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ARTIFICIAL NEURAL NETWORK FOR MIX PROPORTIONING OPTIMIZATION OF REACTIVE POWDER CONCRETE

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ABSTRACT

This work aims to optimize the mix proportions of Reactive Powder Concrete (RPC) mixtures by Artificial Neural Networks (ANN) technique. Ninety-nine sets of RPC mixes with their results from six different sources are used to check the reliability of the model. The values of compressive strength (Fc), Splitting Tensile Strength (Fsp) and Flexural strength (Fr) were specified as the input parameters. The values of sand to powder ratio (S\P), water to powder ratio (W\P) and volume of steel fiber (Vf) are computed and specified as the output parameters. (Fc) model with an architecture Multi Layers Perceptron (MLP) 3-40-1 had (0.95) training performance, (0.4%) training error, (0.93) testing performance and (0.4%) testing error. Fsp model with MLP 4-13-1 has (0.99) training performance, (0.014%) training error, (0.99) testing performance and (0.011%) testing errors. The primary predicting model has the architecture MLP 3-14-3. It also has training performance, training error, testing performance and testing error values of (0.96), (0.8%), (0.93), and (1.2%) respectively. All of the ANN models show very good percentages of correlation between target and output values with very low values of error, and high percentage of matching between targets and outputs, and no clear trend to overestimation or underestimation.

Keywords: *Neural Network, Flexural Strength, Reactive Powder Concrete, Tensile Strength, Optimization*

1. INTRODUCTION

Recently, providing modern technology to improve the properties of construction materials is in high demand [1-4]. Reactive Powder Concrete (RPC) is one of the most modern types of Ultra High Performance Concrete (UHPC) [5-8]. RPC is composed of very fine powders (cement, sand, quartz powder and silica fume), steel fibers (optional) and super plasticizer. The super plasticizer, used at its optimal dosage, decreases the water to powder ratio (w/p) and improves the workability of the concrete. The heterogeneity problems are substantially reduced with RPC and an improvement of the mechanical properties of the paste is attained through reduction in the aggregate/matrix ratio [9-13]. A very dense matrix is achieved by optimizing the granular packing of the dry fine powders [14]. The microstructure is optimized by precise gradation of all particles in the mix to yield maximum density [15]. This compactness gives RPC ultra-high strength and durability [16]. In a typical RPC mixture design, the least costly components of conventional concrete are, basically, eliminated or replaced by more expensive elements. The fine sand used in RPC becomes equivalent to the coarse aggregate of conventional concrete. The Portland cement plays the role of the fine aggregate and the silica fume that of the cement [17, 18]. Steel fibers of different variety that consisted in RPC have a significant role in increasing its strength and cohesion [19]. Through adding fibers, the structural perfection and the post-crack status is improved. These characteristics encourage the use of RPC in such critical section of punching shear. However, some properties of RPC such as density and cost affect its widespread usage [20, 21]. Because of its complex mixture proportions, research on RPC has been highly empirical and very limited numbers of models with reliable predictive capabilities for its behavior have been developed. Therefore, development of an effective model capable to describe the rheological and mechanical properties of RPC using new predictive analysis techniques is in high demand. To attain this objective, this study proposes using Artificial Neural Network (ANN) due to its effectiveness in this domain. The proposed model utilizes the required or predetermined compressive strength, tensile strength and flexural strength and the relationships among the parameters that, strongly, affect the mechanical properties of RPC (S/P, W/P, and Vf) to optimize their proportions in the mix.

2. LITERATURE REVIEW

A number of ANNs were developed in the domain of Portland cement concrete mixtures. Yeh (1998) utilized an ANN to model the strength of high performance concrete [22]. Dias and Pooliyadda (2001) developed ANNs to predict the properties of concrete mixtures contain different types of admixtures [23]. Ji et al. (2006) adopted an algorithm supported by ANNs to attain the optimum proportions of concrete mixture [24]. Öztaş et al. (2006) utilized an ANN to predict the compressive strength of the high strength concrete. In addition, the ANN is capable to predict the slump [25]. Yeh (2007) utilized an ANN in order to model concrete slump; the model was fitted based on second order regression [26]. Topçu and Sarıdemir (2008) used ANN and fuzzy logic for predicting the strength of concrete improved by fly ash [27]. Parichatprecha and Nimityongskul (2009) analyzed the concrete durability using ANN. The study focused on high performance concrete [28]. Kwon and Song (2010) adopted an ANN to analyze carbonation in Portland cement concrete [29]. Khan (2012) covered concrete proportioning using ANNs. The study focused on high performance concrete containing different cementitious materials [30]. Duan et al. (2013) adopted ANN algorithms to predict the strength of concrete containing recycled aggregates [31]. Chandwani et al. (2015) developed a model for ready-mix concrete slump. The model incorporates a genetic algorithm supported by ANN [32]. Chithra et al. (2016) adopted ANN models and regressions to predict concrete compressive strength. The study focused on Portland cement concrete incorporates Nano silica [33]. Abu Yaman et al. (2017) developed a model to predict the mix proportions of Portland cement concrete using ANN. The study focused on self-compacting concrete [34]. Kalman Šipoš et al. (2017) utilized an ANN for mix design of Portland cement concrete containing brick aggregates [35]. However, to the best knowledge of the authors, no such a research was conducted to optimize the mix proportioning of reactive powder concrete using ANN. Therefore, this research can be considered as a novel research in the study domain.

3. ANN PREDICTING MODELS

Manuscripts Artificial Neural Network (ANN) is a branch of artificial intelligence [33, 36-41]. Nowadays ANNs are applicable in several domains of science [42-57]. As in the human brain, these networks are capable of learning from examples. Neural networks can be used for prediction with various levels of success [58-62]. The advantage of these includes automatic learning of dependencies only from measured data without any need to add further information (such as type of dependency like with the regression). Based on its capabilities, ANN can be used to predict the performance of RPC mixtures effectively [31, 63, 64]. It can capture complex interactions among input/output variables in a system without any prior knowledge of the nature of these interactions and without having to explicitly assume a model form. Indeed, the data points themselves generate such a model form [65]. Recently, several ANN systems were implemented in the domain of concrete technology [30-33, 58, 59, 61-64, 66-77].

4. MODEL PREPARATION

The performance of a neural network, largely, depends on the data set that is trained for especially when using the back propagation network as by selecting that algorithm, the ANN model learns from the input and output examples. In general, the better the training data sets represent the domain problem to be solved, the better performance of the neural network. Data preparation procedure includes generation of raw data, data cleansing and selection, and data preprocessing [65].

4.1. Generation of Raw Data

Experimental data from six different sources were used to check the reliability of the model; see Table 1. The number of sources can be considered sufficient as some studies depended on two sources only [34, 78] and others depended on single source [23, 31]. Testing data were assembled for RPC containing cement, sand (0.6–0.15 mm), quartz sand powder (5.3–1.3 µm), super-plasticizer, silica fume (5.3–1.8 µm), steel fiber, W/P, compressive strength, tensile strength and flexural strength.

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Table 1: Sources of Data and Number of Sets

Reference No.	Number of Sets
[18]	12
[79]	5
[80]	1
[81]	18
[82]	2
[83]	35
[84]	26
Total	99

4.2. Data Cleansing and Selecting

In all of 99 RPC mixes from the mentioned investigations were evaluated. The values of compressive strength (Fc), splitting tensile strength (Fsp) and flexural strength (Fr) were specified as the input parameters. The values of S/P, W/P and Vf were computed and specified as the output parameters. The obtained database is shown in Table 2.

4.3. Data Preprocessing

Unavailable of record elements in the input variables affect the sampling method of data sets to train and test sets. Therefore, several pre-models were designed and executed to predict the missing values in the output variables. Each pre-model has three or more input variables and one output variable. When all missing values in the input variables are predicted, a complete ANN model with three inputs and three outputs can be designed and executed.

5. ANN MODELS

All models are fed forward back-propagation neural network which are trained by Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization algorithm. There are no general accepted rules/guidelines to select the architecture or topography of a network. The topography and training parameters are obtained through trial and error for the ANN model. Therefore, it was developed with the aid of a commercial analytic software package called "Stat Soft Statistical version 10" which is used to analyze, design and execute these models. This software contains several important and useful features in constructing ANN models. Among these, its ability to construct and verify number of ANN architectures at the same time and show the degree of their performance (correlation coefficient for training and testing samples) and other outputs such as network weights, data statistics, and correlations diagrams. These architectures are created depending on the parameters selected by the user. These parameters include input and output variables, sampling method and percentages of training, testing and validating (if required) samples, network type, minimum and maximum number of hidden elements, input and output activation functions, training algorithm, minimum and maximum models to be tested, error function, and weight decays for hidden and output layers.

In this study, the ANN architecture that has best performance, lower value of errors and best representation of the predicted data (nature of data, ranges, and mean value) is selected to be the desired model.

6. FC PREDICTING MODEL

In this model S\P, W\P and Vf were considered as the input variables whereas Fc was considered as the output variable. The choices that are fed to the program of this model are shown in Table 3. The best performance and best representation of predicted data is the architecture of MLP 3-40-1 which is a Multi Layers Perceptron with one input layer that contains three elements, one hidden layer contains 40 elements, and one output layer contains one element. Results of this model are listed in Table 4. Figure 1 illustrates correlations diagram between train and test sets for this model. It is very clear that there is a very good percentage of correlation between target and output values with very low values of errors. In addition to very low error value, Figure 2 indicates that there is no clear trend of overestimation or underestimation of the output values. Moreover, very high percentage of matching between the results is illustrated in Figure 2.

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Table 2: Database of the Model

S/P	Vf	W\P	Fc	Fsp	Fr	Ref	S/P	Vf	W\P	Fc	Fsp	Fr	Ref
0.998	0.02	0.18	126	14.78	20.86	[18]	0.952	0.00	0.30	81	NA	22.89	[83]
0.992	0.02	0.17	139	15.90	22.77	[18]	0.956	0.00	0.30	83	NA	22.89	[83]
0.995	0.02	0.16	118	15.19	20.97	[18]	0.938	0.00	0.22	125	NA	19.15	[83]
0.991	0.02	0.17	134	15.40	22.12	[18]	0.907	0.00	0.20	126	NA	18.00	[83]
0.998	0.02	0.17	140	15.90	22.77	[18]	0.904	0.20	0.22	141	NA	27.50	[83]
0.993	0.02	0.17	147	16.23	24.19	[18]	0.904	0.20	0.23	135	NA	22.00	[83]
0.997	0.02	0.18	154	17.25	24.57	[18]	0.889	0.00	0.22	129	NA	19.00	[83]
0.994	0.02	0.19	159	17.55	24.96	[18]	0.890	0.20	0.23	151	NA	29.00	[83]
0.997	0.00	0.17	142	6.32	9.22	[18]	0.892	0.20	0.23	138	NA	22.50	[83]
0.998	0.01	0.18	147	10.50	15.07	[18]	1.132	0.20	0.22	114	NA	24.12	[83]
0.995	0.02	0.18	154	17.25	24.57	[18]	0.909	0.20	0.22	139	NA	24.12	[83]
0.999	0.03	0.19	154	21.59	29.24	[18]	0.909	0.20	0.22	129	NA	24.12	[83]
0.797	0.02	0.20	125	16.29	19.00	[79]	0.906	0.20	0.22	149	NA	24.12	[83]
0.828	0.02	0.20	120	15.24	18.10	[79]	0.906	0.20	0.22	161	NA	24.12	[83]
0.863	0.02	0.20	114	14.86	17.40	[79]	1.013	0.00	0.22	96	NA	17.95	[83]
0.794	0.01	0.20	114	11.95	14.70	[79]	1.051	0.00	0.22	59	NA	18.95	[83]
0.796	0.00	0.20	93	6.71	6.30	[79]	1.086	0.00	0.25	60	NA	18.72	[83]
0.880	0.01	0.18	145	NA	25.50	[80]	1.003	0.00	0.25	97	NA	21.37	[83]
1.748	0.01	0.18	73	5.65	13.89	[81]	1.036	0.00	0.27	86	NA	22.23	[83]
1.527	0.01	0.18	100	8.06	17.99	[81]	1.069	0.00	0.27	92	NA	22.29	[83]
1.347	0.01	0.18	119	9.96	24.51	[81]	0.982	0.00	0.22	59	NA	19.01	[83]
1.634	0.01	0.18	76	7.67	17.64	[81]	0.981	0.00	0.22	104	NA	18.23	[83]
1.423	0.01	0.18	115	9.73	21.05	[81]	0.986	0.00	0.25	66	NA	19.17	[83]
1.256	0.01	0.18	139	10.97	27.61	[81]	0.971	0.00	0.25	100	NA	21.47	[83]
1.529	0.01	0.18	79	8.93	19.98	[81]	0.985	0.00	0.27	86	NA	22.25	[83]
1.327	0.01	0.18	129	10.65	23.22	[81]	0.973	0.00	0.27	99	NA	22.44	[83]
1.174	0.01	0.18	155	11.98	30.26	[81]	0.888	0.02	0.22	NA	NA	24.60	[84]
1.742	0.00	0.18	67	4.98	6.12	[81]	1.759	0.06	0.18	NA	NA	13.89	[84]
1.518	0.00	0.18	96	6.09	7.50	[81]	1.526	0.06	0.18	NA	NA	17.99	[84]
1.346	0.00	0.18	114	7.72	9.49	[81]	1.353	0.06	0.18	NA	NA	24.51	[84]
1.624	0.00	0.18	74	6.08	7.48	[81]	1.625	0.05	0.18	NA	NA	17.64	[84]
1.419	0.00	0.18	112	8.56	9.85	[81]	1.417	0.05	0.18	NA	NA	21.05	[84]
1.256	0.00	0.18	134	9.50	13.31	[81]	1.260	0.05	0.18	NA	NA	27.61	[84]
1.527	0.00	0.18	76	8.12	8.95	[81]	1.525	0.05	0.18	NA	NA	19.98	[84]
1.334	0.00	0.18	125	9.44	10.88	[81]	1.337	0.05	0.18	NA	NA	23.22	[84]
1.175	0.00	0.18	152	10.99	14.73	[81]	1.181	0.05	0.18	NA	NA	30.26	[84]
1.135	0.00	0.20	106	12.00	14.00	[82]	1.750	0.06	0.18	NA	NA	6.12	[84]
0.889	0.02	0.22	151	19.00	27.50	[82]	1.518	0.00	0.18	NA	NA	7.50	[84]
0.994	0.00	0.22	93	NA	17.86	[83]	1.351	0.00	0.18	NA	NA	9.49	[84]
0.978	0.00	0.22	95	NA	17.89	[83]	1.628	0.00	0.18	NA	NA	7.48	[84]
0.963	0.00	0.22	97	NA	17.93	[83]	1.425	0.00	0.18	NA	NA	9.85	[84]
0.951	0.00	0.22	115	NA	18.73	[83]	1.254	0.00	0.18	NA	NA	13.31	[84]
0.939	0.00	0.22	116	NA	18.76	[83]	1.528	0.00	0.18	NA	NA	8.95	[84]
0.925	0.00	0.22	121	NA	18.96	[83]	1.329	0.00	0.18	NA	NA	10.88	[84]
0.956	0.00	0.22	124	NA	19.14	[83]	1.177	0.00	0.18	NA	NA	14.73	[84]
0.954	0.00	0.25	116	NA	21.80	[83]	0.909	0.00	0.20	NA	NA	18.00	[84]
0.954	0.00	0.27	107	NA	22.49	[83]	0.906	0.00	0.22	NA	NA	27.50	[84]
0.908	0.00	0.23	NA	NA	22.00	[84]	0.993	0.17	0.16	NA	NA	29.20	[84]
0.995	0.00	0.16	NA	NA	26.90	[84]	1.129	0.00	0.20	NA	NA	13.50	[84]
NA: Not Available Record							0.892	0.20	0.22	NA	NA	29.00	[84]

Table 3 Choices of Fc Model

Item		Value
Number of Variables	Inputs	3 input variables
	Outputs	Fc
Sampling of Sets	Train	80%
	Test	20%
Number of Hidden Units	Min.	20
	Max.	40
Weight Decay of Hidden Layer	Min.	0.0001
	Max.	0.001
Weight Decay of Output Layer	Min.	0.0001
	Max.	0.001
Max. Number Trained Networks		100
Error Function		Sum of Sequares
Training Algorithm		BFGS
Activation Functions		Identity, Logistic Sigmoid , Negative, Exponential , and Tanh (hyperbolic tangent)

Table 4: Results of Fc Model

Item	Value
Training Performance	0.946232
Test Performance	0.933693
Training Error	0.004088
Test Error	0.003990
BFGS Algorithem Cycles	BFGS 120
Hidden Activation	Tanh
Output Activation	Tanh

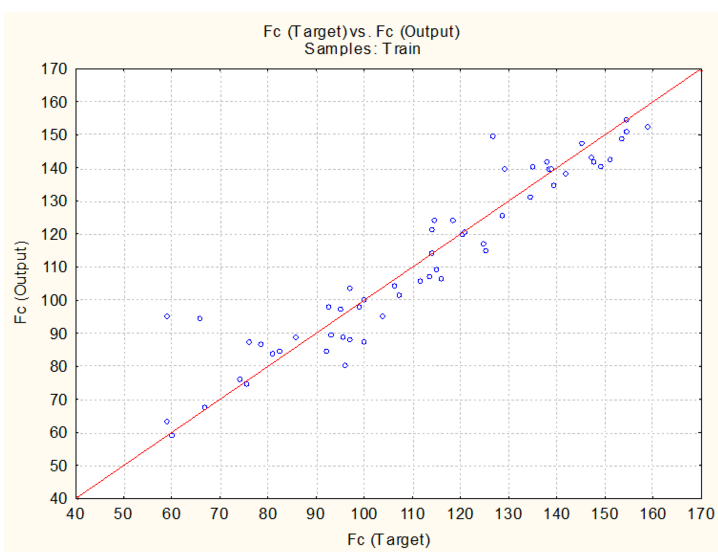

Figure 1: Correlations Diagram of Fc Model

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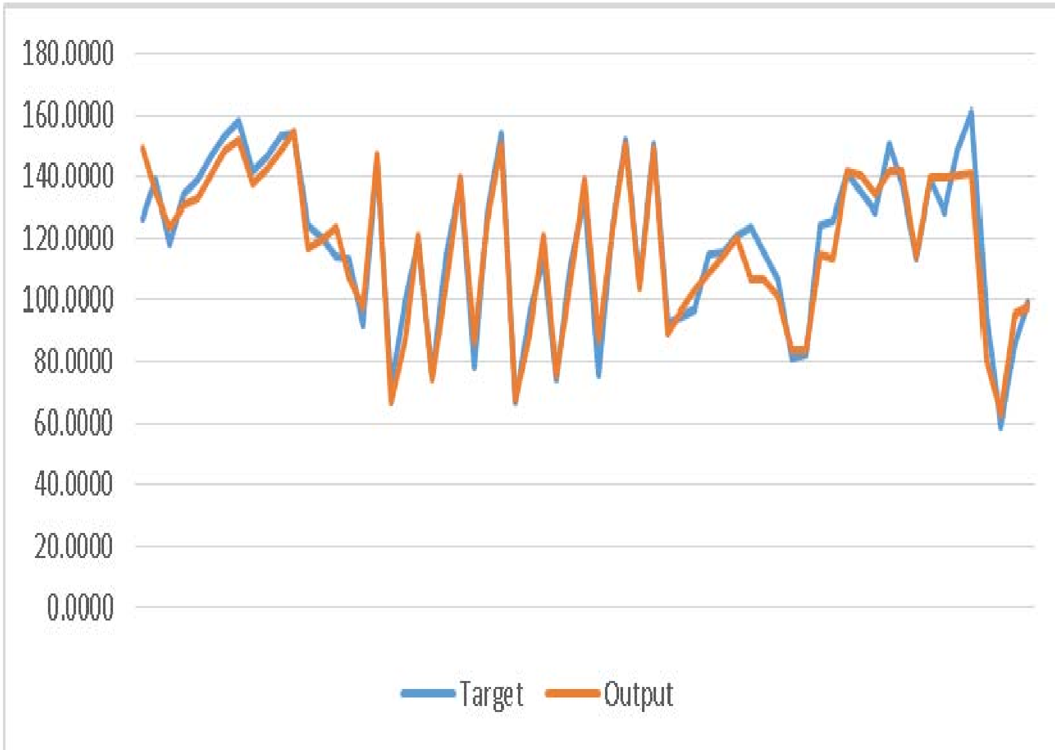

Figure 2: Line Diagram (Targets-Outputs) of Fc Model

7. FSP PREDICTING MODEL

In this model S\P, W\P and Vf were considered as the input variables whereas Fc was considered as the output variable. The choices that are fed to the program for this model are shown in Table 5. The best performance and best representation of predicted data is the architecture of MLP 4-13-1, which is a Multi Layers Perceptron with one input layer contains four elements, one hidden layer contains 13 elements, and one output layer contains one element. Results of this model are listed in Table 6. Figure 3 illustrates correlations diagram between train and test sets for this model. It is very clear that there is a very good percentage of correlation between target and output values with very low errors values. In addition to very low error value, Figure 4 indicates that there is no clear trend of overestimation or underestimation of the output values. Moreover, very high percentage of matching between the results is illustrated in Figure 4.

8. OPTIMIZED MODEL (OM)

After completing the previous models, the data base becomes full with values and becomes ready to construct and run a complete ANN model to predict the main effective relationships between the mix constituents (Optimized Model) with three inputs and three outputs. This model was constructed to predict S\P, W\P and Vf. The choices that are fed to the program for this model are shown in Table 7. The best performance is the architecture of MLP 3-14-3 which is a Multi Layers Perceptron with one input layer that contains three elements, one hidden layer that contains 14 elements, and one output layer that contains three elements. Results of this model are listed in Table 8. Figures 5, 6 and 7 illustrate correlation diagrams between train and test sets for this model. It is very clear that there is a very good percentage of correlation between target and output values with very low error values. Figures 8, 9 and 10 show high percentage of matching between targets and outputs and no clear trend of overestimation; however, very small trend of underestimation can be distinguished. Vf exhibited the highest values of correlation coefficients as shown in Table 9. Table 10 shows that Fsp has more influence on the input variables (more sensitive) than the other input variables.

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Table 5: Choices of Fsp Model

Item		Value
Number of Variables	Inputs	4 input variables
	Outputs	Fsp
Sampling of Sets	Train	80%
	Test	20%
Number of Hidden Units	Min.	10
	Max.	20
Weight Decay of Hidden Layer	Min.	0.0001
	Max.	0.001
Weight Decay of Output Layer	Min.	0.0001
	Max.	0.001
Max. Number Trained Networks		100
Error Function		Sum of Sequares
Training Algorithm		BFGS
Activation Functions		Identity, Logistic Sigmoid , Negative, Exponential , and Tanh (hyperbolic tangent),

Table 6: Results of Fsp Model

Item	Value
Training Performance	0.998015
Test Performance	0.998264
Training Error	0.000140
Test Error	0.000111
BFGS Algorithem Cycles	BFGS 133
Hidden Activation	Tanh
Output Activation	Tanh

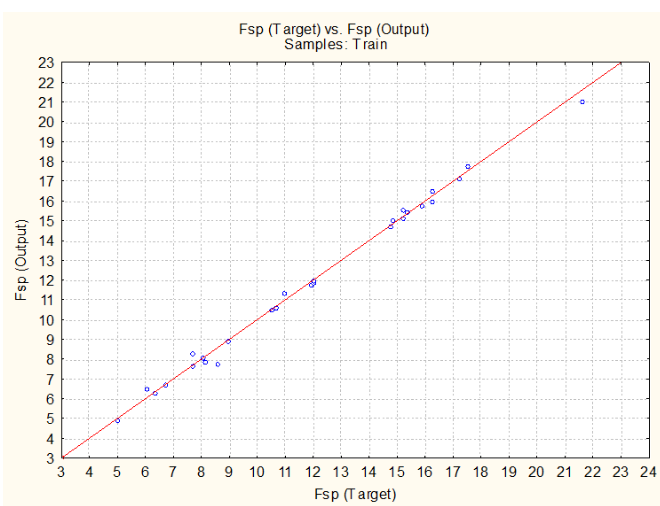

Figure 3: Correlations Diagram of Fsp Model

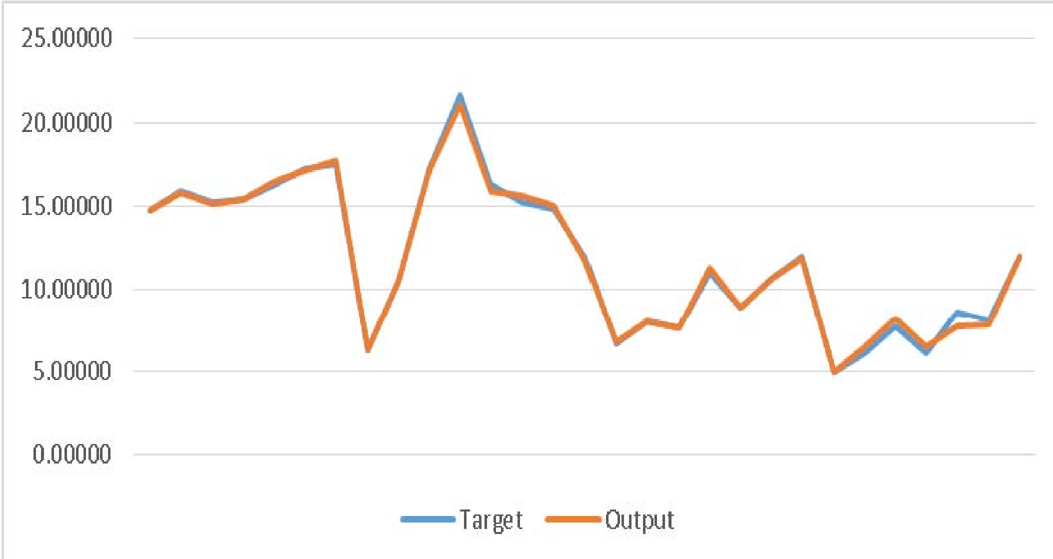

Figure 4: Line Diagram (Targets-Outputs) of Fsp Model

Table 7: Choices of OM Model

Item		Value
Number of Variables	Inputs	3 input variables
	Outputs	3output variables
Sampling of Sets	Train	80%
	Test	20%
Number of Hidden Units	Min.	14
	Max.	14
Weight Decay of Hidden Layer	Min.	0.0001
	Max.	0.001
Weight Decay of Output Layer	Min.	0.0001
	Max.	0.001
Max. Number Trained Networks		200
Error Function		Sum of Sequares
Training Algorithm		BFGS
Activation Functions		Identity, Logistic Sigmoid , Negative , Exponential , and Tanh (hyperbolic tangent).

Table 8: Results of OM Model

Item	Value
Training Performance	0.959174
Test Performance	0.930638
Training Error	0.008335
Test Error	0.011896
BFGS Algorithem Cycles	BFGS 109
Hidden Activation	Tanh
Output Activation	Logistic

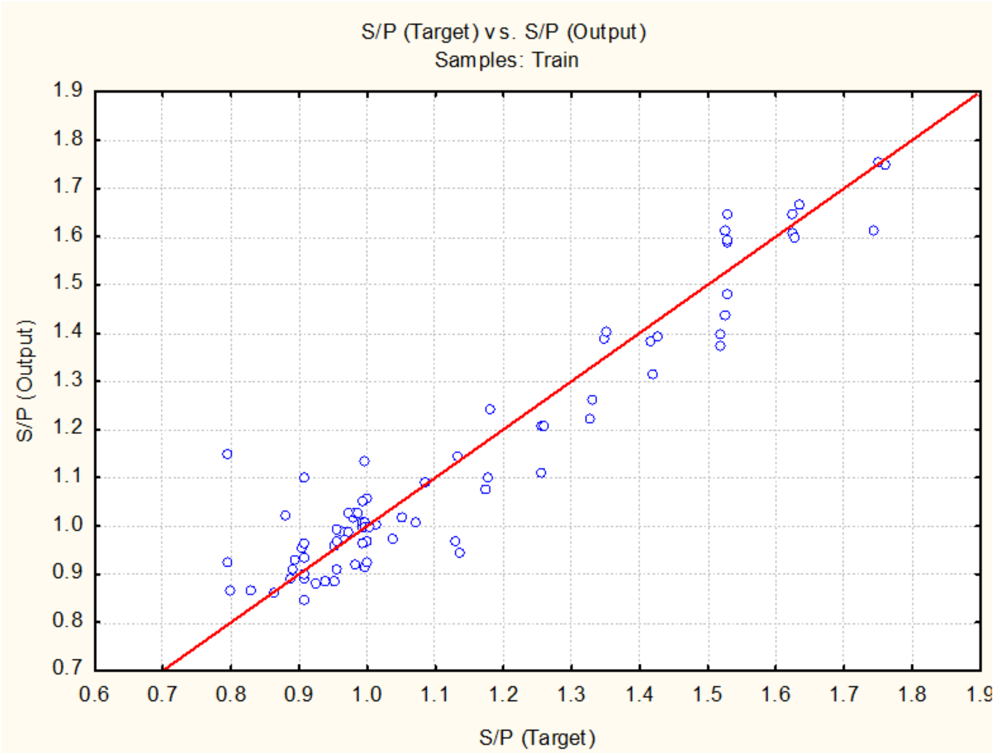

Figure 5: Correlations Diagram of OM Model- S\P

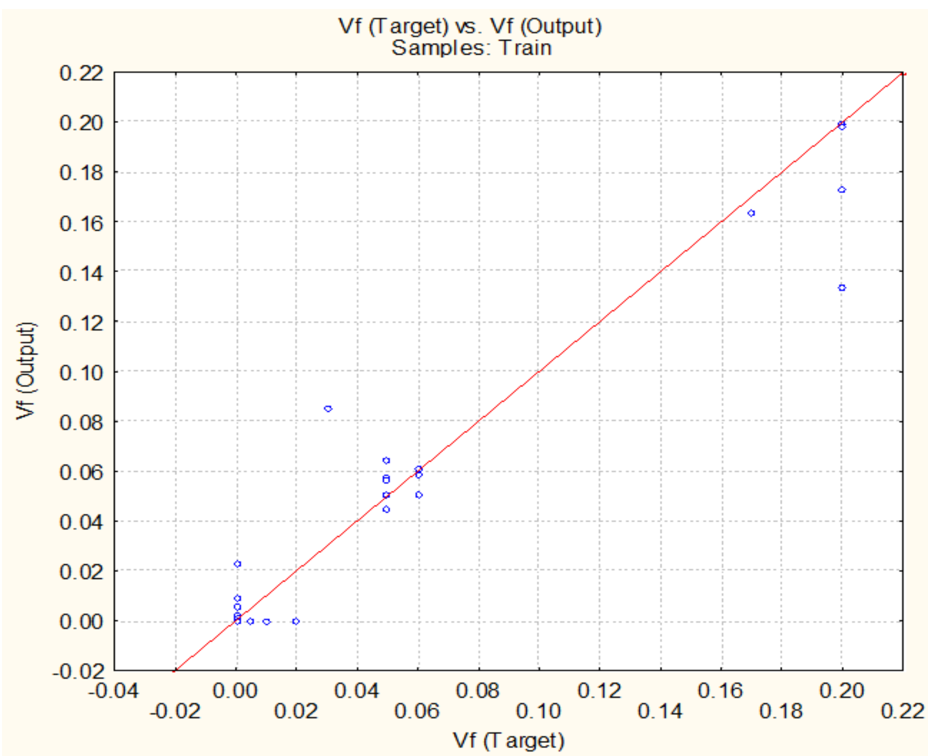

Figure 6: Correlations Diagram of OM Model- Vf

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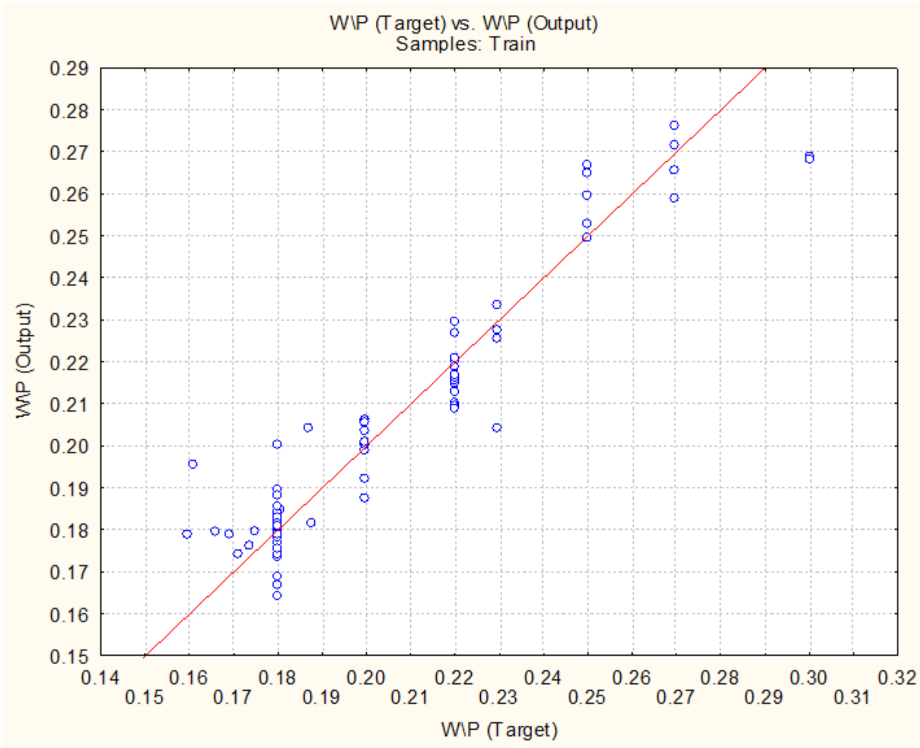

Figure 7: Correlations Diagram of OM Model- W\P

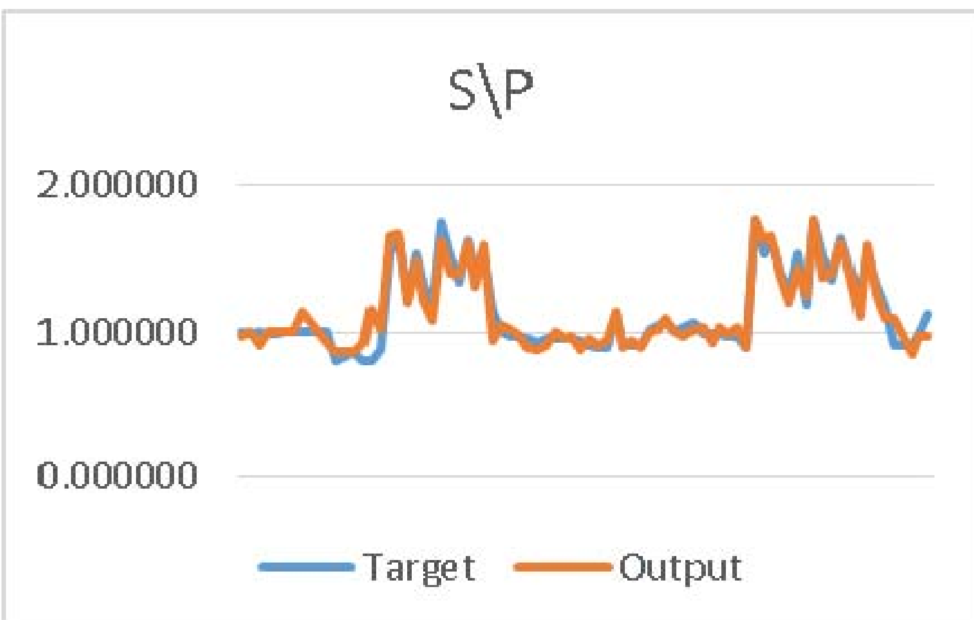

Figure 8: Line Diagram (S\P: Targets-Outputs) of OM Model

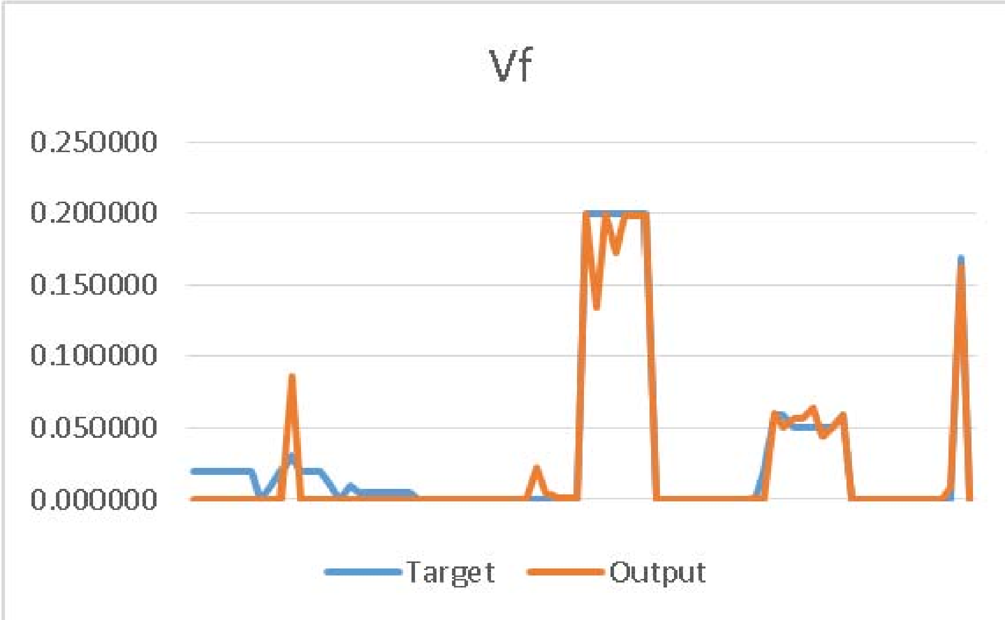

Figure 9: Line Diagram (Vf: Targets-Outputs) of OM Model

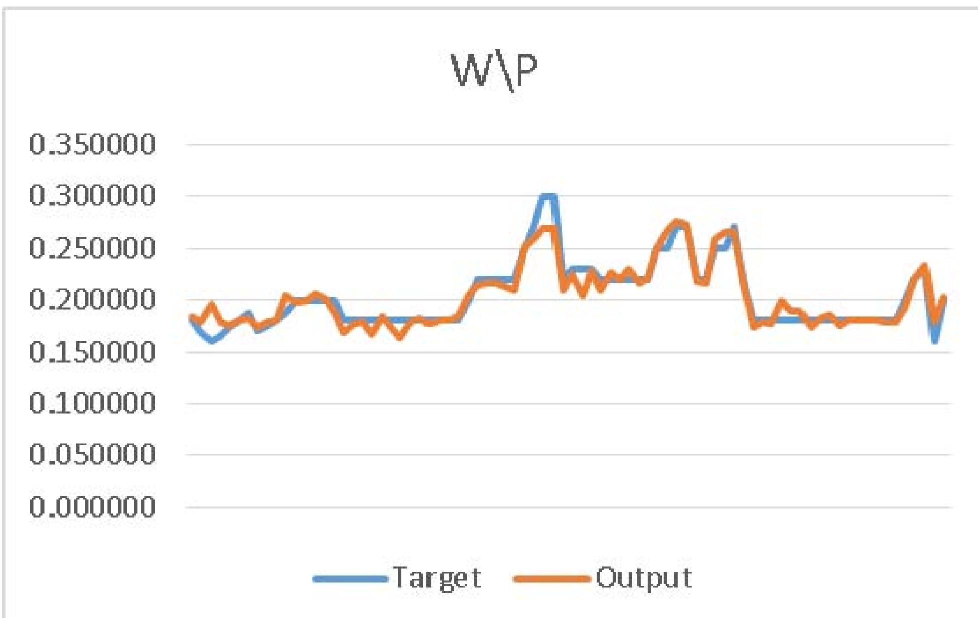

Figure 10: Line Diagram (W\P: Targets-Outputs) of OM Model

Table 9: Correlation of Inputs Train of OM Model

S/P Train	Vf Train	W\P Train
0.951791	0.974858	0.950874

Table 10: Correlation of Inputs Train of OM Model

Fc	Fsp	Fr
5.687900	7.850930	6.181501

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9. DISCUSSION

Ninety-nine sets of RPC mixes with their results from six different sources are used to check the reliability of the model. The values of compressive strength (Fc), Splitting Tensile Strength (Fsp) and Flexural strength (Fr) were specified as the input parameters. The values of sand to powder ratio (S\P), water to powder ratio (W\P) and volume of steel fiber (Vf) are computed and specified as the output parameters. Fc model with an architecture Multi Layers Perceptron (MLP) 3-40-1 had (0.95) training performance, (0.4%) training error, (0.93) testing performance and (0.4%) testing error. Fsp model with MLP 4-13-1 has (0.99) training performance, (0.014%) training error, (0.99) testing performance and (0.011%) testing errors. The primary predicting model has the architecture MLP 3-14-3. It also has training performance, training error, testing performance and testing error values of (0.96), (0.8%), (0.93), and (1.2%) respectively. These values are close to those attained in similar literatures [28-34] All of the ANN models show very good percentages of correlation between target and output values with very low values of error, and high percentage of matching between targets and outputs, and no clear trend to overestimation or underestimation.

10. CONCLUSIONS

1. This paper presents a novel study covered development of an effective ANN for optimum mix proportioning of reactive powder concrete.
2. Experimental data from six different sources were used to check the reliability of the developed model.
3. Fc model with an architecture MLP 3-40-1 got (0.95) training performance, (0.4%) training error, (0.93) testing performance and (0.4%) testing error.
4. Fsp model is MLP 4-13-1 has (0.99) training performance, (0.014%) training error, (0.99) testing performance and (0.011%) testing errors.
5. The primary predicting model, which represents all input and output parameters (OM) has the architecture MLP 3-14-3, training performance (0.96), training error (0.8%), testing performance (0.93) and the testing error (1.2%).
6. All ANN models show very good percentages of correlation between target and output values with very low values of errors and high percentage of matching between targets and outputs and no clear trend to overestimation or underestimation.
7. The developed ANN models can be adopted effectively in the domain of the study. In addition, the models can be modified to cover more parameters.

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