	0,0397	0,2436	0,6217	0,3743	0,1860	0,3061	0,4600	0,035088	0,176371	0,36612	Training
47	0,2230	0,3291	0,0397	0,1779	0,8142	0,9287	0,1920	0,7788	0,4600	0,033085	0,167908	0,488681	Training
48	0,2230	0,2976	0,0397	0,1809	1,0000	0,3743	0,2117	0,2182	0,0000	0,058572	0,301625	0,374707	Training
49	0,2230	0,3291	0,0397	0,1779	0,8993	0,9287	0,1920	0,8818	0,8200	0,022241	0,131686	0,450429	Training

50	0,2230	0,4043	0,3601	0,2018	0,8558	0,6139	0,2071	0,2394	0,7600	0,065824	0,319228	0,5363	Test
51	0,2230	0,4043	0,3601	0,2526	0,8558	0,6139	0,1957	0,1424	0,7000	0,036055	0,029452	0,446526	Training
52	0,2230	0,4043	0,3601	0,2317	0,8558	0,6139	0,2071	0,2394	0,7200	0,042616	0,037238	0,163934	Test
53	0,3345	0,2476	0,2180	0,1181	0,7847	0,1921	0,4382	0,1727	0,3000	0,040682	0,034868	0,359875	Training
54	0,3345	0,2476	0,5025	0,1181	0,7847	0,1921	0,4382	0,1727	0,3000	0,049938	0,039269	0,342701	Training
55	0,3345	0,2476	0,6448	0,1181	0,7847	0,1921	0,4382	0,1727	0,3000	0,040199	0,022343	0,552693	Test
56	0,3345	0,2476	0,2180	0,1181	0,7847	0,0455	0,4382	0,1727	0,3000	0,029079	0,053487	0,693208	Training
57	0,3345	0,2476	0,2180	0,1181	0,7847	0,4871	0,4382	0,1727	0,3000	0,079983	0,146919	0,348946	Training
58	0,3345	0,3731	0,1469	0,1704	0,6869	0,4376	0,4382	0,2303	0,3400	0,069623	0,172986	0,671351	Training
59	0,3345	0,3731	0,5025	0,1704	0,6869	0,4376	0,4382	0,2303	0,3400	0,065824	0,053487	0,700234	Test
60	0,3345	0,3731	0,6448	0,1704	0,6869	0,4376	0,4382	0,2303	0,3400	0,078602	0,048409	0,505074	Training
61	0,3275	0,4043	0,1435	0,1241	0,7187	0,2772	0,1871	0,1242	0,2600	0,049385	0,126269	0,286495	Test
62	0,3275	0,4043	0,1435	0,1719	0,7187	0,2772	0,1871	0,1242	0,2400	0,05201	0,134394	0,380172	Training
63	0,3275	0,4043	0,1435	0,1480	0,7801	0,2772	0,1914	0,2061	0,2400	0,054773	0,141842	0,506635	Test
64	0,0716	0,0800	0,1254	0,6263	0,5816	0,5465	1,0000	0,4273	0,7800	0,008012	0,013879	0,629196	Training
65	0,0716	0,0800	0,1254	1,0000	0,5816	0,5465	1,0000	0,4273	1,0000	0,009739	0,014218	0,313817	Training
66	0,0716	0,0850	0,1254	1,0000	0,5816	0,5465	0,4000	0,4909	1,0000	0,00967	0,013879	0,189696	Training
67	0,0716	0,1176	0,1254	1,0000	0,5816	0,5465	0,1714	0,4879	1,0000	0,009117	0,014557	0,334114	Training
68	0,0716	0,0800	0,1254	1,0000	0,5816	0,5465	1,0000	0,4273	0,5800	0,008081	0,015234	0,624512	Test
69	0,0716	0,0800	0,1254	1,0000	0,5816	0,5465	1,0000	0,4273	1,0000	0,009394	0,013879	0,191257	Training
70	0,0716	0,0800	0,1254	1,0000	0,5816	0,5465	0,1714	1,0000	1,0000	0,012295	0,019296	0,705699	Test
71	0,2602	0,2294	0,1113	0,4948	0,8227	0,0931	0,2214	0,0000	0,4200	0,032187	0,091063	0,255269	Training
72	0,2602	0,2294	0,1113	0,4963	0,8227	0,0931	0,2214	0,0000	0,3800	0,029977	0,089709	0,307572	Test
73	0,2602	0,2294	0,1113	0,5067	0,8227	0,0931	0,2214	0,0000	0,3600	0,027697	0,083277	0,334114	Training
74	0,2602	0,2294	0,1113	0,4425	0,8227	0,0931	0,2214	0,0000	0,3800	0,027145	0,080569	0,448087	Test
75	0,3345	0,2476	0,2180	0,2108	0,7849	0,1921	0,4382	0,1727	0,4000	0,055878	0,089032	0,248244	Training
76	0,3345	0,2476	0,2180	0,2108	0,7849	0,1921	0,4382	0,0667	0,2800	0,047935	0,082938	0,361436	Test
77	0,3345	0,2036	0,3602	0,1420	0,0903	0,4000	0,0737	0,0121	0,5400	0,059884	0,065335	0,357533	Training
78	0,1860	0,1040	0,1498	0,2003	0,7683	0,1287	0,5593	0,1212	0,1600	0,00746	0,018957	0,418423	Training
79	0,1860	0,0146	0,0557	0,1839	0,7683	0,1287	0,5593	0,0394	0,1600	0,010775	0,05281	0,370023	Training

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