PREDICTION OF ULTIMATE LOAD CARRYING CAPACITY OF CFST COLUMNS (SCC INFILLS) USING MATLAB AT AMBIENT AND ELEVATED TEMPERATURE

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Abstract: Concrete Filled Steel Tubular (CFST) columns have significance in recent years due to superior structural aspects especially in developed countries. It is crucial to study the ultimate load carrying capacity of concrete-filled steel tubular columns to ensure the safe operation of Engineering structures. Numerous studies were reported on the behaviour of the ultimate load carrying capacity of CFST columns with Self Compacting Concrete (SCC) as infill's at Ambient and Elevated temperature for varies length, thickness and diameter. This study further presents an analytical model to predict the ultimate load carrying capacity of CFST columns with SCC infill's at Ambient and Elevated temperature by using ANN and PSO, which are the tools of the MATLAB-R2018b. The experimental dataset that presented in previous studies were utilized to verify the reliability of the ANN & PSO and the prediction performance of the model and it is compared with that of traditional design methods. The consolidated input datasets consisting of all ranges of variables, which are used for the development of the model. It is shown that the proposed method can predict well, the ultimate load carrying capacity of circular section concrete filled steel tube columns are found to match with the corresponding experimental results.

Keywords: CFST; SCC; Artificial Neural Network(ANN); PSO (Particle Swarm Optimization); Ambient and Elevated Temperature.

1. INTRODUCTION

a. Concrete Filled Steel Tubes

Concrete Filled Steel Tubes (CFSTs) refers to a composite structure in which steel columns are infilled with the concrete. CFSTs are primarily used in the lateral resistance structural members of the braced and unbraced structural members. CFSTs having significant properties like ductility, high bearing capacity, plasticity, toughness, ability of energy absorption and convenient in construction. CFSTs offers good structural performance, They can be used in the construction of high-rise buildings, bridges, subway platforms multi-storey buildings and further CFSTs used for retrofitting technique in earthquake prone regions. Compared to the traditional method construction buckling of structural members can be prevented, which improves the axial carrying capacity, thus the use composite materials in construction which significantly reduces the cross section and section of the structural member and thereby considerably reduction in the cost of construction.

Fig1: CFST structures

b. **Self Compacted Concrete (SCC)**

Self Compacting Concrete , otherwise called as self consolidating concrete, is in the spotlight throughout the previous two decades in development industry. SCC can be placed and compacted in each and every corner of the formwork by its self-weight. So it doesn't require compaction at site or plants. It has been invented to improve the durability and uniformity of concrete. The mix composition is chosen to satisfy all performance criteria for the concrete in both the fresh and hardened states. To accomplish this, fly ash and silica fumes were utilized as mineral admixtures, and super plasticizers were utilized in blend as chemical admixtures for the design of mix. The advancement of SCC and its outcomes on hypothetical and experiments were audited in different investigations . The important property of a SCC is to have workable and segregation resistant concrete which can flow through the reinforcement without any external vibrations or compactions .The bond quality of strengthened steel and the SCC are higher when compared to conventional concrete, which made the SCC as predominating material.

c. **MATLAB-R2018b**

The name MATLAB represents Matrix Laboratory. MATLAB was written originally to provide easy access to matrix software developed by the LINPACK and EISPACK projects. MATLAB is widely used in all areas of applied mathematics, in education and research at universities, and in the industry. MATLAB stands for MATrix LABoratory and the software is built up around vectors and matrices. This makes the software particularly useful for linear algebra but MATLAB is also a great tool for solving algebraic and differential equations and for numerical integration. MATLAB has powerful graphic tools and can produce nice pictures in both 2D and 3D. It is also a programming language, and is one of the easiest programming languages for writing mathematical programs. MATLAB also has some tool boxes useful for signal processing, image processing, optimization, etc.

I. **Artificial Neural Network [ANN]**

Artificial Neural Networks (ANN), are computing systems vaguely inspired by the biological neural networks that constitute animal brains. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. An artificial neural network is an interconnected group of nodes, akin to the vast network of neurons in a brain. Here, each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another.

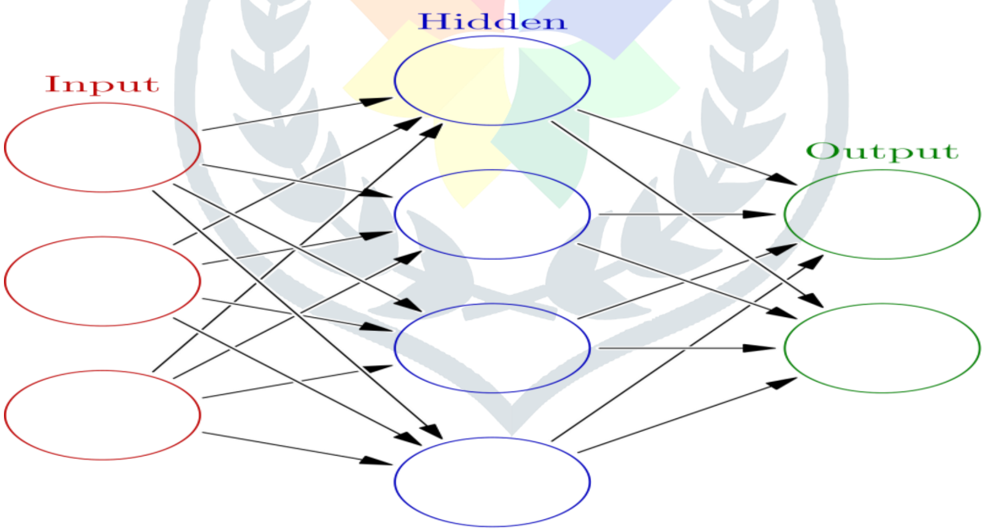


Fig2: Schematic representation of ANN

An ANN is a model based on a collection of connected units or nodes called "artificial neurons", which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit information, a "signal", from one artificial neuron to another. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it. In common ANN implementations, the signal at a connection between artificial neurons is a real number, and the output of each artificial neuron is computed by some non-linear function of the sum of its inputs. The connections between artificial neurons are called "edges". Artificial neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Artificial neurons may have a threshold such that the signal is only sent if the aggregate signal crosses that threshold. Typically, artificial neurons are aggregated into layers. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times.

II. Particle Swarm Optimization [PSO]

A swarm is a large number of agents interacting locally with themselves. In swarm, there's no supervisor or central control to give orders on how to behave. Swarm-based algorithms are popular in this age hence its passion for nature-inspired, population based algorithms that can produce high-quality product with low cost and fast solutions to situations that are identified as complex and hard to solve. Because of that reason Swarm intelligence is becoming a million-dollar gem in the category of Artificial Intelligence that is ready to collect the pattern, lifestyle and behaviour of social swarms in the environment, for example, bird flocks, honey bees, ant colonies, and fish schooling. PSO was originally conceived as a representation of organisms in a bird flow or fish school. Later it was simplified and was used for solving optimisation problems. PSO uses a bunch of particles called the swarm. These particles are allowed to move around & explore the search space. The global best or the swarm best will the optimum value. Each particle describes a set of parameter values and a initial velocity (vector). And we compute the fitness by just plugging in those values in the cost function. That will give us the fitness of the particle. In each iteration we calculate fitness for each particle. We get the best fitness value of the swarm.

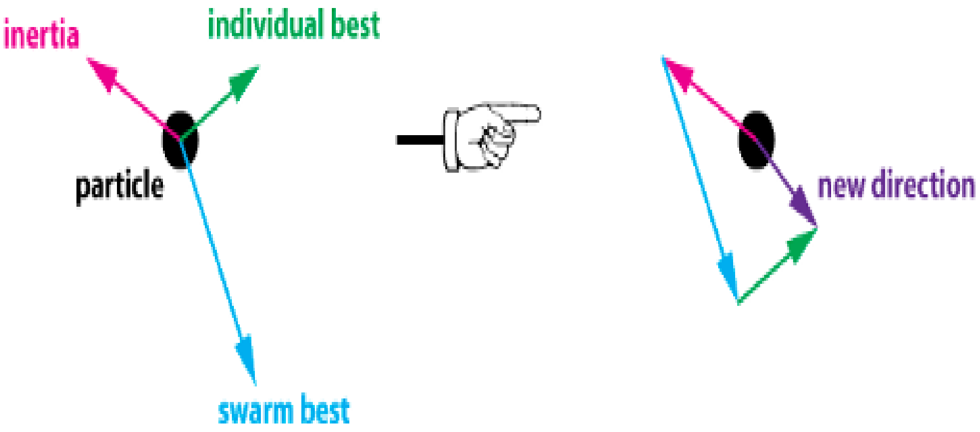


Fig3: Schematic representation of PSO

2. EXPEIMENTAL RESULTS (PREVIOUS PAPERS) FOR CFST WITH CIRCLE SECTION

Numerous studies were conducted on CFSTs various cross sections through experimentally at ambient and elevated temperature, It was noted in literature that ultimate capacity of CFSTs depends on various parameters like length of CFST(L), wall thickness of steel tube(ts), diameter(D), unconfined strength concrete strength(fc), young's modulus of concrete(Ec), young's modulus of steel(Es), confinement factors(ξ) and ultimate load carrying capacity(Pu) corresponding to table-1. Experimental datasets are audited from the different sources related to CFSTs for Ambient temperature, for the prediction of the experimental results using ANN and PSO.

Table:1 Experimental datasets that are audited from the different sources related to CFST at Ambient temperature.

D(mm)	ts(mm)	fc (MPa)	fy (MPa)	$Ec(MPa)$	Es (MPa)	L (mm)	L/D	D/t	Pu (kN)	References
120.8	4.06	34.4	452	27566	191536	241.3	0.3	29.7	1201	Yamamoto et al. [2000]
101.7	3.07	31.16	605	26236	207050	203.3	0.4	33.1	1068	
150	3.2	28.71	287	25183	190120	450	0.2	46.8	998	
150	2	18.03	336	19957	211680	450	0.2	75	656	
150	2	21.95	336	22020	211680	450	0.2	75	756	
150	3.2	18.03	287	19957	190120	450	0.2	46.8	790	
179	5.5	22.15	248	22120	200000	360	0.2	32.5	1467	Huang et al.[2002]
179	5.5	22.15	248	22120	200000	360	0.2	32.5	1530	
179	5.5	43.61	248	31038	200000	360	0.2	32.5	2040	
179	5.5	43.61	248	31038	200000	360	0.2	32.5	2030	Han and yao [2004]
174	3	23.91	266	22982	200000	360	0.2	58	1135	

It was noted in literature that ultimate capacity of CFSTs depends on various parameters like length of CFST(L), wall thickness of steel tube(ts), diameter(D), unconfined strength concrete strength(fc), young's modulus of concrete(Ec), young's modulus of steel(Es), and ultimate load carrying capacity(Pu) corresponding to table-2. Experimental datasets are audited from the different source related to CFSTs for Elevated temperature, for the prediction of the experimental results using ANN and PSO.

Table:2 Experimental datasets that are audited from the different sources related to CFST at Elevated temperature.

D(mm)	ts(mm)	fc (MPa)	fy (MPa)	$Ec(MPa)$	Es (MPa)	T(^{0}C)	L (mm)	L/D	D/t	Pu (kN)	Reference
133	4.5	72.4	433	32765	200000	20	399	3	29.5	1692	Tian-yi song et al.[2009]
133	4.5	72.4	433	32765	200000	200	399	3	29.5	1425	
133	4.5	72.4	433	32765	200000	300	399	3	29.5	1352	
133	4.5	72.4	433	32765	200000	400	399	3	29.5	1321	
133	4.5	72.4	433	32765	200000	500	399	3	29.5	927	
133	4.5	72.4	433	32765	200000	600	399	3	29.5	893	
133	4.5	72.4	433	32765	200000	700	399	3	29.5	732	
133	4.5	72.4	433	32765	200000	800	399	3	29.5	647	
133	4.5	72.4	433	32765	200000	900	399	3	29.5	615	
133	4.9	40.8	324	32765	213000	20	399	3	27.1	1080	
133	4.9	40.8	324	32765	213000	300	399	3	27.1	1080	
133	4.9	40.8	324	32765	213000	500	399	3	27.1	785	
133	4.9	40.8	324	32765	213000	800	399	3	27.1	561	

3. METHODOLOGY

Machine learning (ML) is the study of computer algorithms that improve automatically through the experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or infeasible to develop conventional algorithms to perform the needed tasks.

Procedure

- Definition of problems.
- Corresponding datasets that are related to study are audited from the literature survey.
- Programming in the MATLAB-R2018b are developed for the ANN and PSO.
- Necessary care should be taken for the minimum error.
- Run the programme by uploading relevant datasets.
- Once the training part is completed, validation should be done for the required datasets to check the accuracy of the results.
- Solutions are obtained by using algorithms(ANN) and optimization(PSO) methods.

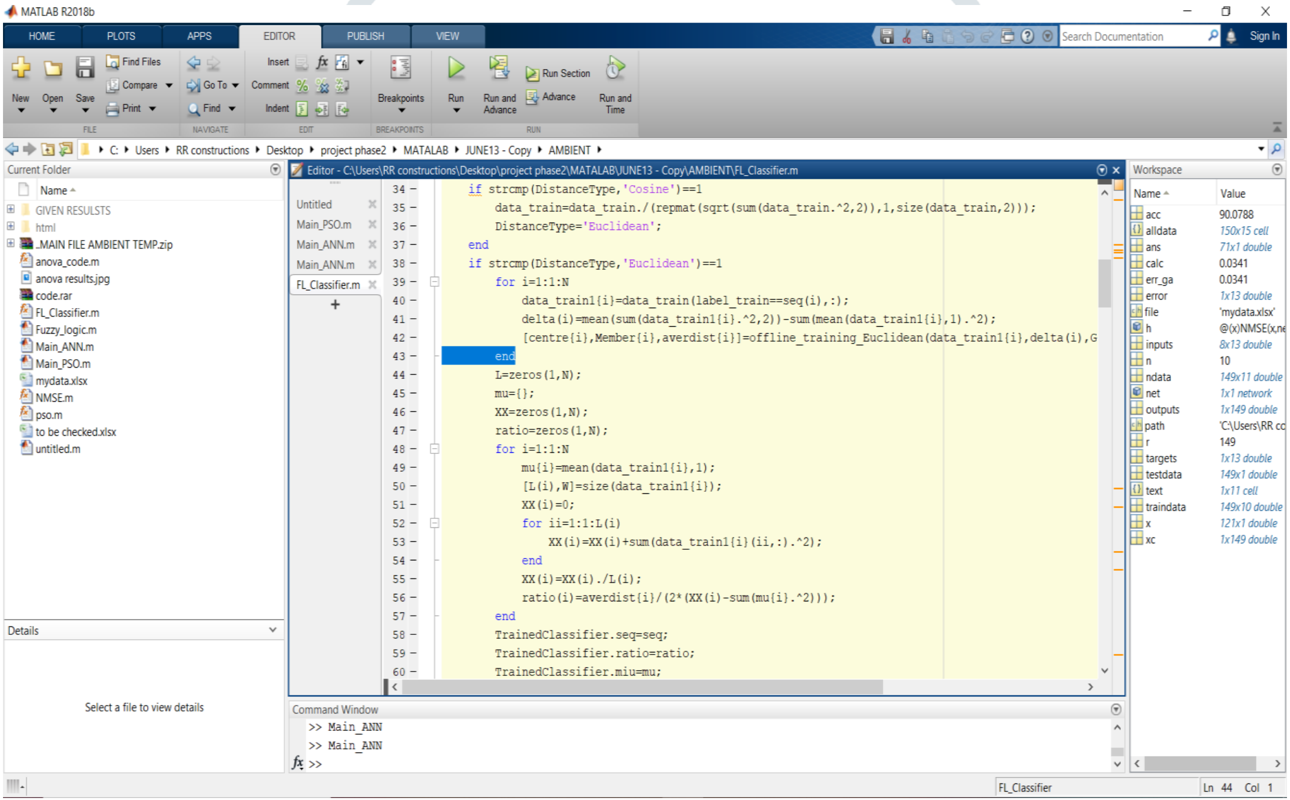


Fig:4 Programming in MATLAB-R2018b

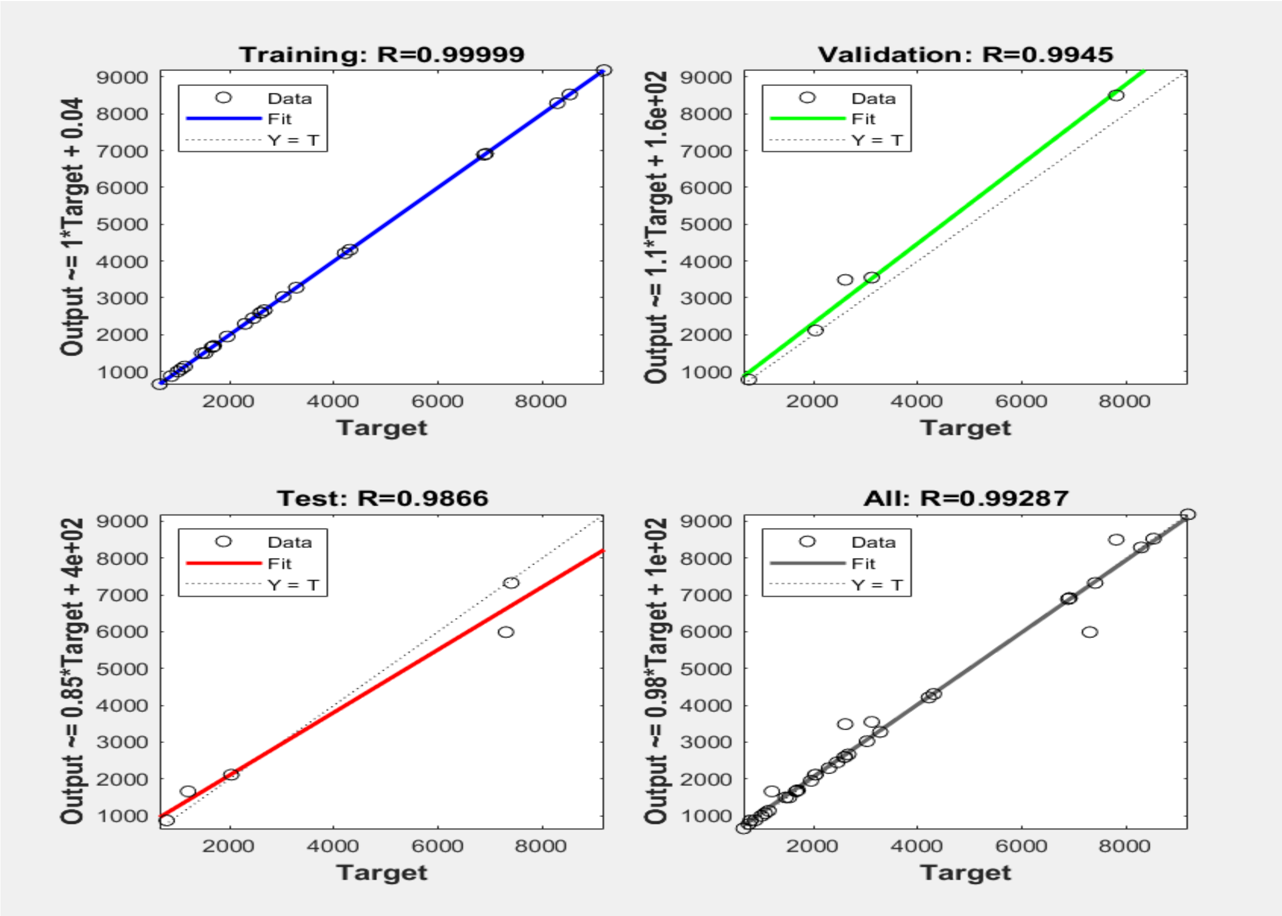
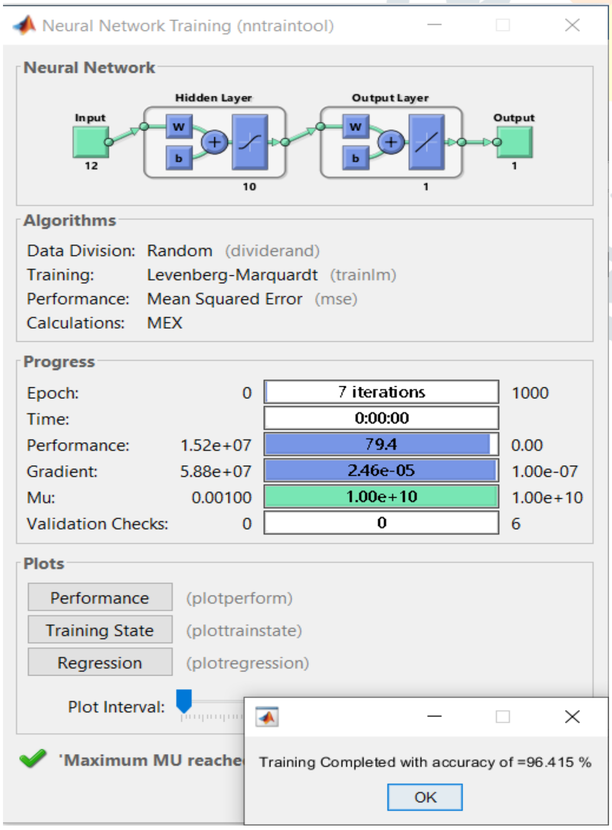


Fig:5 Regression from ANN



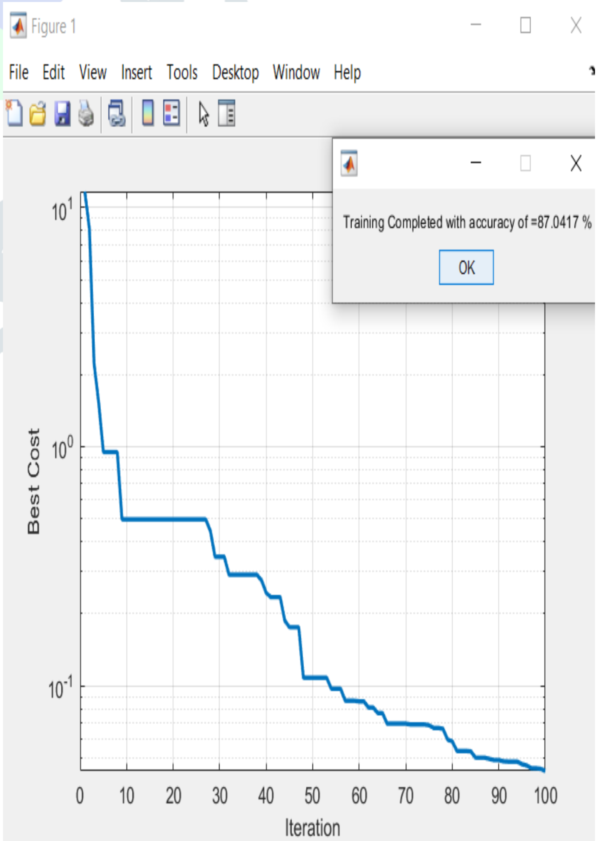


Fig:6 Training and accuracy from ANN at Ambient temperature.

Fig:6.a Iteration and accuracy from PSO at Ambient temperature.

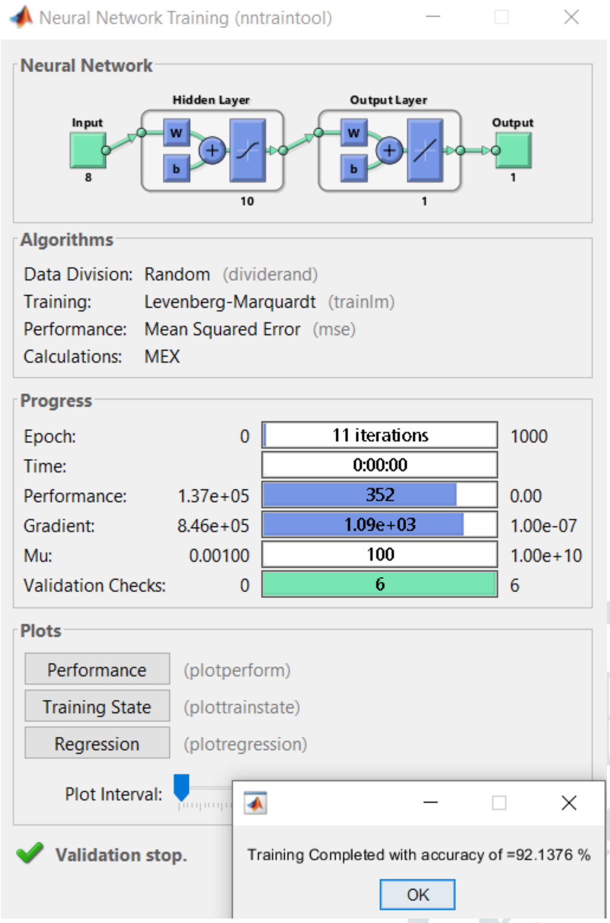


Fig:7 Training and accuracy from ANN at Elevated temperature.

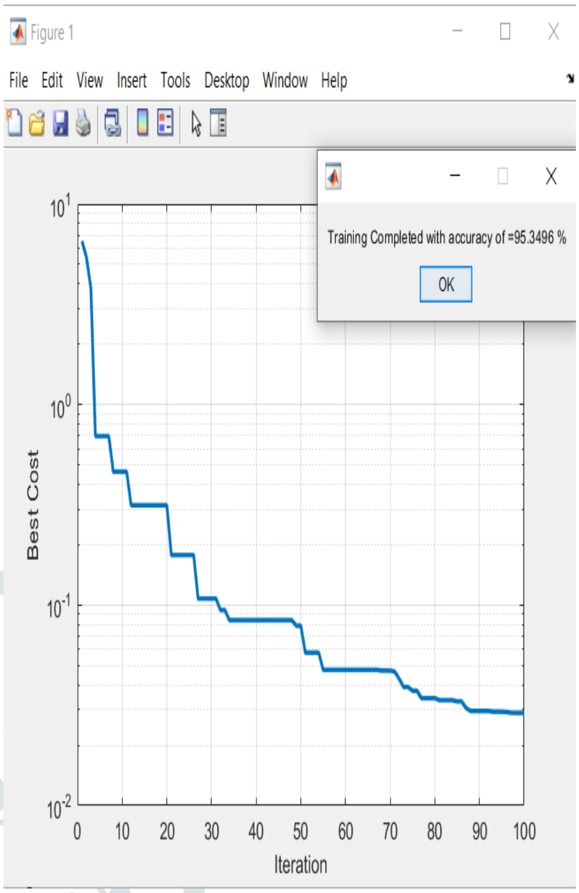


Fig:7.a Iteration and accuracy from PSO at Elevated temperature.

4. RESULTS

In the present study, in order to derive the ANN and PSO model from the available experimental data sets were used as it mentioned in the table-1 & 2 which are related to the research. The ultimate carrying capacity of the CFST's for the values Pu from the ANN and PSO are found to be close agreement with the related experimental results with accuracy of 96% & 87% for ambient temperature and 92% & 95% for elevated temperature . Table-3 and table-4 shows the predicted values of Pu from the ANN and PSO at Ambient and Elevated temperature respectively.

Table:3 Comparison of ultimate load carrying capacity (Pu) between experimental and predicted values of ANN and PSO modelling at Ambient temperature.

D (mm)	Ts (mm)	fc (MPa)	fy (MPa)	Ec (MPa)	Es (MPa)	L (mm)	L/D	D/t	Pu (kN)	ANNPu (kN)	PSO Pu (kN)
120.8	4.06	34.4	452	27566	191536	241.3	0.3	29.7	1201	1201	1358.4
101.7	3.07	31.16	605	26236	207050	203.3	0.4	33.1	1068	1068	989.6
150	3.2	28.71	287	25183	190120	450	0.2	46.8	998	998	1216.7
150	2	18.03	336	19957	211680	450	0.2	75	656	656	786.6
150	2	21.95	336	22020	211680	450	0.2	75	756	756	883.2
150	3.2	18.03	287	19957	190120	450	0.2	46.8	790	790	890.6
179	5.5	22.15	248	22120	200000	360	0.2	32.5	1467	1467	1547.9
179	5.5	22.15	248	22120	200000	360	0.2	32.5	1530	1530	1431.8
179	5.5	43.61	248	31038	200000	360	0.2	32.5	2040	2040	2068.3
179	5.5	43.61	248	31038	200000	360	0.2	32.5	2030	2030	1994.5
174	3	23.91	266	22982	200000	360	0.2	58	1135	1135	1244.7

Table:4 Comparison of ultimate load carrying capacity (Pu) between experimental and predicted values of ANN and PSO modelling at Elevated temperature.

D(mm)	ts(mm)	fc (MPa)	fy (MPa)	Ec(MPa)	Es (MPa)	T(^{0}C)	L (mm)	L/D	D/t	Pu (kN)	ANN Pu (kN)	PSO Pu (kN)
133	4.5	72.4	433	32765	200000	20	399	3	29.5	1692	1668.3	1672.1
133	4.5	72.4	433	32765	200000	200	399	3	29.5	1425	1476.6	1491.4
133	4.5	72.4	433	32765	200000	300	399	3	29.5	1352	1341.9	136.5
133	4.5	72.4	433	32765	200000	400	399	3	29.5	1321	1189.5	1209.7
133	4.5	72.4	433	32765	200000	500	399	3	29.5	927	1030.2	1041
133	4.5	72.4	433	32765	200000	600	399	3	29.5	893	880.1	869.5
133	4.5	72.4	433	32765	200000	700	399	3	29.5	732	754.8	726
133	4.5	72.4	433	32765	200000	800	399	3	29.5	647	662.7	646.2
133	4.5	72.4	433	32765	200000	900	399	3	29.5	615	603.5	615.2
133	4.9	40.8	324	32765	213000	20	399	3	27.1	1080	1077.3	1104.1
133	4.9	40.8	324	32765	213000	300	399	3	27.1	1080	940.2	992.7
133	4.9	40.8	324	32765	213000	500	399	3	27.1	785	785.3	874.7
133	4.9	40.8	324	32765	213000	800	399	3	27.1	561	560.7	570.6

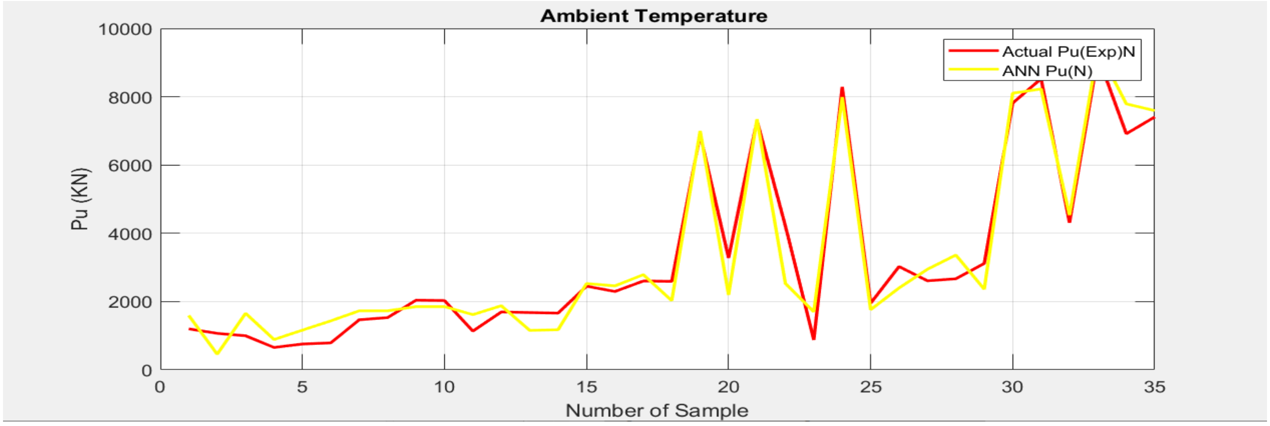


Fig:8 Comparison of ultimate load carrying capacity of Experimental Pu vs ANN Predicted Pu at Ambient temperature.

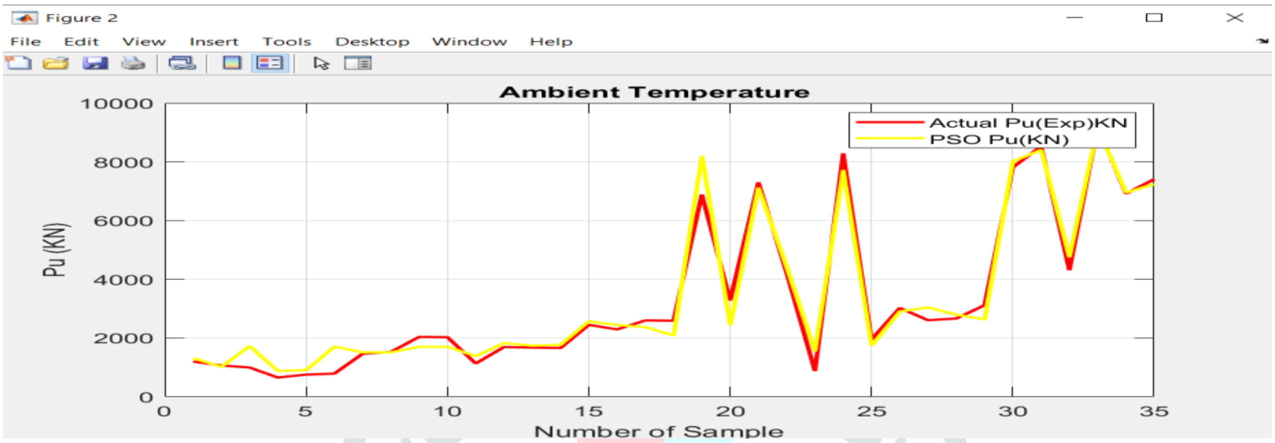


Fig:9 Comparison of ultimate load carrying capacity of Experimental Pu vs PSO Predicted Pu at Ambient temperature.

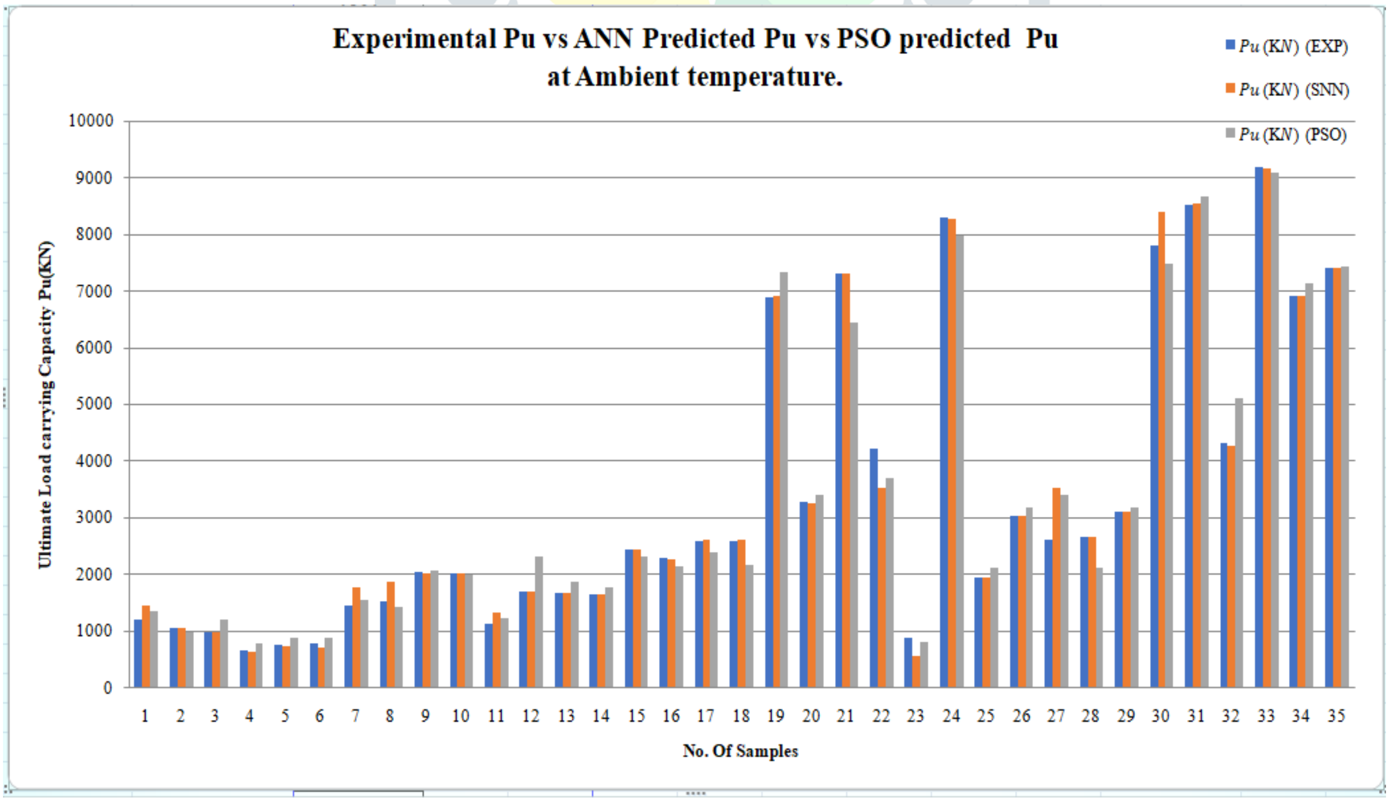


Fig:10 Comparison of ultimate load carrying capacity of Experimental Pu vs ANN Predicted Pu vs PSO predicted Pu at Ambient temperature.

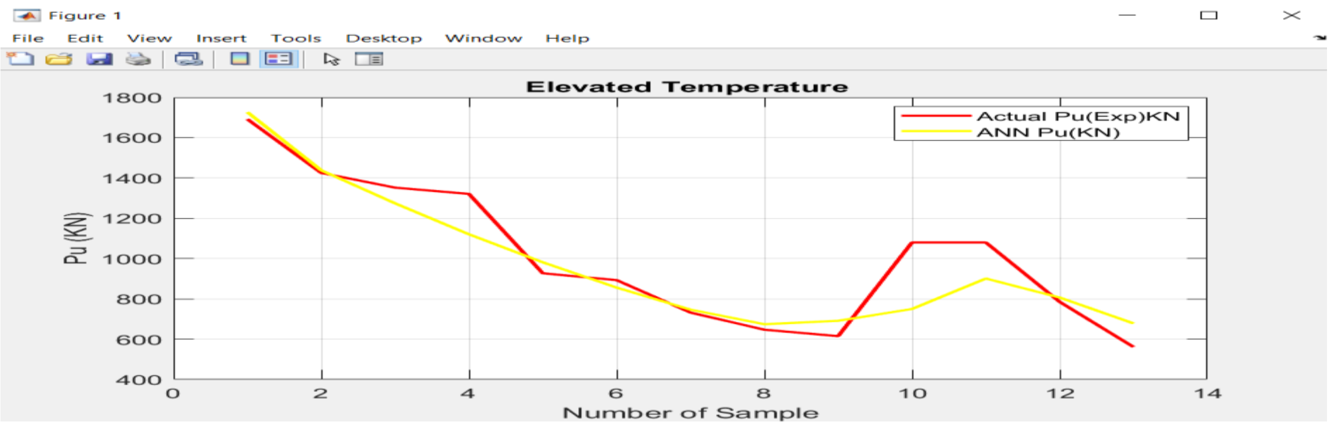


Fig:11 Comparison of ultimate load carrying capacity of Experimental Pu vs ANN Predicted Pu at Elevated temperature.

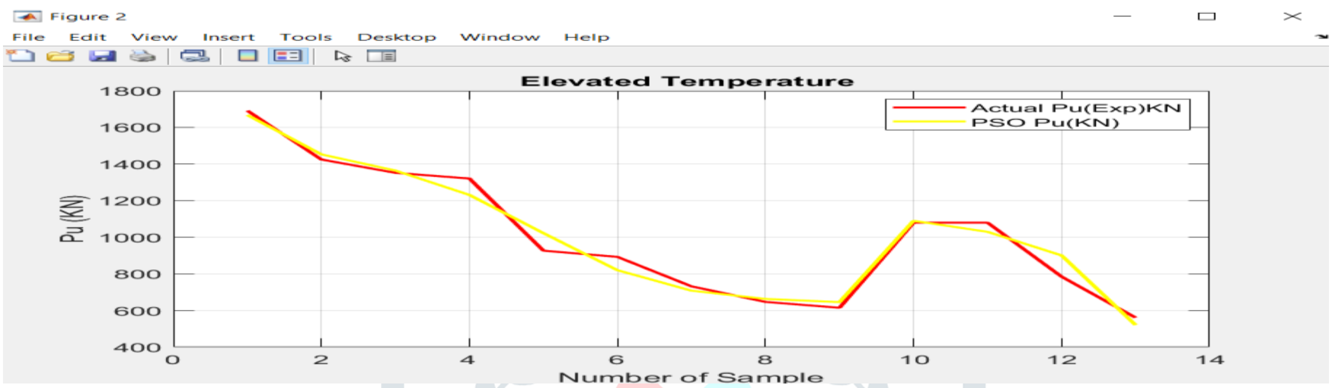


Fig:12 Comparison of ultimate load carrying capacity of Experimental Pu vs PSO Predicted Pu at Elevated temperature.

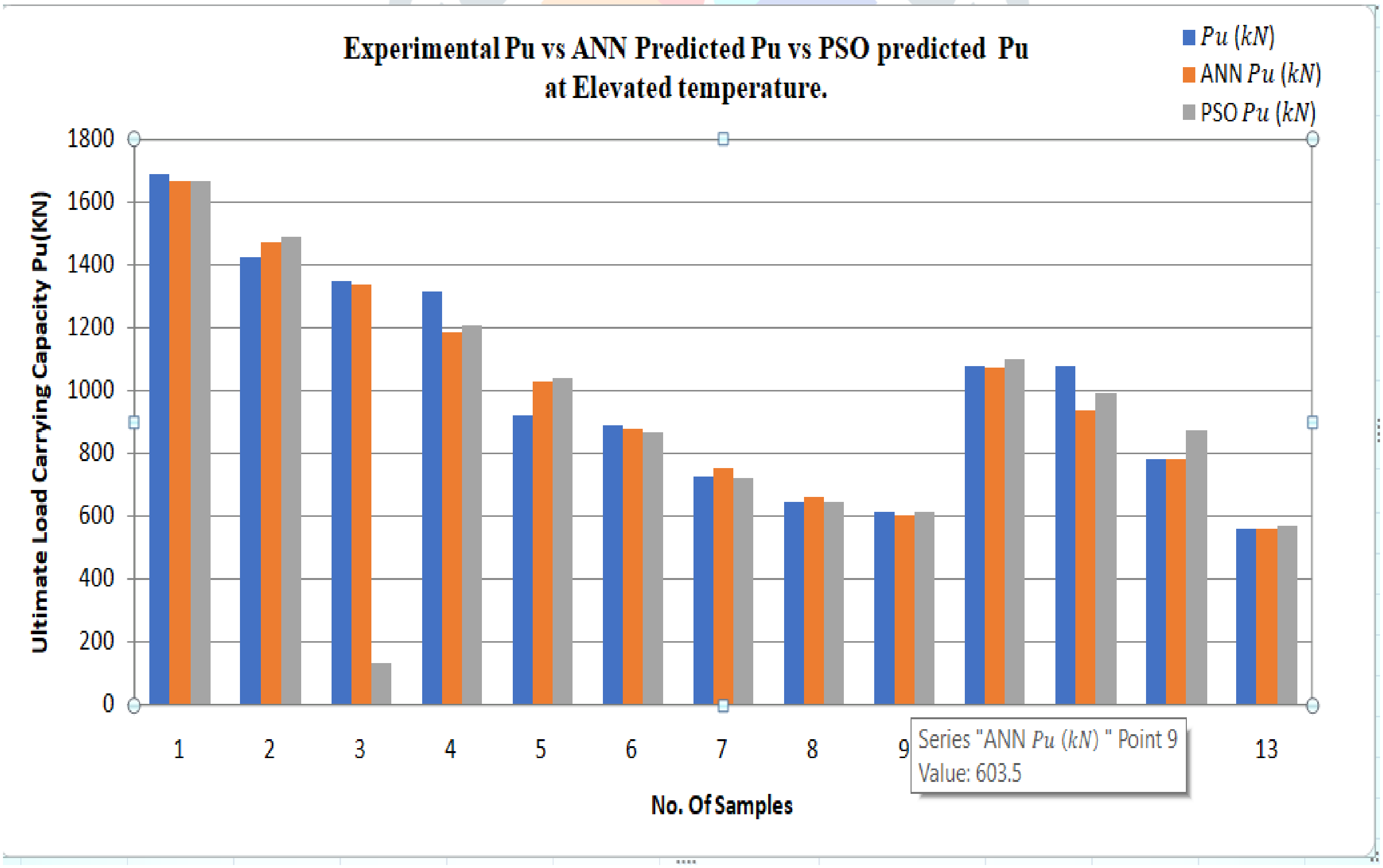


Fig:13 Comparison of ultimate load carrying capacity of Experimental Pu vs ANN Predicted Pu vs PSO predicted Pu at Elevated temperature.

5. CONCLUSION

1. It has been observed that the predicted values from ANN and PSO models are lies very close to the experimental results as shown in table no. 3 &4 respectively.
2. The predicted value of Ultimate load carrying capacity of the CFST columns of SCC infill's from ANN and PSO are varies by 8-15% and 5-12% for ambient and elevated temperatures respectively, when it is compared with the experimental results as shown in fig no. 10& 13 respectively.
3. Therefore we can conclude that ANN and PSO model can be used as one of the alternate method for the prediction method of ultimate load carrying capacity of CFST's for the time saving and eliminating the errors upto some extent.

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