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An apt material model for drying shrinkage and specific creep of HPC using artificial neural network

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Abstract. In the present work appropriate concrete material models have been proposed to predict drying shrinkage and specific creep of High-performance concrete (HPC) using Artificial Neural Network (ANN). The ANN models are trained, tested and validated using 106 different experimental measured set of data collected from different literatures. The developed models consist of 12 input parameters which include quantities of ingredients namely ordinary Portland cement, fly ash, silica fume, ground granulated blast-furnace slag, water, and other aggregate to cement ratio, volume to surface area ratio, compressive strength at age of loading, relative humidity, age of drying commencement and age of concrete. The Feed-forward backpropagation networks with Levenberg-Marquardt training function are chosen for proposed ANN models and same implemented on MATLAB platform. The results shows that the proposed ANN models are more rational as well as computationally more efficient to predict time-dependent properties of drying shrinkage and specific creep of HPC with high level accuracy.

Keywords: artificial neural network, high performance concrete, prediction models, drying shrinkage, specific creep

1. Introduction

The time-dependent concrete properties such as shrinkage and creep plays significant role in long-term performance of HPC concrete infrastructures. Hence, a reasonable accurate estimation of actual shrinkage and creep is an often requirement for good design practice especially for structures which are sensitive to secondary effects. The problem associated with prediction of shrinkage and creep of HPC is that the existing prediction models primarily developed for ordinary concrete does not considered the influence of some basic parameters such as secondary cementitious material and aggregate (Brooks 1999, Brooks 2005, Buil *et al*. 1985, Nasser *et al*. 1986, Mazloom *et al*. 2004). In fact, such properties prediction for HPC is very complex and complicated mechanism and there has been no model which can satisfactorily predict the same (Brooks 2005, Mazloom 2008, Bazant 2001, Huo *et al*. 2001, Pan *et al.* 2013, Karthikeyan *et al.* 2008, Gedam *et al.* 2013). The existing shrinkage and creep prediction models ACI (2008), *fib*

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Table 1 Input parameters range used to construct ANN models

Sr. No.	Input Parameters	Unit	Data used in ANN models	
			Min.	Max.
1	Cement	kg/m^3	300	500
2	Fly Ash	kg/m^3	17	190
3	Silica Fume	kg/m^3	30	75
4	GGBS	kg/m^3	64	240
5	Water	kg/m^3	113.2	195.3
6	a/c	-	2.85	6.4
7	v/s	mm	16.32	44.44
8	f_{ck}	MPa	20	85
9	RH	%	40	90
10	Age of specimens ($t_{env.}$)	day	1	73
11	Age of concrete			
	• drying commencement (t_s)	day	7	73
	• loading (t_0)	day	7	73
12	Age of concrete (t)	day	It vary based on experimental measured data sets	

(2010), B3 (2000) and GL (2001) are empirical in nature and based upon test data spread over different geographic locations.

Earlier, Karthikeyan *et al.* (2008) have trained ANN to predict drying shrinkage strain and creep coefficient of HPC using experimental measured data along with the published database of other researchers to train the ANN model. The employed ANN model is a multi-layer network and employed nonlinear differentiable functions a back propagation training algorithm (Widrow-Haff) learning rule. Bal *et al.* (2013) have presented the application of a nonparametric ANN approach to predict effectively dimensional variations due to drying shrinkage. This model employed multilayer back propagation function using experimental data of RILEM Data Bank. The drying shrinkage and specific creep of HPC depends upon large number of parameters including the use of secondary cementitious materials which is quite important (Brooks 1999, Brooks 2005, Buil *et al*. 1985, Nasser *et al*. 1986, Mazloom *et al*. 2004). In this study an attempt has been made to predict drying shrinkage and specific creep of HPC made from locally available ingredients using ANN. The test data of seven different HPC mixes using different alternative cementitious material have been used for training, testing and validation of the proposed models.

2. Objective and methodology

The main object of this work is to demonstrate the applicability of ANN in predicting the secondary effect of drying shrinkage and specific creep of HPC especially in indigenous condition. The level of accuracy of ANN model prediction depends on the randomly selected input data point for training. Therefore, to train the ANN architecture sufficient input data points have been collected from different studies reported in literatures, namely Shariq (2007), Puri (1978), Nautiyal (1974), Jain (1976), Karthikeyan (2008), Huo (2001), Mazloom (2004) and Gedam (2013).

The input data used in ANN model are classified into twelve basic parameters that cover the ordinary Portland cement (*OPC*), fly ash (*FA*), silica fume (*SF*), ground granulated blast-furnace slag (*GGBS*), water (*w*), aggregate to cement ratio (*a/c*), volume to surface area ratio (*v/s*), compressive strength at age of loading (f_{ck}), relative humidity (*RH*), age of concrete when moved to controlled environmental condition ($t_{env.}$), age when drying commencement (t_s) or age of concrete loading (t_0), and age of concrete at which shrinkage or creep repaved (*t*), respectively. The applicability of drying shrinkage and specific creep models is limited to the values of input parameters lying within the range shown in Table 1. Furthermore, its performance has also been compared with the existing shrinkage and creep prediction models available in different international codes and design procedure as mentioned earlier.

2.1 Artificial neural network (ANN)

The development of ANN was inspired by neuroscience which studies brain, biological neurons, and synapse (Duan *et al.* 2013). Nowadays this study finds application in many research fields and adopted widely to solve the problems that are computationally difficult to solve (Duan *et al.* 2013, Hakim *et al.* 2011, Kumar *et al.* 2010, Tanyildizi *et al.* 2010, Pala *et al.* 2007, Noorzaei *et al.* 2007, Nagendra *et al.* 2006, Oztas *et al.* 2006, Maru *et al.* 2004, Atis *et al.* 2005, Nagendra *et al.* 2004, Kim *et al.* 2004, Lee *et al.* 2003, Dias *et al.* 2001, Al-Khaleefi *et al.* 2002, Guang *et al.* 2000, Yeh *et al.* 1998, Lai *et al.* 1997, Lek *et al.* 1996). The main advantage of use of ANN is that it can deal with all complexities, insufficient data or imprecise information. Further, ANN approach enables to continuously re-train and where new data sets are made available so that it can conveniently adopt to the new set of data of HPC drying shrinkage and specific creep (Hakim *et al.* 2011).

The proposed ANN models have potential to predict drying shrinkage and specific creep of HPC. The network architecture of ANN is optimized and its performance is evaluated by using correlation coefficient (R^2), root mean square error (RMSE) and mean absolute percentage error (MAPE) between outputs and targets, as given below

$$R^2 = 1 - \frac{\sum_j \left(t_j - o_j\right)^2}{\sum_j \left(o_j\right)^2} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_j \left(t_j - o_j\right)^2}{p}} \tag{2}$$

$$MAPE = \frac{\left(o - t\right)}{o} \times 100 \tag{3}$$

Where, *t* and *o* are the predicted and actual output of the ANN, and *p* is the total number of training, testing and validation patterns.

Use of Feed-forward backpropagation networks with Levenberg-Marquardt training function have been made and the same were implemented on MATLAB (2007). The models were trained using extensively compiled experimental database of HPC drying shrinkage and specific creep under controlled environmental condition. The models takes into account all more all basic input parameters which affect the time-dependent properties of drying shrinkage and specific creep and have been considered in the proposed models.

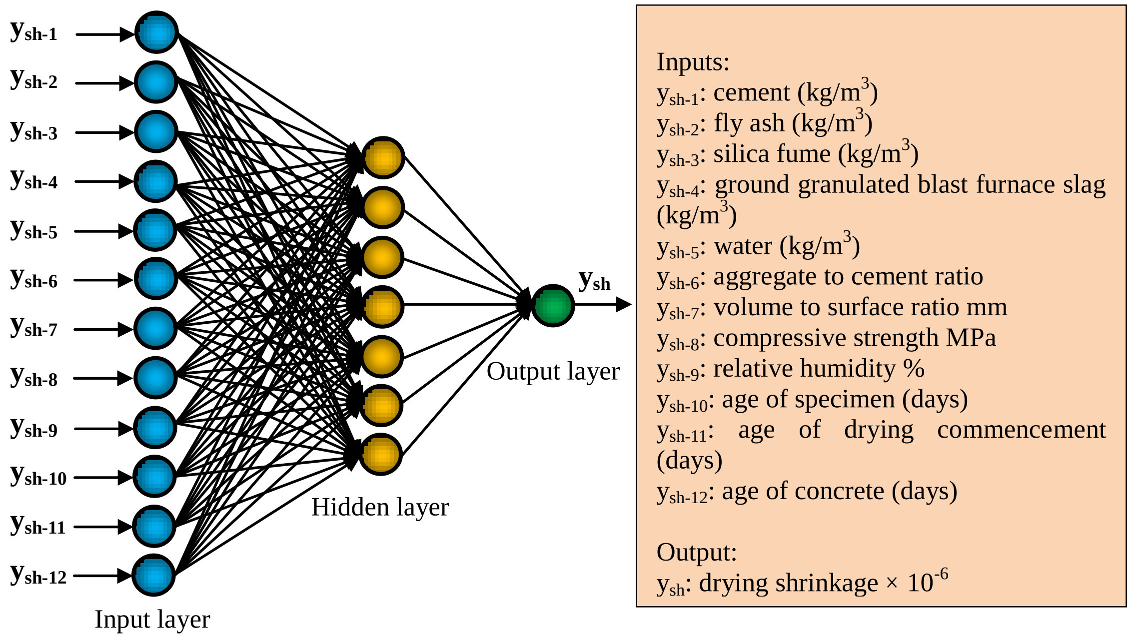

Fig. 1 Proposed 12-7-1 architecture of ANN model for drying shrinkage

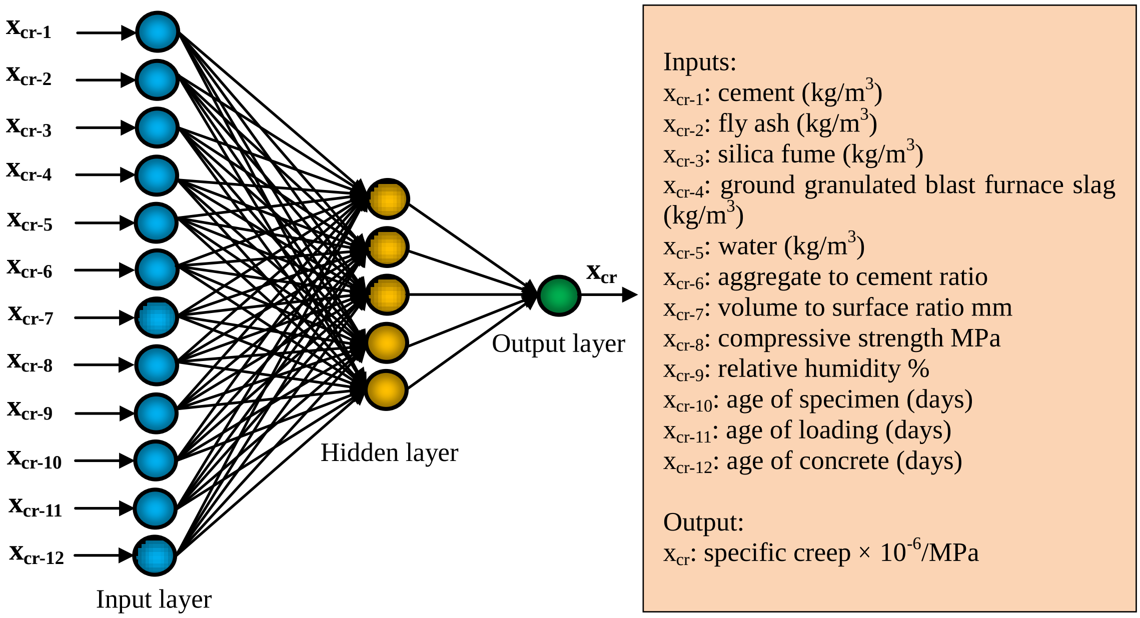

Fig. 2 Proposed 12-5-1 architecture of ANN model for specific creep

2.2 ANN architecture for drying shrinkage and specific creep

The optimized ANN architectures for drying shrinkage and specific creep are shown in Fig. 1

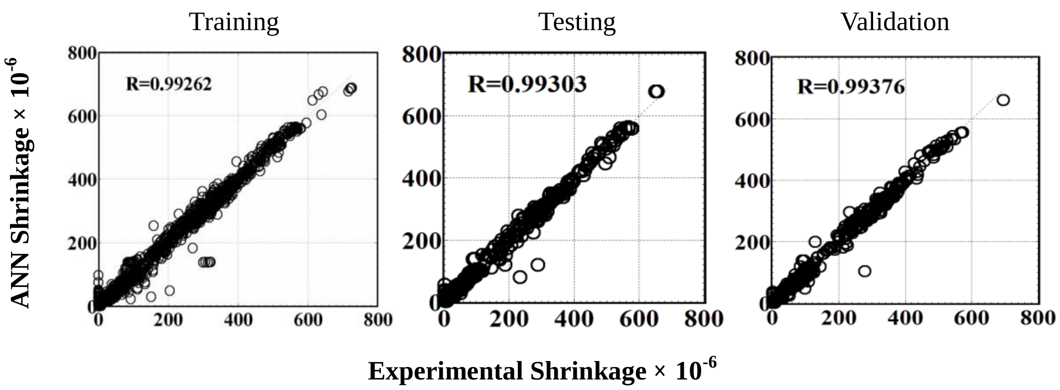

Fig. 3 Performance evaluation of drying shrinkage using ANN (12-7-1) model

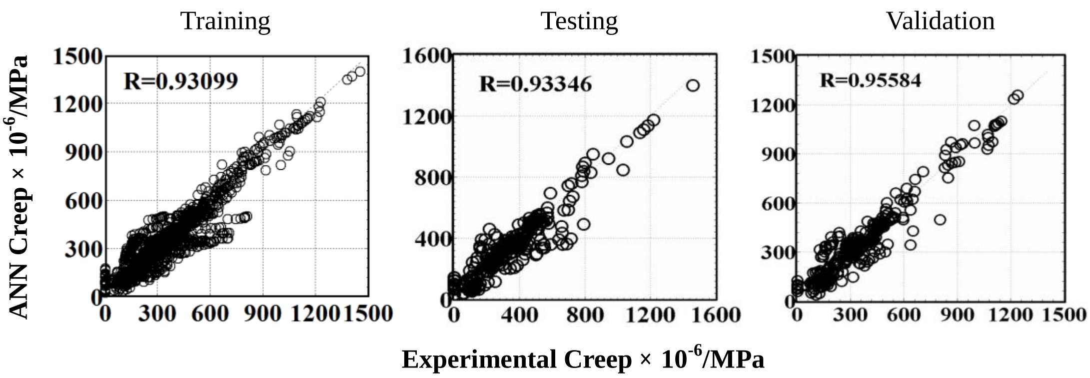

Fig. 4 Performance evaluation of specific creep using ANN (12-5-1) model

Table 2 Parameters of ANN model

Parameters	Drying shrinkage	Specific creep
	12-7-1	12-5-1
Number of input layer neurons	12	12
Number of hidden layer	1	1
Number of hidden layer neurons	7	5
Number of output layer	1	1
Number of output layer neurons	1	1
Momentum rate	0.9	0.9
Learning rate	0.001	0.001
Learning cycle	1000	1000

and Fig. 2. There are three layers in ANN architecture, first is the input layer, second is hidden layer and third is the output layer. The input and output layer neurons depend on the type of problems and its parameters. The hidden layer neurons vary based on modified learning rate and weights, such that it correctly reproduced the output results with presented input parameters. The performance of proposed ANN models on training, testing and validation data sets are shown in

Table 3 Performance evaluation of ANN models

Sets	Drying shrinkage (12-7-1)			Specific creep (12.5-1)		
	R^2	RMSE	MAPE (%)	R^2	RMSE	MAPE (%)
Training	0.9926	2.4413	6.06	0.9309	1.0201	2.88
Testing	0.9937	3.1719	6.96	0.9558	1.0136	3.49
Validation	0.9930	3.6110	7.45	0.9334	1.0050	4.97

Table 4 HPC mix proportion testing data sets

Component	Unit	HPC mix proportion						
		Mix-I	Mix-II	Mix-III	Mix-IV	Mix-V	Mix-VI	Mix-VII
Cement	kg/m^3	340	425	400	420	420	440	450
Fly ash	kg/m^3	34	-	40	-	-	-	-
Silica fume	kg/m^3	-	-	-	21	-	44	-
GGBS	kg/m^3	-	-	-	-	42	-	90
Fine aggregate	kg/m^3	680	709	647	663	675	678	614
Coarse aggregate	kg/m^3	1110	1150	1055	1082	1102	1107	1002
Water	kg/m^3	153	148.75	162	168	151.2	135.52	129.60
Superplasticizer	kg/m^3	2.72	1.7	1.12	4.2	3.36	3.52	3.60
w/c	-	0.45	0.35	0.36	0.38	0.32	0.28	0.24
fck	MPa	23.19	48.09	44.41	43.57	48.94	57.72	57.72
t_0 *and* t_s	Days	28	28	28	28	28	28	28

Fig. 3 and Fig. 4. The results of training phase indicated that the proposed ANN architectures were successful in learning the relationship between the different input and output parameters. The best ANN architecture observed for drying shrinkage is 12-7-1 and that for specific creep is 12-5-1. The simulation of ANN architecture has been done by using feed-forward backpropagation, hyperbolic tangent sigmoid neural transfer function, the weigh and bias values update according to Levenberg-Marquardt backpropagation training function and gradient descent with momentum weight and bias learning function. Its selected parameters for training, testing and validation are shown in Table 2.

3. ANN model performance evaluation

Two separate ANN models have been developed to predict drying shrinkage and specific creep. Total 106 experimental data sets (2176 data points) of drying shrinkage and specific creep have been used in three parts, 70% for learning process, 15% for testing and 15% for validation. All input data points have been selected randomly and their performances of training, testing and validation have been evaluated based on correlation of coefficient between outputs and targets using Eq. (1), the higher value of R^2 means better prediction relationship. The error computed by root mean square error (RMSE) using Eq. (2) and mean absolute percentage error (MAPE) using Eq. (3), and computed error results are shown in Table 3.

Further, to check performance of the proposed ANN models, the predicted value of drying shrinkage and specific creep have been compared with seven different HPC mixes that were

Table 5 Drying shrinkage in microstrain

Concrete mixes	80×270 mm high specimens after 587 days			150×300 mm high specimens after 406 days		
	Measured value	Predicted value		Measured value	Predicted value	
		Mazloom	ANN (12-7-1)		Mazloom	ANN (12-7-1)
OPC	532	505	525.869	468	445	475.077
SF6	528	504	533.382	462	443	450.319
SF10	523	503	520.092	446	442	442.010
SF15	512	501	508.903	435	441	438.313
Error coefficient (*M*)		4.08 %	0.88 %		3.39 %	1.61 %

Table 6 Specific creep of 80×270 mm high specimens in microstrain/MPa

Concrete mixes	Creep after 400 days at age of loading 7 days			Creep after 400 days at age of loading 28 days		
	Measured value	Predicted value		Measured value	Predicted value	
		Mazloom	ANN (12-5-1)		Mazloom	ANN (12-5-1)
OPC	595	596	589.312	413	447	410.405
SF6	510	518	506.390	407	390	407.070
SF10	459	457	496.520	381	344	395.588
SF15	417	366	436.599	328	276	341.248
Error coefficient (*M*)		5.16 %	4.33 %		9.61 %	2.60 %

investigated according to ASTM standard C512 (2011) and whose mix proportions are shown in Table 4.

To check the performance of proposed ANN models of drying shrinkage and specific creep with proposed model by Mazloom *et al*. (2004), Mazloom (2008) the comparative study also has been done using their own experimental measured data. This additional study corroborated the importance of ANN model prediction for drying shrinkage and specific creep in concrete using cement with cementitious material. The comparative results of ANN models and Mazloom's models with experimental measured data are shown in Tables 5 and 6 for shrinkage and creep respectively. The accuracy of prediction models are evaluated according to Brooks and Neville. (1978) the error coefficient (*M*) for drying shrinkage and specific creep is defined as follows

$$M = \frac{1}{\bar{C}_{(sh/cr)}} \sum \left[\frac{\left[C_{(sh/cr)} - Cp_{(sh/cr)} \right]^2}{n} \right]^{0.5} \times 100 \quad (4)$$

Furthermore, it can be seen that, Mazloom's data of shrinkage and creep included in study, which covers a range of concrete mixes using cementitious material silica fume that partially replaced cement by 0 to 15%, different size of specimen and test age. The error coefficient is computed using Eqs. (4) and for drying shrinkage it varies 3% to 4%, for Mazloom's model while for ANN model this error varies 0.8 to 1.6% only. Similarly, the error coefficient for creep varies 5 to 9.6 % for Mazloom's model, while ANN model it shows 2 to 4.3 % error. As seen in these results, the error of ANN prediction models are much less than the Mazloom's proposed models.

Table 7 Comparison of testing data sets with predicted results of proposed ANN model with existing prediction models for drying shrinkage

HPC mix	Predicted results mean absolute percentage error (%) and correlation coefficient									
	ANN (12-7-1)		ACI		*fib*		B3		GL	
	MAPE	R^2	MAPE	R^2	MAPE	R^2	MAPE	R^2	MAPE	R^2
Mix-I	11.43	0.9951	36.80	0.8682	19.89	0.9401	48.28	0.7977	50.19	0.7851
Mix-II	6.99	0.9976	47.49	0.7714	12.34	0.9918	61.59	0.6523	56.39	0.7127
Mix-III	9.14	0.9965	50.85	0.6918	20.07	0.9707	63.67	0.6295	61.81	0.6417
Mix-IV	4.86	0.9981	54.47	0.6316	20.78	0.9401	50.90	0.7567	55.44	0.6572
Mix-V	6.61	0.9978	12.68	0.9939	39.94	0.2819	32.14	0.8940	19.84	0.9713
Mix-VI	6.47	0.9975	41.53	0.7962	12.82	0.9858	38.91	0.8676	45.37	0.8160
Mix-VII	11.99	0.9925	51.56	0.7368	19.48	0.9925	51.00	0.7858	57.90	0.7230
Avg.	8.21	0.9964	42.20	0.7843	20.76	0.8718	49.50	0.7691	49.56	0.7581

4. Results and discussion

Based on the comparison of predicted and test results of different HPC mixes investigated it is inferred that the proposed ANN models of drying shrinkage and specific creep satisfactorily predict the time-dependent properties of HPC. Using these ANN models, around seven data sets (133 data points) of simulations have been performed to evaluate the time-depended properties of drying shrinkage and specific creep of different grades of HPC using different material properties. These models are showing very good learning relationship between predicted and experimental measured values. It consist one hidden layers and minimum numbers of neurons in connection weights. The test phase of drying shrinkage and specific creep shows that the ANN architecture is capable to generalizing between input and the output variable with reasonable good prediction. Attempt has also been made to compare the performance of the standard prediction models/practices of international codes, described earlier, against the available test results of the seven HPC mixes studied. The results of comparison are given separately for drying shrinkage and specific creep, one by one. It may be nodded that error margin of prediction has marginally increased as compared to ANN.

4.1 Drying shrinkage

Drying shrinkage strain for seven different HPC testing data sets has been predicted using Eqs. (5), (7), (9), (11) (see appendix) and compared with the test results. The error has been evaluated statistically using coefficient of correlation and mean absolute percentage error with respect to test values and results listed in Table 7. It has been observed that the mean absolute errors of the existing prediction models lie in the range of 20% to 50% with *fib* model having minimum error. It is thus evident that the existing models ACI, *fib*, B3 and GL used to predict drying shrinkage of normal concrete are not suitable to predict drying shrinkage of HPC. The coefficient of correlation of experimental results vs. predicted value from different models i.e. ANN, ACI, *fib*, B3 and GL are shown in Fig. 5.

Furthermore, the proposed ANN model for drying shrinkage performs best with its average coefficient of correlation is 99.64% and the mean absolute percentage errors lies between 4.86%

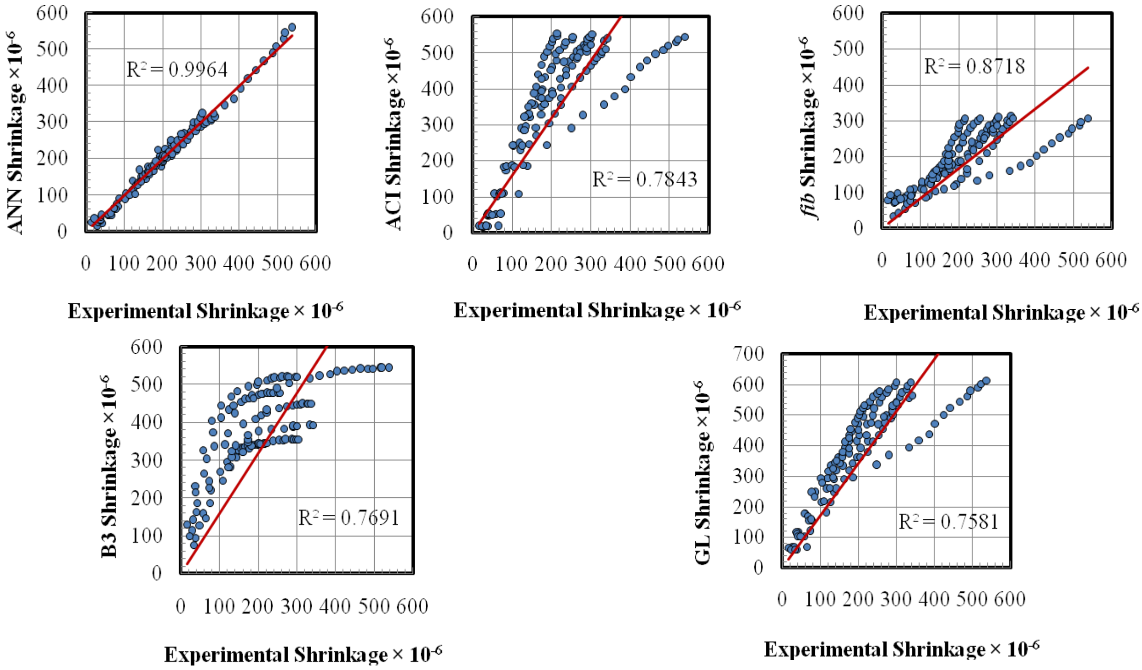

Fig. 5 Comparison between HPC training data sets and predicted output from the models ANN, ACI, *fib*, B3 and GL

Table 8 Comparison of testing data sets with predicted results of proposed ANN model with existing prediction models for specific creep

HPC mix	Predicted results mean absolute percentage error (%) and correlation coefficient									
	ANN (12-5-1)		ACI		*fib*		B3		GL	
	MAPE	R^2	MAPE	R^2	MAPE	R^2	MAPE	R^2	MAPE	R^2
Mix-I	5.41	0.9963	64.61	-1.666	9.51	0.9899	51.85	0.7354	88.68	0.2211
Mix-II	6.99	0.9976	47.50	0.7714	12.34	0.9918	61.59	0.6523	56.39	-0.317
Mix-III	6.99	0.9927	47.50	0.5519	12.34	0.9715	61.59	0.5456	56.39	0.3231
Mix-IV	7.90	0.9912	43.69	0.9447	15.60	0.8439	65.57	0.4172	82.92	0.4304
Mix-V	8.17	0.9906	50.87	0.1608	6.37	0.9950	61.86	0.6075	84.87	0.2864
Mix-VI	13.96	0.9786	11.23	0.9883	52.64	0.7010	71.22	0.4917	74.49	0.4581
Mix-VII	1.93	0.9989	47.21	0.3866	12.61	0.9987	41.64	0.8181	89.48	0.2060
Avg.	7.71	0.9923	40.94	0.3053	21.23	0.9274	61.47	0.6097	78.89	0.2296

and 11.99%, only. It may be further seen that individually, three of HPC sets has relative errors in the range 9 to 12%, and the other four sets has error in prediction less than 7% for the ANN model. The average relative error of the total seven HPC testing data set is about 8.21 %, which can considered as a good and acceptable for drying shrinkage.

4.2 Specific creep

Specific creep for seven different HPC test data sets has been predicted using proposed ANN

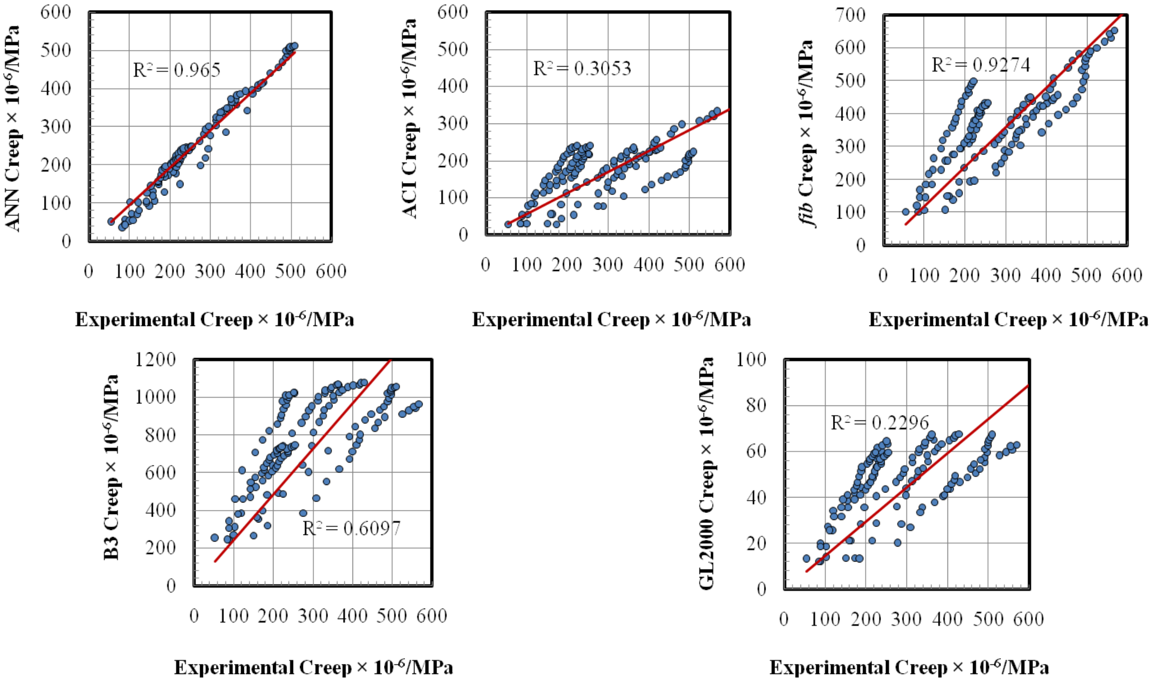

Fig. 6 Comparison between HPC training data sets and predicted output from the models ANN, ACI, *fib*, B3 and GL

model by Eqs. (6), (8), (10), (12) (see appendix) and compared with respective test results. Further, the error has been computed using coefficient of correlation and mean absolute percentage error with respect to experimental data and the results are listed in Table 8. Mean absolute errors of predicted value using existing prediction models are over 21% while for ANN model this error 7.71 % only. Thus it is evident that the existing model ACI, *fib*, B3 and GL used to predict specific creep are not suitable to predict specific creep of HPC. The coefficient of correlation of experimental results vs. predicted value of different models i.e. ANN, ACI, *fib*, B3 and GL are shown in Fig. 6.

In case of the proposed ANN model for specific creep, the average coefficient of correlation is observed 99.23% and its maximum and minimum value of the mean absolute errors in the testing sets are 13.96% and 1.93%, respectively. The average error for the seven HPC testing data set is about 7.71 %, which can be considered as a good and acceptable for specific creep. It may be seen that average error correlation coefficient for other prediction models are much higher in the range 21.23% for *fib* to 78.89% for GL models.

5. Conclusions

Present study demonstrate that the proposed ANN model for drying shrinkage and specific creep predicts time dependent properties of HPC which are very close to experimental results. Further, ANN model predictions are far better than the existing prediction models ACI, *fib*, B3 and

GL, which are commonly used by designers and researchers. Some silence findings are:

• The developed ANN models have potential to predict drying shrinkage and specific creep of HPC with high level accuracy for all type of concrete with and without supplementary cementitious materials namely FA, SF and GGBS.

• The proposed ANN modes is far superior to existing models proposed in international codes of practices for prediction of drying shrinkage and specific creep of HPC.

References

ACI Committee 209R-92 (2008), *Prediction of Creep, Shrinkage, and Temperature Effects in Concrete Structures*, ACI Special Publication.

Al-Khaleefi, A., Terro, M.J., Alex, A.P. and Wang, Y. (2002), “Prediction of fire resistance of concrete filled tubular steel columns using neural networks”, *Fire Saf. J.*, **37**, 339-352.

American Concrete Institute Committee 209 (201), *Report on Factors Affecting Shrinkage and Creep of Hardened Concrete*, Americam Concrete Institute, 1R-01-1R-12.

ASTM Standard C512/C512M-10 (2011), *Standard Test Method for Creep of Concrete in Compression*, ASTM Standard, 1-5.

Atis, C.D., Ozcan, F., Kilic, A., Karahan, O., Bilim, C. and Severcan, M.H. (2005), “Influence of dry and wet curing conditions on compreddive strength of silica fume concrete”, *Build. Environ.*, **40**, 1678-1683.

Bal, L. and Buyle-Bodin, F. (2013), “Artificial neural network for predicting drying shrinkage of concrete”, *Construct. Build. Mater.*, **38**, 248-254.

Bazant, Z.P. (2001), “Prediction of concrete creep and shrinkage: past, present and future”, *Nucl. Eng. Des.*, **203**, 27-38.

Bazant, Z.P. and Baweja, S. (2000), “Part 1: creep and shrinkage prediction model for analysis and design of concrete structures: model B3”, *ACI Spec. Publicat.*, **194**, 1-83.

Brooks, J.J. (1999), “How admixtures affect shrinkage and creep”, *Mag. ACI*, 35-38.

Brooks, J.J. and Neville, A.M. (1978), “Predicting long-term creep and shrinkage from short-term test”, *Mag. Concrete Res.*, **30**, 51-61.

Brooks, J.J. (2005), “30-year creep and shrinkage of concrete”, *Mag. Concrete Res.*, **57**, 545-556.

Buil, M. and Acker, P. (1985), “Creep of a silica fume concrete”, *Cement Concrete Res.*, **15**, 463-466.

CEB-FIP Model Code (1993), *Design of Concrete Structures, CEB-FIP-Model-Code 1990*, British Standard Institution, London, UK.

Dias, W.P.S. and Pooliyadda, S.P. (2001), “Neural networks for predictiong properties of concrete with admixtures”, *Construct. Build. Mater.*, **15**, 371-379.

Draft of *fib Model Code* (2010), *International federation for structural concrete (fib),* Lausanne, Switzerland.

Duan, Z.H., Kou, S.S. and Poon, C.S. (2013), “Using artificial neural netwrol for predicting the elastic modulus of recycle aggregate concrete”, *Construct. Build. Mater.*, **44**, 524-532.

Duan, Z.H., Kou, S.S. and Poon, C.S. (2013), “Prediction of compressive strength of recycle aggregate concrete using artificial neural networks”, *Construct. Build. Mater.*, **40**, 1200-1206.

Gardner, N. and Lockman, M. (2001), “Design provisions for drying shrinkage and creep of normal-strength concrete”, *ACI Mater. J.*, **98**, 159-162.

Gedam, B.A., Upadhyay, A. and Bhandari, N.M. (2013), “Study of an apt creep and shrinkage prediction model for high performance concrete”, *Proceedings of the 22nd International Conference on Structural Mechanics in Reactor Technology*, San Francisco, USA, August.

Gedam, B.A., Upadhyay, A. and Bhandari, N.M. (2013), “Performance of creep and shrinkage prediction models for normal strength concrete”, *J. Int. Ass. Bridge Struct. Eng.*, 137-148.

Guang, N.H. and Zong, W.H. (2010), “Prediction of compressive strength of concrete by neural networks”, *Cement Concrete Res.*, **30**, 1245-1250.

Hakim, S., Noorzaei, J., Jaafar, M.S., Jameel, M. and Mohammadhassani, M. (2011), "Application of artificial neural networks to predict compressive strength of high strength concrete", *Int. J. Phys. Sci.*, **6**, 975-981.

Huo, X.S., Omaishi, N. and Tadros, M.K. (2001), "Creep, shrinkage, and modulus of elasticity of high performance concrete", *ACI Mater. J.*, **98**, 440-449.

Jain, K.K. (1976), "A study of structural properties of concrete with fly ash", Ph.D. Dissertation, University of Roorkee, Roorkee.

Karthikeyan J. (2008), "Long-term deformation of high performance prestressed concrete", Ph.D. Dissertation, Indian Institute of Technology, Roorkee.

Karthikeyan, J., Upadhyay, A. and Bhandari, N.M. (2008), "Artificial neural networks for predict creep and shrinkage of high performance concrete", *J. Adv. Concrete Tech.*, **6** , 1-8.

Kim, J., Lim, D.K., Feng, M.Q. and Yazdani, F. (2004), "Application of neural networks for estimation of concrete strength", *J. Mater. Civil Eng.*, ASCE, **16**, 257-264.

Kumar, S. and Barai, S.V. (2010), "Neural network modeling of shear strength of SFRC corbels without stirrups", *Appl. Soft Comput.*, **10**, 135-148.

Lai, S. and Serra, M. (1997), "Concrete strength prediction by means of neural network", *Construct. Build. Mater.*, **11** , 93-98.

Lee, S. (2003), "Prediction of concrete strength using artificial neural networks", *Eng. Struct.*, **25**, 849-857.

Lek, S., Delacoste, M., Baran, P., Dimopoulos, I., Lauga, J. and Aulagnier, S. (1996), "Application of neural networks to modelling nonlinear relationships in ecology", *Ecolog. Model.*, **90** , 39-52.

Maru, S. and Nagpal, A.K. (2004), "Neural network for creep and shrinkage deflections in reinforced concrete frames", *J. Comput. Civil Eng., ASCE*, **18**, 350-359.

MATLAB R2011a (2007), *Neural networks toolbox user's guide*, Version 7.12.0 (R2011a), The math works, Inc., Prentice Hall.

Mazloom, M., Ramexaniapour, A.A. and Brooks, J.J. (2004), "Effect of silica fume on mechanical properties of high-strength concrete", *Cement Concrete Compos.*, **26**, 347-357.

Mazloom, M. (2008), "Estimating long-term creep and shrinkage of high-strength concrete", *Cement Concrete Compos.*, **30**, 316-326.

Nagendra, S.M. and Khare, M. (2004), "Artificial neural network based line source models for vehicular exhaust emission predictions of an urban roadway", *Tran. Res. Part D*, **9**, 199-208.

Nagendra, S.M. and Khare, M. (2006), "Artificial neural network approach for modelling nitrogen dioxide dispersion from vehicular exhaust emissions", *Ecolog. Model.*, **190**, 99-115.

Nasser, K.W. and Al-Manaseer, A.A. (1986), "Creep of concrete containing fly ash and superplasticizer at different stress/strength ratios", *ACI J.*, 668-673.

Nautiyal, B.D. (1974), "Time dependent properties of fly ash concrete", Ph.D. Dissertation, University of Roorkee, Roorkee.

Noorzaei, J., Hakim, S., Jaafar, M. and Thanoon, W. (2007), "Development of artificial neural network for predicting concrete compressive strength", *Int. J. Eng. Tech.*, **4**, 141-153.

Oztas, A., Pala, M., Ozbay, E., Kanca, E., Caglar, N. and Bhatti, M. A. (2006), "Prediction the compreddive strength and slump of high strength concrete suing neural network", *Construct. Build. Mater.*, **20**, 769-775.

Pala, M., Ozbay, E., Oztas, A. and Yuce, M. I. (2007), "Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks", *Construct. Build. Mater.*, **21**, 384-394.

Pan, Z., Li, B. and Lu, Z.(2013), "Re-evaluation of CEB-FIB 90 prediction models for creep and shrinkage with experimental database", *Construct. Build. Mater.*, **38**, 1022-1030.

Puri, N. (1978), "Probabilistic study of time dependent properties of plain and fly ash concrete", Ph.D. Dissertation, University of Roorkee, Roorkee.

Shariq, M. (2007), "Studies in creep characteristics of concrete and reinforced concrete", Ph.D. Dissertation, Indian Institute of Technology, Roorkee.

Tanyildizi, H. and Cevik, A. (2010), "Modeling mechnical performance of lightweigth concrete containing silica fume exposed to high temperature using genetic programming", *Construct. Build. Mater.*, **24**, 2612-

2618.
Yeh, I.C. (1998), "Modeling of strength of hih-performance concrete using artificial neural networks", *Cement Concrete Res.*, **28**, 1797-1808.

Nomenclature

The following symbols are used in this paper:

A_c	cross-section area (mm^2)
a/c	aggregate to cement ratio
$C_{(sh/cr)}$	mean value of measured shrinkage/creep of concrete
$Cp_{(sh/cr)}$	predicted value of shrinkage/creep of concrete
$C_{(sh/cr)}$	measured shrinkage/creep of concrete
c	cement contain in concrete (kg/m^3)
d	constant, 10 days for standard condition and 6 to 30 days for other than standard condition
E_{ci}	modulus of elasticity of concrete at the time of t_0 initial load (MPa)
E_{cm}	modulus of elasticity of concrete at the time of 28 days (MPa)
f	constant, depends on type of curing, 7 days for moist cured concrete and 1-3 days for steam cured concrete under the standard condition for other than standard condition 20 to 130 days
f_{ck}	mean compressive strength of concrete cylinder at the age of loading (MPa)
f_{cm}	mean compressive strength of concrete at the age of t_0 days (MPa)
$J(t,t_0)$	creep strain in microstrains per unit MPa
k_h	factor depends on relative humidity
k_s	shape factor depends on cross section
n	number of measured values
RH	relative humidity of the ambient environment, percentage
s	coefficient which depend on the strength class of cement
t	age of concrete at the time of observation (days)
$t_{env.}$	age of concrete contact with controlled environmental condition (days)
t_0	age of concrete at the time of loading (days)
t_s	age of concrete at which drying is commenced (days)
v/s	volume to surface area ratio (mm)
w	water contain in concrete (kg/m^3)
w/c	water cement ratio in concrete
α_{as} α_{ds1}, α_{ds2}	are coefficients, depended on the type of cement
α	constant coefficient, 1 for standard condition and 0.90 to 1.10 for other than standard condition
α_1	factor depends on type of cement
α_2	factor depends on type of curing
$\varepsilon_{sh}(t,t_s)$	shrinkage stain in microstrains
$(\varepsilon_{sh})_\upsilon$	ultimate shrinkage strain in microstrains
$\varepsilon_{sh\infty}$	time-dependence of ultimate shrinkage (10^{-6})
μ	perimeter of the member in contact with the atmosphere (mm)
$\varphi(t,t_0)$	creep coefficient as ratio of creep strain to initial strain

ψ	constant coefficient, 0.60 for standard condition and normally rage between 0.40 to 0.80 for other than standard condition
$\sigma_c(t_0)$	uniaxial constant stress at an age of loading t_0 (MPa)

Appendix

The different drying shrinkage and specific creep models implemented in international codes and design practices are as follows:

ACI model provision:

Shrinkage

$$\varepsilon_{sh}(t,t_s)=\left[\frac{t_s^{\alpha}}{f+t_s^{\alpha}}\right](\varepsilon_{sh})_{\upsilon} \tag{5}$$

$(\varepsilon_{sh})_{\upsilon}=780\gamma_{sh}$

Creep

$$J(t,t_0)=\sigma_c(t)\cdot\delta_t \tag{6}$$

$\delta_t=\left[\dfrac{t^{\psi}}{d+t^{\psi}}\right]\left[\dfrac{\varphi(t,t_0)_{\upsilon}}{E_{ci}}\right]$

$\varphi(t,t_0)_{\upsilon}=2.35\cdot\gamma_c$

where γ_{sh} and γ_c represent applicable correction factors for shrinkage and creep compliance function.

fib model provision:

Shrinkage

$$\varepsilon_{cs}(t,t_s)=\varepsilon_{cas}(t)+\varepsilon_{cds}(t,t_s) \tag{7}$$

$\varepsilon_{cas}(t)=-\alpha_{as}\left(\dfrac{f_{cm}/10}{6+f_{cm}/10}\right)^{2.5}\cdot10^{-6}\cdot\left(1-\exp\left(-0.2\cdot\sqrt{t}\right)\right)$

$\varepsilon_{cds}(t,t_s)=\left[(220+110\cdot\alpha_{ds1})\cdot\exp\cdot(-\alpha_{ds2}\cdot f_{cm})\right]\cdot10^{-6}\cdot\left(-1.55\cdot\left[1-\left(\dfrac{RH}{100}\right)^3\right]\right)\cdot\left(\dfrac{(t-t_s)}{0.034\cdot h^2+(t-t_s)}\right)^{0.5}$

Creep

$$J(t,t_0)=\frac{\sigma_c(t_0)}{E_{ci}}\varphi(t,t_0) \tag{8}$$

$E_{ci}(t_0)=\left[\exp\left\{s\cdot\left[1-\left(\dfrac{28}{t}\right)^{0.5}\right]\right\}\right]^{0.5}E_{ci}$

$\varphi(t,t_0)=\left(1+\dfrac{1-\mathrm{RH}/100}{0.1\sqrt[3]{\mathrm{h}}}\alpha_1\right)\alpha_2\left(\dfrac{16.8}{\sqrt{f_{cm}}}\right)\left(\dfrac{1}{0.1+(t_0)^{0.2}}\right)\left(\dfrac{(t-t_0)}{\beta_H+(t-t_0)}\right)^{0.3}$

$\beta_H=1.5\cdot h\cdot[1+(1.2\cdot RH/100)^{18}]+250\cdot\alpha_3\leq1500\cdot\alpha_3$

$$h=\frac{2A_c}{\mu} \quad \alpha_1=\left[\frac{35}{f_{cm}}\right]^{0.7} \qquad \alpha_2=\left[\frac{35}{f_{cm}}\right]^{0.2} \qquad \alpha_3=\left[\frac{35}{f_{cm}}\right]^{0.5}$$

B3 model provision:

Shrinkage

$$\varepsilon_{sh}(t,t_0)=-\varepsilon_{sh\infty}k_h S(t) \tag{9}$$

$$\varepsilon_{sh\infty}=\alpha_1\alpha_2\left[1.9\times10^{-2}w^{2.1}\left(f_{cm}\right)^{-0.28}+270\right]$$

$$\varepsilon_{sh\infty}=\alpha_1\alpha\left[1.9\times10^{-2}w^{2.1}\left(f_{cm}\right)^{-0.28}+270\right]$$

$$S(t)=\tanh\sqrt{\frac{t-t_s}{\tau_{sh}}}$$

$$\tau_{sh}(t,t_0)=8.5t_s^{-0.08}\left(f_{cm}\right)^{-0.25}\left[k_s 2\left(\frac{v}{s}\right)\right]^2$$

Creep

$$J(t,t_0)=\left[q_1+C_0(t,t_0)+C_d(t,t_0,t_s)\right]\cdot\sigma_c(t_0) \tag{10}$$

$$q_1=\frac{0.6\times10^6}{E_{ci}} \qquad q_2=185.4c^{0.5}\left(f_{cm}\right)^{-0.9} \qquad q_3=53.766(w/c)^4c^{0.5}\left(f_{cm}\right)^{-0.9}$$

$$q_4=20.3(a/c)^{-0.7} \qquad q_5=7.57\times10^5\left(f_{cm}\right)^{-1}\left|\varepsilon_{sh\infty}\right|^{-0.6}$$

$$C_0(t,t_0)=q_2Q(t,t_0)+q_3In\left[1+(t-t_0)^n\right]+q_4In\left(\frac{t}{t_0}\right)$$

$$Q(t,t_0)=Q_f(t_0)\left[1+\left(\frac{Q_f(t_0)}{Z(t,t_0)}\right)^{r(t_0)}\right]^{-1/r(t_0)}$$

$$m=0.5 \qquad n=0.1$$

$$r(t_0)=1.7(t_0)^{0.12}+8$$

$$Q_f(t_0)=\left[0.086(t_0)^{2/9}+1.21(t_0)^{4/9}\right]^{-1}$$

$$Z(t,t_0)=(t_0)^{-m}In\left[1+(t-t_0)^n\right]$$

$$C_d(t,t_0,t_s)=q_5\sqrt{\exp\left[-8H(t)\right]-\exp\left[-8H(t_0)\right]}$$

GL model provisions:

Shrinkage

$$\varepsilon_{sh}(t,t_0)=\varepsilon_{sh\upsilon}\beta(h)\beta(t_0) \tag{11}$$

$$\varepsilon_{sh\upsilon} = 1000K\left(\frac{30}{f_{cm}}\right)^{0.5} \times 10^{-6}$$

$$\beta(h) = \left(1 - 1.18h^4\right)$$

$$\beta(t_0) = \left(\frac{t - t_s}{t - t_s + 0.15(v/s)^2}\right)^{0.5}$$

Creep

$$J(t, t_0) = \frac{1}{E_{ci}} + \frac{\varphi(t, t_0)}{E_{cm}} \tag{12}$$

$$E_{cm} = 3500 + 4300\left[\frac{f_{cm} t_0^{3/4}}{a + b t_0^{3/4}}\right]^{0.5}$$

$$\varphi(t, t_0) = \Phi(t_c) \cdot \Phi(t_{c'})$$

$$\Phi(t_{c'}) = \left(\frac{2(t - t_0)^{0.3}}{(t - t_0)^{0.3} + 14}\right) + \left(\frac{7(t - t_0)^{0.3}}{t_0(t - t_0 + 7)}\right)^{0.5} + 2.5\left(1 - 1.08h^2\right) \cdot \left(\frac{(t - t_0)}{\left(t - t_0 + 0.15(v/s)^2\right)}\right)^{0.5}$$

If $t_0 = t_c$, $\Phi(t_c) = 1$ when $t_0 > t_c$

$$\Phi(t_c) = \left[1 - \left(\frac{(t_0 - t_c)}{t_0 - t_c + 0.15(v/s)^2}\right)^{0.5}\right]^{0.5}$$