Kufa Journal of Engineering
Vol. 10, No. 2, April 2019, P.P. 90-100
Received 2 May 2018, accepted 12 June 2018

Prediction of Creep Strain for Self-Compacting Concrete by Artificial Neural Networks

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http://dx.doi.org/10.30572/2018/kje/100207

ABSTRACT

Artificial Neural Networks, ANN, technique is a computerized system that is built to simulate the neural networks in the human brain. Throughout the recent couple decades, ANNs had solved with a good degree of success many problems. In the present work, ANN model was developed by SPSS software for estimating creep strain development of self-compacting concrete mixes produced with different types of Portland cement, Type I and Type IL. The independent variables in this model were: age, compressive strength, modulus of elasticity, applied stress, initial strain, water to powder ratio, water to binder ratio, filler to cement ratio, clinker to cement ratio, aggregate size, and slump flow. The used data for model building were local, extracted from the present work. The predictions of the model have been compared to those of an international well-known model, ACI 209 Committee. The comparison revealed the good reliability of the present models in predictions (r = 0.998).

KEYWORDS: Artificial Neural Networks, Creep, Modelling, Portland-limestone cement, Self-compacted concrete.

1. INTRODUCTION

Artificial Neural Networks, ANN, were invented to simulate the way in which the human brain works. The structure of the network is mainly built of a large number of highly interconnected processing elements (neurons), working in parallel to solve a certain problem. Neural networks learn by examples, which must be selected carefully, otherwise useful time is wasted, or even worse where the network might be functioning incorrectly (Awodele and Jegede, 2009).

The nonlinear and inelastic behavior of concrete under service loads has complicated the serviceability calculations in codes. Creep is one of the time-dependent deformations that causes part of this complexity.

Maia and Figueiras, (2012) revealed that the loading time and stress level have a serious influence on the deformation of a SCC used in pre-stressed bridge girders. It was concluded if the subjected load is about 30% of the actual strength, even if it is applied within the first 24 hours, the acceptability of the Eurocode 2 expressions to predict the stress depends on strain after one year. Therefore, it was recommended to measure deformations during at least one year to clarify the tendency.

ACI Committee, (2014) studied a direct solution methods estimating by that the response behavior at time step with a computational effort regarding to that of an elastic solution. They have been substantiated logically for laboratory conditions and intended for structures designed using the (ACI Committee, 2014). They are not intended to be used for the creep recovery analysis due to unloading, but they primarily applied to an isothermal and relatively uniform environment.

Researchers introduced many definitions for ANN in accordance to their points of view. According to Hussain, (2017), ANNs, are similar to the biological neuron, consisting of very tiny computational elements in very a large number. Perception is the main structural element inside the ANN. Meanwhile IBM SPSS Neural Networks, (2010) see that neural networks are the preferred tool for many predictive data mining applications because of their power, flexibility, and ease of use. The term neural network used by IBM Software Business Analytics IBM Corporation, (2012) applies to a loosely related family of models, characterized by a large parameter space and flexible structure. Specific definitions of neural networks are as varied as the fields in which they are used. It is a parallel distributed big processor that has a natural propensity for preserving experiential knowledge and making it available for use.

2. APPLICATIONS OF ANN IN CIVIL ENGINEERING

Predictive neural networks are practically valuable in applications where the fundamental process is complex, such as IBM SPSS Neural Networks, (2010):

a. Consumer demand estimating to streamline production and costs of delivery.

b. The probability of response prediction to direct mail marketing in order to determine the suitable offer to send it on a mailing list.

c. Identifying fraudulent transactions in a database for insurance claims.

Recently, researchers adopted the ANN in data processing in the field of durability, and they are very efficient compared with the simple regression method from experimental data.

Hodhod and Salama, (2013) research results proved that using ANN models to predict the expansion in concrete cylinders is practical and valuable. They also investigated the prediction of ANN model to determine its appropriateness in modeling for assessing the sulfate resistance of OPC and mineral admixture. Hodhod, (2013) developed an artificial neural network model to evaluate chloride diffusivity in high performance concrete. In geotechnical- structural aspect, Ismael [10] developed a model to test the laterally loaded piles under a horizontally scoured condition.

3. MATERIALS AND METHODS:

Creep test was done according to the ASTM C512 [11] on cylindrical specimens for 4 SCC mixes with 2 strength levels, 40 and 60 MPa, and 2 Portland cement types, Type I and IL. The test included 240 days of loading. All details of mixes are described in Table 1 (Al-Attar et al., 2017).

Table 1. Mix Details.

<table>
<tr><th rowspan="2">Mix</th><th colspan="2">Binder, kg/m^3</th><th rowspan="2">Limestone Dust, kg/m^3</th><th colspan="2">Aggregate, kg/m^3</th><th rowspan="2">Max Size of Agg., mm</th><th rowspan="2">Water, kg/m^3</th><th rowspan="2">Visco Crete L/m^3</th></tr>
<tr><th>Cement - Type</th><th>Silica Fume</th><th>FA</th><th>CA</th></tr>
<tr><td>AI40</td><td>400 – I</td><td rowspan="2">0</td><td rowspan="2">100</td><td rowspan="4">764</td><td rowspan="4">800</td><td rowspan="2">20</td><td rowspan="2">152</td><td rowspan="2">8</td></tr>
<tr><td>AIL40</td><td>400 – IL</td></tr>
<tr><td>BI60</td><td>450 – I</td><td rowspan="2">50</td><td rowspan="2">50</td><td rowspan="2">10</td><td rowspan="2">155</td><td rowspan="2">13</td></tr>
<tr><td>BIL60</td><td>450 – IL</td></tr>
</table>

4. EQUATIONS OF ANN MODELLING

The general equations used in predicting the models of the present work are illustrated below according to their hierarchical:

$$\text{Stand. Input}_i(X_i^*) = \frac{\text{Normalized Input}\,(X_i) - \text{mean}_X(\bar{X})}{\text{Std. deviation}(\sigma_X)} \quad 1$$

$$\text{Hidden in}_j = \text{Bias}_{\text{input}_j} + \sum_{i=1}^{n}\left(\text{Vmatrix}_{i,j} \times X_i^*\right) \quad 2$$

$$\text{Hidden out}_j = \frac{2}{1+\text{Exp}^{-2\times\text{Hidden in}_j}} - 1 \quad 3$$

$$\text{Stand. Output}_K = \text{Bias}_{\text{output}_K} + \sum_{j=1}^{m}\left(\text{Wmatrix}_{j,K} \times \text{Hidden out}_j\right) \quad 4$$

$$\text{Normalized Out Value}_K = \text{Standarized Output}_K \times \sigma_y + \bar{Y} \quad 5$$

$$\text{Out Predicted value}_j = \text{Normalized Out Value}_j \times \text{Maximum value} \quad 6$$

Where:

Vmatrix: Predicted Parameter Input

Wmatrix: Predicted Parameter Output

BIAS: matrices can deliver valued information about the confounding of the effects and the estimation of the selected contrasts. If there is a confounded of two effects, then entry corresponding to them will be nonzero in the BIAS matrix; but if the effects are orthogonal, the entry will be zero. This article is mainly beneficial in designs with un-patterned empty cells.

5. MODELING OF CREEP STRAIN

A creep prediction model was developed as MCS model and was based on the data of the present work. The independent variables in this models were: loading age, compressive strength, modulus of elasticity, applied stress, initial strain, water to powder ratio, water to binder ratio, filler to cement ratio, clinker to cement ratio, aggregate size, and slump flow.

A model represented by Tables 2 - 5 and Figs. 1 - 3 was adopted.

Tables 2A and B explain the descriptive statistics for real and normalized creep data. Table 3 introduces the modelling summary and case processing summary which discovered that a total of (96) sets of creep data were distributed into (65.6%) for training, (15.6%) for testing, and (18.8%) for holdout. For each scale variable, the relative errors were (0.004) through training, testing (0.005), and holdout (0.007).

Table 2A. Descriptive Statistics of Real Data for Model MCS

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	96	1.00	240.00	87.0000	80.91477
FCwithTime	96	9.75	75.40	50.6027	16.62433
Creep	96	.00	1035.00	542.7135	312.74663
WtoPowder	96	.28	.30	.2915	.01072
WtoCement	96	.34	.38	.3611	.01905
ApplyStress	96	16.40	26.80	21.4000	4.50011
AggSize	96	10.00	20.00	15.0000	5.02625
SlumpFlow	96	750.00	790.00	770.0000	20.10499
DusttoCement	96	.11	.25	.1803	.07009
E	96	29.00	38.00	33.5000	4.05229
InitailStrain	96	565.00	705.00	631.7500	57.93663
ClinkertoCement	96	.95	1.00	.9750	.02513
Valid N (listwise)	96				

Table 2B. Normalization for Descriptive Statistics of Creep Data

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	96	.00	1.00	.3625	.33714
FcwithTime	96	.13	1.00	.6711	.22048
Creep	96	.00	1.00	.5244	.30217
WtoPowder	96	.93	1.00	.9667	.03351
WtoCement	96	.89	1.00	.9474	.05291
ApplyStress	96	.61	1.00	.7985	.16791
AggSize	96	.50	1.00	.7500	.25131
SlumpFlow	96	.95	1.00	.9747	.02545
DusttoCement	96	.44	1.00	.7200	.28147
E	96	.76	1.00	.8816	.10664
InitialStrain	96	.80	1.00	.8961	.08218
ClinkertoCement	96	.95	1.00	.9750	.02513
Valid N (listwise)	96				

Table 3. Modelling Summary and Case Processing Summary for Model M_{CS}

Case Processing Summary

		N	Percent
Sample	Training	63	65.6%
	Testing	15	15.6%
	Holdout	18	18.8%
Valid		96	100.0%
Excluded		0	
Total		96	

Model Summary

Training	Sum of Squares Error	.126
	Relative Error	.004
	Stopping Rule Used	1 consecutive step (s) with no decrease in error[a]
	Training Time	0:00:00.02
Testing	Sum of Squares Error	.036
	Relative Error	.005
Holdout	Relative Error	.007

Dependent Variable: Creep

a. Error computations are based on the testing sample.

Table 4. Details of Network Information for Model M_{CS}

Network Information

Input Layer	Covariates	1	Age
		2	FcwithTime
		3	WtoPowder
		4	WtoCement
		5	ApplyStress
		6	AggSize
		7	SlumpFlow
		8	DusttoCement
		9	E
		10	InitialStrain
		11	ClinkertoCement
	Number of Units[a]		11
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Creep
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

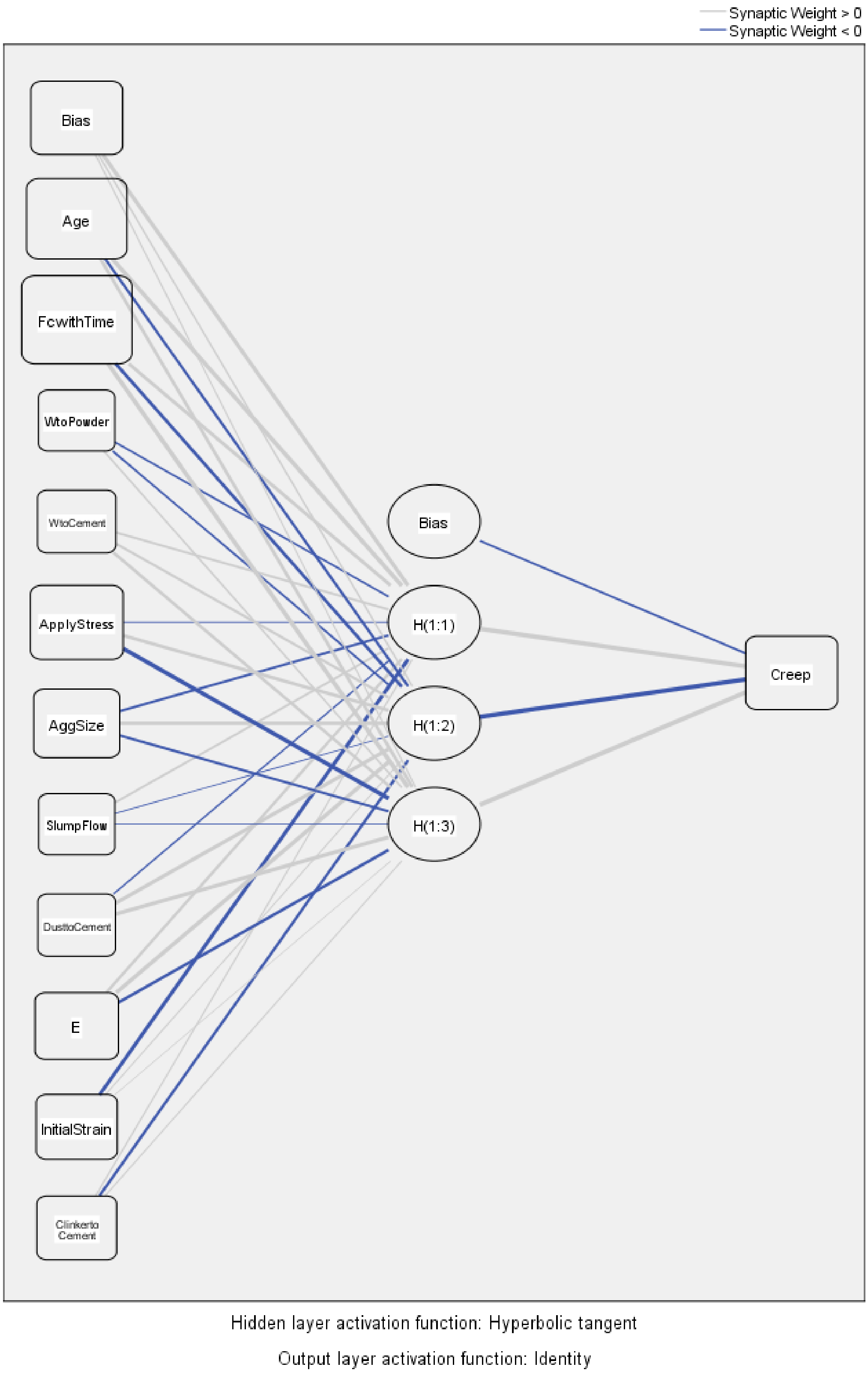

Fig. 1. ANN Structure for the Model M_{CS}

Table 5 determines the estimated parameters for input and hidden layers with their predicted hidden and output layers and their corresponding biases. The weights values were introduced.

Table 5. Estimated Parameter used in Model M_{CS}

Parameter Estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	Creep
Input Layer	(Bias)	.466	.127	.079	
	Age	.601	-.206-	.342	
	FcwithTime	.382	-.333-	.632	
	WtoPowder	-.133-	-.142-	.128	
	WtoCement	.180	.191	.319	
	ApplyStress	-.064-	.350	-.547-	
	AggSize	-.183-	.407	-.186-	
	SlumpFlow	.171	-.059-	-.050-	
	DusttoCement	-.099-	.450	.460	
	E	.225	.511	-.291-	
	InitialStrain	-.433-	.069	.008	
	ClinkertoCement	.080	-.221-	.079	
Hidden Layer 1	(Bias)				-.162-
	H(1:1)				.655
	H(1:2)				-.635-
	H(1:3)				.957

Table 6 and Fig. 2 display the importance of the independent variables. It is observed that creep was controlled by the compressive strength f 'c with time which has importance factor (27.7%) followed by the age with importance factor (20.2%) and finally by the slump flow with importance factor (2%).

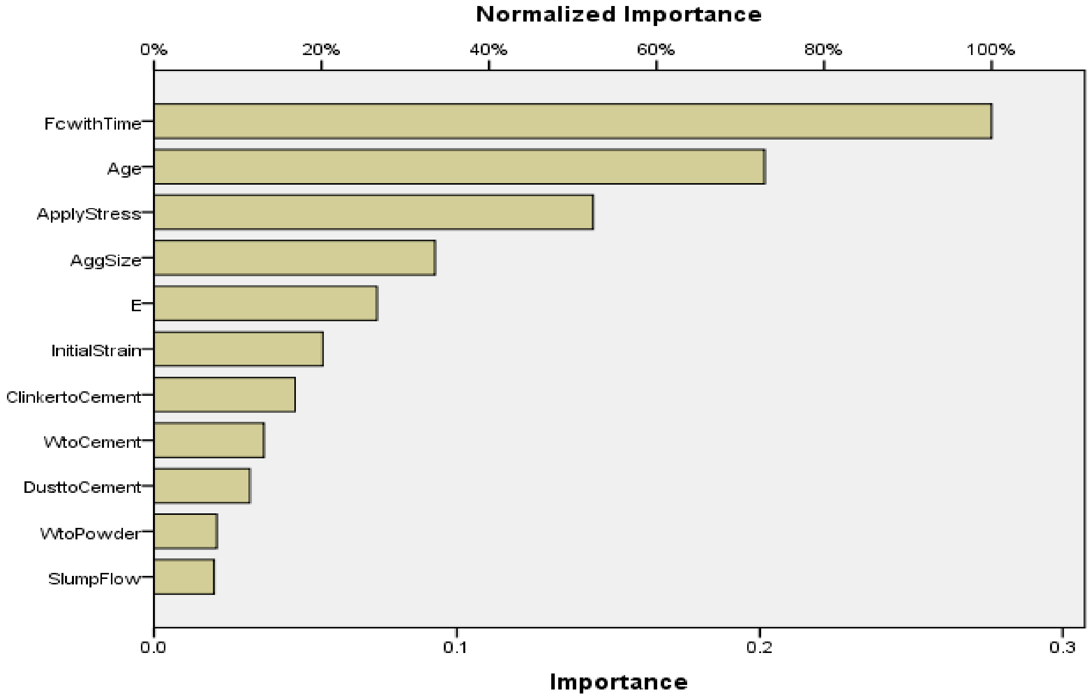

Fig. 2. Importance Values with the Parameters that Affected on the Creep

Table 6. The Importance of the Independent Variables.

Independent Variable Importance

	Importance	Normalized Importance
Age	.202	72.9%
FcwithTime	.277	100.0%
WtoPowder	.021	7.5%
WtoCement	.036	13.1%
ApplyStress	.145	52.4%
AggSize	.093	33.5%
SlumpFlow	.020	7.2%
DusttoCement	.032	11.4%
E	.074	26.6%
InitialStrain	.056	20.2%
ClinkertoCement	.047	16.8%

The program customs same procedure to attain the estimated output data from Eqs. 1 - 6 as showed in article (3).

The relationship between the observed and the predicted values for Model MCS were displayed in Fig. 3. It is documented that ANN offers logical creep prediction with respect to age, compressive strength, modulus of elasticity, applied stress, initial strain, water to powder ratio, water to binder ratio, filler to cement ratio, clinker to cement ratio, aggregate size, and slump flow and attained a R^2 of 0.996.

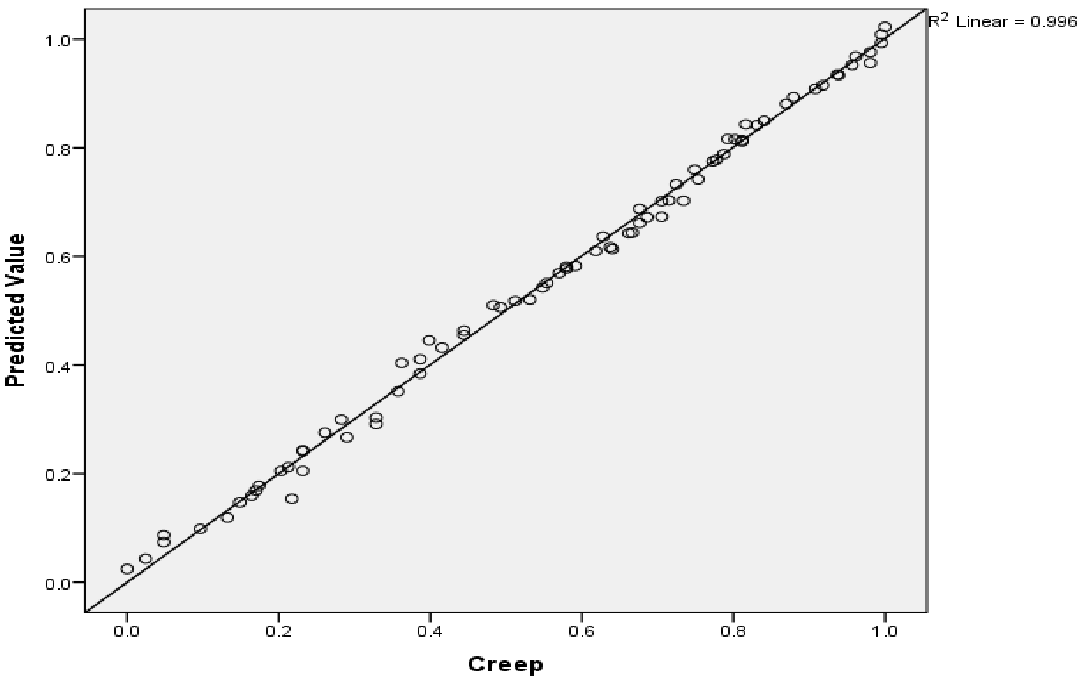

Fig. 3. Relationship between the Observed and the Predicted Values for Model M_{CS}

From Fig. 4, it could be concluded that the ACI 209 model has overestimated the creep strain for the present work (r = 0.82). Otherwise, when using model MCS to predict creep strain it gives better accurate predictions (r = 0.998).

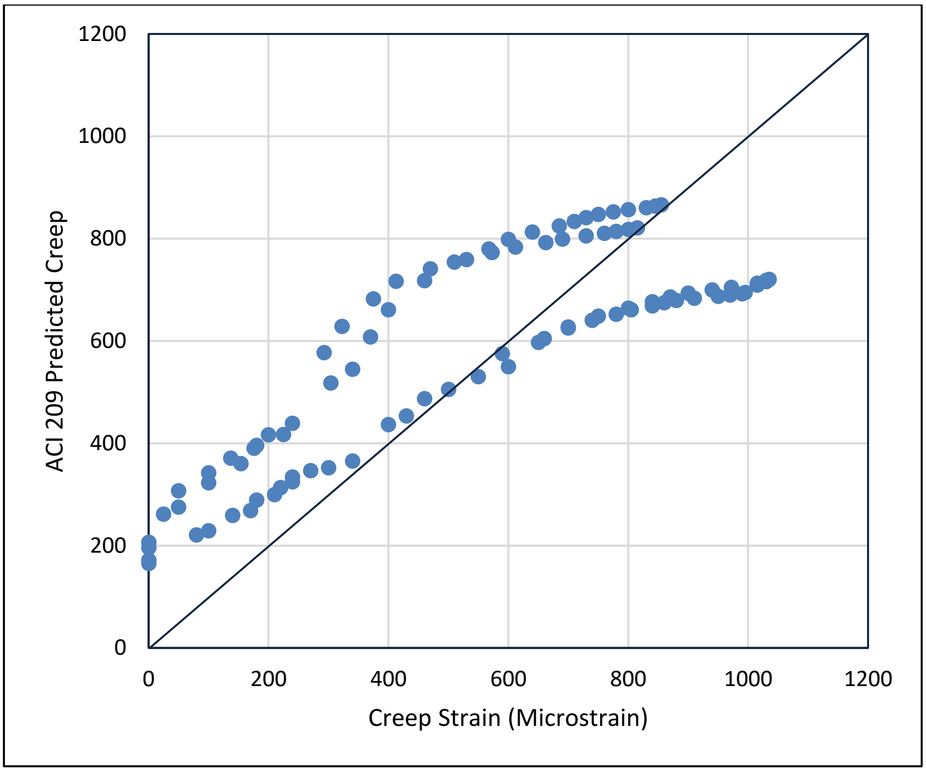

Fig. 4. Relationship between the observed and the predicted values for ACI 209 model (data from prism work)

6. CONCLUSIONS

1. ANN could be adopted to model time-dependent deformations of concrete, such as creep.
2. MCS model was developed by adopting ANN. This model comprised available and easy to get variables. These variables were: age, compressive strength, modulus of elasticity, applied stress, initial strain, water to powder ratio, water to binder ratio, filler to cement ratio, clinker to cement ratio, aggregate size, and slump flow.
3. The predictions of this model were highly correlated to the experimental observations, r = 0.998.
4. The comparisons with the ACI 209 model proved the good reliability of the developed model MCS.

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