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Optimum Prediction of the Transfer Length of Strands Based on Artificial Neural Networks

Mohammad A. Alhassan[a,b]*, Ayman N. Ababneh[b], and Nour A. Betoush[c]

[a]*Civil Engineering Program, Al Ain University, Al Ain, UAE*
[b]*Department of Civil Engineering, Jordan University of Science and Technology, Irbid, Jordan*
[c]*Graduate Student, Department of Civil Engineering, Jordan University of Science and Technology, Irbid, Jordan*

Abstract

As the effectiveness of prestressing is crucially linked to the transfer length (TL) of the strands, this study used Artificial Neural Network (ANN) technique for optimal prediction of TL based on more than 458 data points collected from various literature works. The ANN technique allowed for investigating the effect of various key parameters classified into major categories including: strand characteristics, concrete properties, geometric details, and manufacturing method. The MATLAB software was utilized to build, train, and test the ANN using 19 input variables and one targeted output. The proposed ANN showed high prediction capability with a low mean square error. The sensitivity analysis of the TL gave a good indication regarding the significance of the parameters influencing the TL determination. Mathematical expression was developed considering the most significant parameters according to the ANN results and sensitivity analysis.

*Keywords:*Transfer Length; Prestressing; Artificial Neural Networks.

1. Introduction

Transfer length (TL) is the essential length needed to transfer the bond stress from prestressing strands to the adjacent concrete. Within the transfer zone, the prestress linearly increases from zero to the effective stress (f_{se}).

**E-mail address:* maalhassan@just.edu.jo

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Determining the transfer length is necessary to ensure that the beam has adequate shear and flexural capacities to control and limit the cracks at the ends of the members [1-2]. The general research agreed that there are many factors affect the TL, however, it is not clear, how the transfer length is affected by these parameters. Agreement has not yet been reached to determine the most significant parameters affecting the transfer length [3-4]. Many experimental studies were conducted to investigate the transfer length of prestressing strands using various methods [5-17]. Also, many formulas exist in the design codes [18, 19] and many authors proposed models derived from theoretical studies based on experimental results. However, most of these equations and expressions cannot be generalized for results and data from other studies. In addition, many parameters were considered as the traditional methods are not able to digest the large data size and its complex nature. Therefore, a new technique is needed to provide accurate prediction; which can be accomplished using statistical machine learning and Artificial Intelligence [20].

Table 1. Factors considered in the ANN.

Number	input	Descriptions	Parameter Ranges
1	fpu	Ultimate tensile strength of the prestressing strand	(1751-2400) MPa
2	fpi/fpu	Relation between initial tensile strength and Ultimate tensile strength of the prestressing strand	(0.48-0.81)
3	ds	Nominal diameter of prestressing strand	Selected ds = (6.35,9.5,12.7, 15.2 and 17.8) mm
4	N	Number of prestressing strands in the cross-section of the member	(1-9)
5	c to c	Vertical strand spacing (center to center)	(0-90) mm c to c=0 if N=1(vertical direction)
6	Cond	Strand surface codition	Bright=1 or Rusty=0 Slightly rust=0.5
7	Coat	Coat of strand surface epoxy coated with grit	No coat=0,light coat=1/3 ,medium coat=2/3, heavy coat=1
8	fci	Concrete compressive strength at transfer	(12-180) MPa
9	Agg.	Normal weight or light weight concrete	Normal weight =1, or light weight=0
10	Beam type	Beam section type	(I =0 , T =0.5 , Rectangular =1)
11	bw	Width cross-section of the member width web for I or T section	(60- 265) mm
12	h	Depth cross-section of the member	(60 - 710) mm
13	Lc	Length of beam	(0.6-12) m
14	Cover	Vertical concrete cover	(13-100) mm
15	Fibers	% of fibers in the concrete	(0-2) %
16	Release	Release method	Gradual (G) =1 , sudden (S)=0
17	Trans	Transverse reinforcement	Yes =1 , No=0
18	curing	Curing condition	Moisture=0 , Steam=1
19	end-cond	Type of member end region	Cut end=1 , Dead end =0
output	TL	Transfer length	(160-1880) mm

One of the recent and trendy approaches for predicting the transfer length is through the use of Artificial Neural Networks (ANNs). The widely used ANN model is considered as a representative of machine learning methodologies and as the foundation of the artificial intelligence. The ANN can handle large amount of data sets and has the ability to implicitly detect complex nonlinear relationships between dependent and independent variables [21]. The ANN method is ideal for the TL problem as it can digest the data size and its complexity as well it allows involving new parameters which are not considered by other researchers. A neuron in ANN is an information-processing unit, which forms the basis for designing a large family of neural networks. The neurons are connected to each other by links by which they interact. The nodes take input data to perform simple operations; each link is associated with weight, which can be modified depending upon the results that are passed to other neurons.Many types of research used the ANN in solving the engineering problems which may be unsolvable using the traditional methods [22-24].

2. ANN Architecture

The human brain is composed of billions of nerve cells called neurons; specialized cells transmitting nerve impulses. The same procedure is adopted in the ANN, which is composed of multiple nodes. The neurons are connected to each other by links through which they interact. The nodes take input data to perform simple operations. Each link is associated with a weight modified depending on the results. The results are passed to other neurons. A neuron in ANN is an information-processing unit forms the basis for designing a large family of neural networks. The ANN architecture can be divided into three main parts: input layer, middle or hidden layers, and output layer. The hidden layer consists of many neurons. At each neuron, mathematical calculations occur to the input to provide the output. Those neurons are connected with links to receive and send the values. Each link has a weight as the received values differ from the sent depending on these weights. The weight value is changeable based on the intended task. The ANN is an unconstrained optimization problem and the neuron weights are design variables to be modified. Another parameter that enhances the neural network performance is a bias term included in every neuron in hidden and output layers. Constructing a suitable architecture is the key in ANNs modelling.

In this study, a feed-forward back-propagation neural network was used. A simple architecture of a back-propagation network consists of an input layer, number of hidden layers and an output layer. Bayesian regularization (BR) algorithm was used for training, which updates the weight and bias values according to Levenberg Marquardt optimization. A hyperbolic tangent function was considered as an activation function in the hidden and output layers. The NN toolbox of MATLAB was used to develop the program. The flow chart in Fig. 1 represents the network architecture determined based on a trial and error procedure to minimize the mean square error MSE and max R^2. The optimum network architecture consists of one input layer with 19 input parameters, one hidden layer with 10 neurons and one output layer with one targeted output (Fig. 2). A hyperbolic tangent function was considered as an activation function in the hidden layer and for the output layer. The fitting and predictive capability of the network was examined using the training and testing data as shown in Fig. 3. Fig. 4 shows a validation with high accuracy using 15 experimental points randomly selected from literature included min and max TL values.

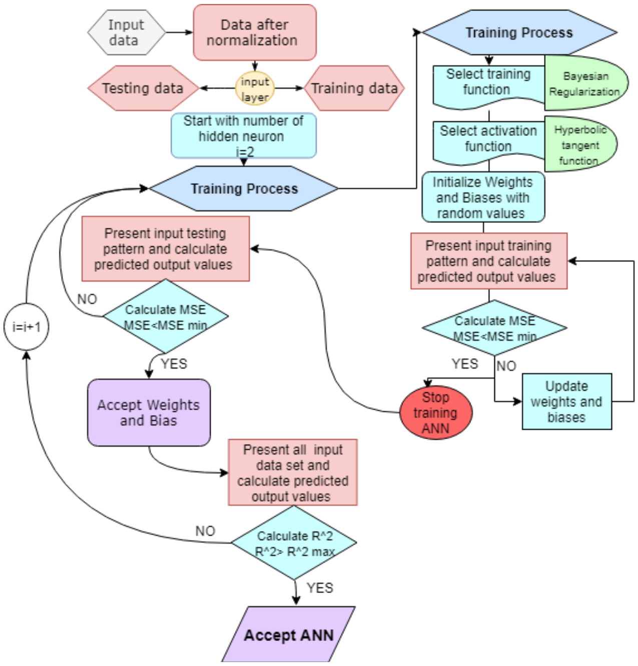

Fig. 1. Flow chart representing th ANN architecture

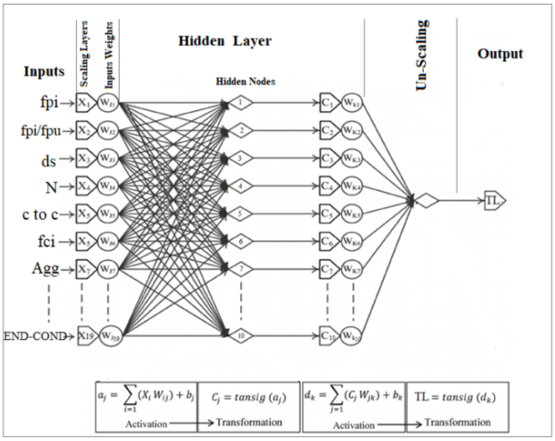

Fig. 2: ANN structure with 19 input and 10 hidden layer nodes for the prediction of TL using a hyperbolic tangent function

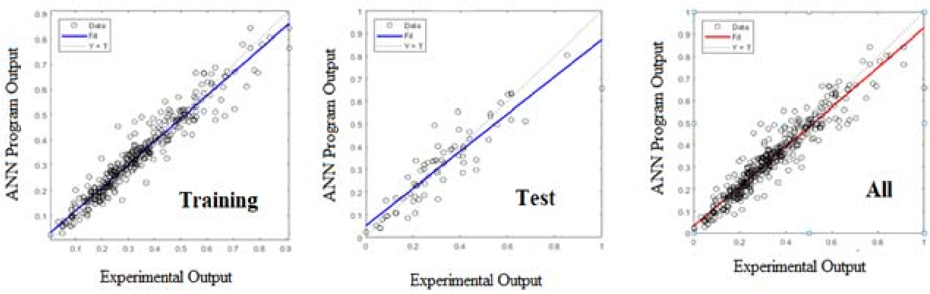

Fig. 3: Correlation between predicted and experimental values

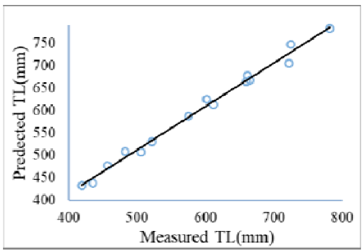

Fig. 4: Accuracy of predicting TL by the proposed ANN program

3. Results and discussion

The prediction capability (MAE and R^2) of the proposed NN was compared to the other published analytical models using the 15 points as shown in Table 3. The NN has the minimum MAE and maximum R^2 comparing to the others. The factors used to predict TL divided as four categories; the fourth category is the manufacturing method. Each category was drawn separately (Fig. 5-8) to compare between the different parameters in each category as well to determine their relative significance and their ignorance possibility in the modeling. Fig. 5 (top left) shows the relation between TL and the 5 parameters of the first category of the strand material properties. According to the significant change in TL, the diameter of the strand is highly important comparing to others, followed by the coat, the (fpi/fpu), and the surface condition. Fig. 5 (top right) shows the relation between TL and the 4 parameters in the second category of the concrete material properties, the most significant is the compression strength of the concrete, the remaining parameters are less important. Fig. 7 (bottom left) shows the relation between TL and the 5 parameters in the third category of the geometric properties of the concrete beam, the depth of concrete beam (h) and the bottom cover of the concrete beam are the most important while the remaining parameters are less important. Fig.8 (bottom right) shows the relation between TL and the 3 parameters in the fourth category of the manufacturing method of the concrete beam (Release method, curing method, and End condition) relatively only the release method is a significant parameter in this category. The most relatively significant parameters from all categories are: h, cover, fpi, fci, ds, N, C to C, and release method.

Table 2. Comparison of the results with other models (TL values are in mm)

Experimental TL	ACI	AASHTO	Mahmoud et al.(1999)	Kose and Burkette (2005)	MartiVargas et al.(2007-b)	Oh et al.(2014)	Dang et.al.(2016)	Mohandoss et.al (2018)	ANN
160	832	762	246	692	203	1283	281	-	402
483	811	762	789	1642	653	2266	684	550	509
506	502	570	625	862	518	1609	616	439	507
522	770	762	592	1307	490	1966	574	440	531
602	770	762	580	1288	480	1951	565	436	625
612	922	912	701	1910	580	2461	681	524	613
660	922	912	691	1889	571	2445	674	521	664
662	922	912	701	1910	580	2461	681	524	679
665	770	762	610	1336	504	1995	586	447	667
722	922	912	643	1790	532	2359	638	509	705
725	770	762	577	1282	478	1945	563	435	748
782	922	912	842	2190	697	2696	781	592	783
904	922	912	673	1852	557	2416	661	515	970
1880	811	762	827	1700	685	2322	709	575	1653
MAE	229	210	140	963	173.9	1565	128	215	48.6
R^2	0.13	0.11	0.60	0.41	0.60	0.45	0.52	0.52	0.96

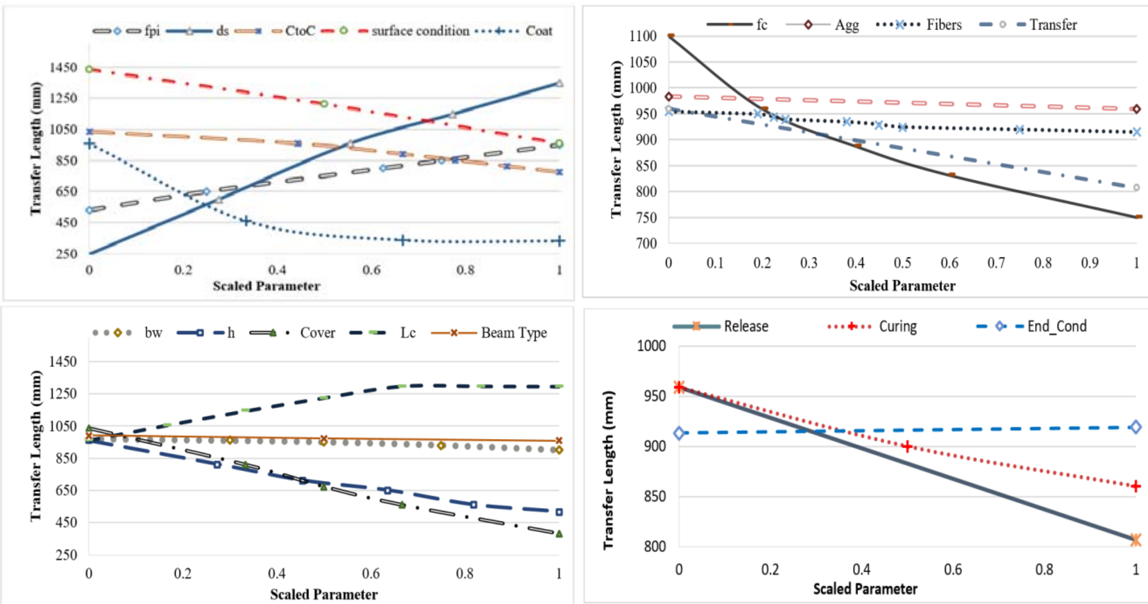

Fig. 5: TL versus the most significant Parameters

4. A New ANN Model

The new ANN model was only created based on independent variables, in addition to the variables that remain after the sensitivity analysis test (9 variables). The data size used in this model was also reduced from 458 to 137 experimental points according to the references which are used in training and testing. These data points remained after deleting the repeated data points and the points that were not matching the condition. With the total number of instances is 137, the number of training instances is 83 (60%), the number of selection instances is 27 (20%), and the number of testing instances is 27 (20%).The number of layers in the neural network is 3. Fig. 6 depicts the size of each layer and its corresponding activation function. The architecture of this neural network can be written as 9:7:3:1. The network architecture contains a scaling layer, a neural network and unscaling layer. The yellow circles represent scaling neurons, blue circles represent perceptron neurons, purple circle represents unscaling neurons. The number of inputs is 9and the number of outputs is 1. The complexity represented by the numbers of hidden neurons is 7:3.The quasi-Newton method is used as training algorithm. It does not require calculation of second derivatives. Instead, it computes an approximation of the inverse Hessian at each iteration of the algorithm by only using gradient information. Fig. 7 shows the linear regression parameters for the scaled output TL. The intercept, slope and correlation are very similar to 0, 1 and 1, respectively, so the neural network is predicting well the testing data.

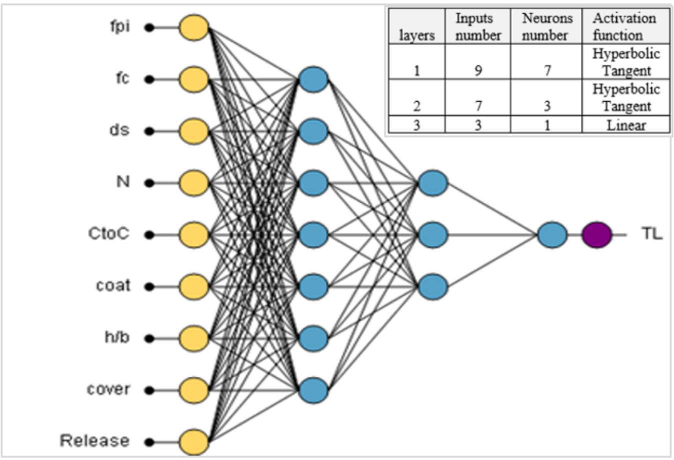

Fig. 6. Feedforward backpropagation neural network used for predicting the TL

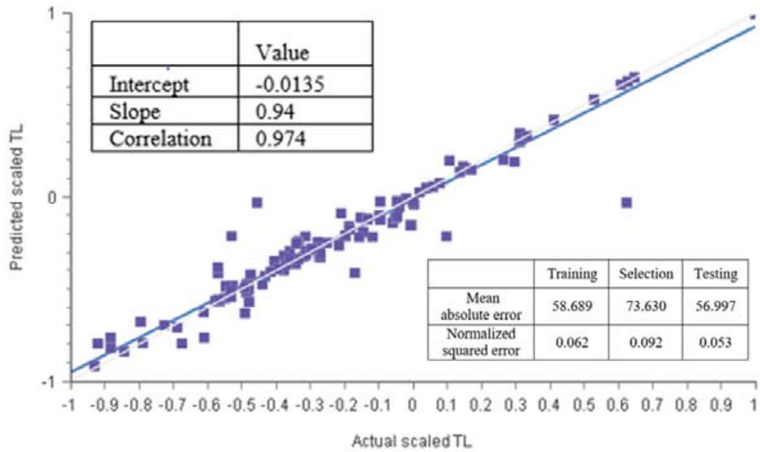

Fig. 7. Linear regression parameters for the predicted TL

5. Conclusions

The complexity in predicting the TL is attributed to the multiple factors that have significant effects on it. The ANN model was proven to be a powerful numerical technique capable of handling large database, various key parameters, and materials' nonlinearity.The ANN converges very fast within the first few Epochs then remains flat with relatively small change in the MSE. The fitting and prediction capability of the network was examined using training and testing data at 80% and 20% of the total database, respectively. The corresponding correlation factors (R) was 0.98 for training data and 0.93 for testing data. The overall correlation maintained similar level when both training and testing data were fit against real values. The most significant factors that influences the TL identified as the diameter of strands, fpi, fci, the bottom cover, number of strands, spacing between them, and coat of strand.The end condition, concrete type, beam length and curing condition showed miner influence on the TL.Increasing the fci, dimension of section, fibers content, bottom cover, coat of strand, and use of gradual release method instead of sudden release have inverse relations with the TL. Increasing the diameter of strands, fpi, and number of strands resulting in a proportional increase in the TL. The developed ANN model was created based on the most important parameters leading to satisfying Mathematical Expression results comparing to its simplicity and quick use.

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