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Full Length Research Paper

Estimation of slump value and Bingham parameters of fresh concrete mixture composition with artificial neural network modelling

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High performance is the most important expectation from concrete which is commonly used in today's construction technology. To form a high performance concrete "HPC", two fundamental properties are required. These properties are optimization of the materials used to form the concrete and the workability of fresh concrete during shaping. Many scientists have used rheological properties in conjunction with Bingham model to determine the workability of fresh concrete. Bingham model is represented by two parameters: yield stress and plastic viscosity. Even though, many models are developed to explain rheological properties, there is no acceptable easy to use method. In this study, artificial neural network "ANN" is used to determine the rheological properties of fresh concrete. Ferraris and de Larrard's experimental slump, yield stress and viscosity data from different composed concretes is used in this study. Slump, yield stress and viscosity are estimated with respect to mixture design parameters. Obtained results from this study indicates that ANN is a utilizable method to determine the rheological proporties (Bingham model) of fresh concrete.

Key words: Fresh concrete, Bingham flow, slump value, artificial neural network.

INTRODUCTION

Normal concrete is a composition of cement, fine agregate, coarse aggregate, and water. It is designed to obtain a mixture of certain characteristics and is one of the most commonly materials used in the world. The recent technical improvements and innovations have enhanced not only the quality of concrete, but also the fields of its usage. Today's concrete technology makes the production of concrete with high quality and of high performance to meet specific needs. The desired high quality in concrete is only possible, if it has high compacity without seggregation during moulding, and forming and if it has the characteristics of workability. It needs to have a special mixture design and rheological properties, in order to have such a result. The selection of mix proportions of high performance concrete "HPC" is a process of choosing suitable concrete ingredients and determining their relative quantities with an objective of producing as economically as possible concrete of certain required properties, namely workability, strength, and durability (Metha and Aïtcin, 1990). However, the main problem for HPC mix proportion design lies in establishing analytical relationships between the mix composition and the properties of concrete (Parichatprecha and Nimityongskul, 2009). There are unidentified, complex relationships between the characteristics and diversities of the components that form HPC.

As concrete construction applications become more demanding, there is an increasing pressure on engineers to ensure high workability while at the same time to maintain the structural properties necessary to meet design specifications (Saak et al., 2004). Moreover, each mixture added to normal concrete generates an important effect on workability. For production of high performance concrete "HPC" that is characterized by low water-cement ratio and a high dosage of super plasticizer "SP", workability properties may be more complex than that of the normal concrete (Kwan, 2000). The workability prediction of concrete is an important piece of information in the design process of concrete mixture. Especially, with the development of concrete technology, HPC has been increasingly used in practice. There is, therefore, an urgent need to take a consistent and reliable approach to estimate the workability of concrete made with modern materials (Yeh, 2008). An inexpensive and efficient workability design is to predict and further optimize the workability of concrete by flow simulation for the selected construction processes, e.g. transportation, casting, compaction, finishing, etc. Clarifying and modeling the rheological behaviors of fresh concrete, and establishing a suitable flow analysis method are the most basic conditions of workability design (Li, 2007).

Ferraris (1999) defined the workability either qualitatively as the ease of placement or quantitatively by rheological parameters. Tattersall's (1976), interpretation of workability is "the ability of concrete to flow in mould or formwork perhaps through congested reinforcement, the ability to be compacted to a minimum volume, perhaps the ability to perform satisfactorily in some transporting operation or forming process and may be other requirements as well". According to Tattersall (1976), the most common rheological parameters of the flow concrete, used to qualify workability, are the yield stress and plastic viscosity as defined by the Bingham equation. It has become insufficient to use the slump test to characterize consistency of new types of concrete, and the consistency set empirically is likely not to meet the actual demands.

Therefore, workability design of concrete has become necessary, which is a process of optimizing concrete's consistency to be well adapted for certain structure and construction conditions. The establishment of rheological test method and workability design technology is an extremely important problem awaiting solution in fresh concrete sphere (Li, 2007). Workability tests are useful as quality control tools, but these are largely qualitative measures based on arbitrarily defined scales. Several authors have acknowledged the need for a more quantitative measure of the workability of fresh concrete (Tattersall and Banfill, 1983; Tattersall, 1991).

Researchers treat fresh concrete as fluid and use fluid rheology methods to describe concrete behavior (Laskar and Talukdar, 2008). Numerous constitutive equations have been proposed to characterize the rheology of fresh concrete as suspensions, but only Bingham model and Herschel and Bulkley "HB" model have received wide acceptance (Chidiac and Mahmoodzadeh, 2009). Concrete as a fluid is most often assumed to behave like a Bingham fluid with good accuracy (Laskar and Talukdar, 2008). Bingham fluid have got two characteristics; yield stress and plastic viscosity. These two parameters were first used by Tattersall using the definition given by the Bingham equation as follows (Ferraris and de Larrard, 1998).

$$\tau = \tau_0 + \mu\gamma \qquad (1)$$

τ = shear stress (Pa) applied to the fresh concrete, τ_0 = yield stress (Pa), μ = plastic viscosity (Pa.s) and γ = shear strain rate.

Yield stress gives the quantitative measure of initial resistance of concrete to flow and plastic viscosity governs the flow after it is initiated. Yield stress is the contribution of the skeleton that is, It is a manifestation of friction among solid particles. It is the result of an accumulative contributions of each granular class. These contributions involve size and roughness of particles and high range water reducing admixtures "HRWRA". Plastic viscosity is the contribution of suspending liquid that results from viscous dissipation due to the movement of water in the sheared material. Plastic viscosity appears to be controlled essentially by the ratio of solid volume to the packing density of granular mixture, including aggregates and cement (Ferraris and de Larrard, 1998). These two rheological properties are therefore needed to quantitatively characterize the flow of fresh concrete (Chidiac and Mahmoodzadeh, 2009; Chidiac and Habibbeigi, 2005). Quantitative characterization of the rheological properties is important to the sustainability of the concrete construction industry for the following reasons: (1) workability of fresh concrete forms one of the bases of concrete mixture design for quality control purposes – establishing a quantitative measure for workability will mitigate material waste by properly controlling the quality of fresh concrete as a priority; (2) flow behaviour of fresh concrete impacts the quality of concrete hardened properties (Chidiac and Mahmoodzadeh, 2009; Chidiac et al., 2000).

In an attempt to quantify the rheological behaviour of fresh concrete, rheometers of different types and qualities have been developed. One of the most famous and oldest tests is the slump test. Because of its simplicity, this method is used extensively in site work all over the world. The apparatus was developed in the USA around 1910. It is believed that it was first used by Chapman although in many countries the test apparatus is associated with Abrams. The slump test gives only a single value, namely the slump value. It discusses the need for describing the rheological properties of fresh concrete in terms of fundamental physical quantities, not depending on the details of the apparatus with which they are measured (Wallevik, 2006). Slump, which has been correlated to yield stress, is not a sufficient measurement for characterizing the flow properties of fresh concrete.

The most common approach adopted for quantifying the rheological properties of fresh concrete is to experimentally measure shear stress versus shear strain rate using concrete rheometer. Several research efforts have been made to develop equations for predicting the yield stress of concrete (Chidiac and Mahmoodzadeh, 2009). Some researchers tried to create empirical or analytical equations that relate the yield stress of concrete to its measured slump, since in practice the slump test is routinely measured for quality control (Saak et al., 2004; Ferraris and de Larrard, 1998; Wallevik, 2006; Murata, 1984; Murarta and Kikukawa, 1992; Al Martini and Nehdi, 2009; Cazacliu and Roquet, 2009; Patzák and Bittnar, 2009).

Fundamental models proposed to quantify plastic viscosity are based on the science of rheology and fluid mechanics. These models are divided into two groups. The first group includes the models that are prevailing in concrete technology, whereas the second group compiles the models proposed to quantify the plastic viscosity of concentrated suspensions in solvent, typically used for other engineering applications (Chidiac and Mahmoodzadeh, 2009). The representatives of the important models for the first group are given by Murata and Kikukawa (1992), Hu and deLarrard (1996) and Roshavelov (2005) in the literature. The models of the second group are classified to four sub-groups as generalized models, analogous approach, cell method, and average method (Chidiac and Mahmoodzadeh, 2009).

MATERIALS AND METHODS

Modern research in material modeling aims to construct mathematical models to describe the relationship between material behaviours and compositions (Yeh, 2008). However, when there are nonlinearities between the dependent variables and independent variable and interactions between dependent variables, it is very difficult to find an accurate model for simulating material behaviour. Artificial neural networks "ANN" provide a fundamentally different approach to the derivation and representation of material behaviour relationships (Ghaboussi et al., 1991). A neural network is a computer model whose architecture essentially mimics the knowledge acquisition of the human brain. Artificial neural networks may take various forms and are applicable to a wide variety of problems (Yeh, 2008). A number of applications in material have been proposed by several researchers (Yeh, 1999; Nehdi et al., 2001; Yeh, 2005; Ji et al., 2006; Sobhani et al., 2010; Nehdi and Al Martini, 2009). However, little research has been done on the modeling workability of concrete using neural networks. The basic strategy for developing a neural network for material behaviour is to train it with the results of a series experiments on a material. If the experimental results contain the relevant information about the material behaviour, then the trained neural network would contain sufficient information about the material behaviour (Ghaboussi et al., 1991).

The neural network modeling approach is simpler and more direct than traditional statistical methods, particularly when modeling nonlinear multivariate interrelationships (Ji et al., 2006). The main advantage of ANNs is that one does not have to explicitly assume a model form, which is a prerequisite in the parametric approach. Indeed in ANN's, a relationship of possibly complicated shape between input and output variables is generated by the data points themselves. In response to the complex interaction between concrete behaviours and concrete mix proportions, many researchers have applied neural networks to predict various properties of concrete (Parichatprecha and Nimityongskul, 2009). As a result, identifying rheological characteristics of fresh concrete by means of theoretical approaches is relatively hard. ANN method was used in this study to determine rheological characteristics of fresh concrete with regard to mixture parameters. In the study, the experimental data that were shown in Table 1 and supplied by Ferraris and de Larrard were used as materials.

Multılayer perceptıon-MLP

A general structure of an artificial neural networks model is shown in Figure 1 (Haykin, 1994). There are three types of layers in the feed-back ANN model; the layer of input, the hidden layer and the layer of output. Each layer of the network is composed of processing units that have certain characteristics. The input layer possesses processing units which represented by x_i in the figure. In this layer, the duty of processing units is to transfer the input data to the hidden layer.

These units do not perform summation and tranformation operations and as they act as bumpers, they do not use a transfer function. Also, the processing units in input layer, do not have bias inputs. The hidden layer is composed of processing units represented by z_j. The task of the hidden layer is to transfer the data coming from input or from previous hidden layers, to layer of output or to the next hidden layer. Connection weights of hidden layer processing units were represented by w_{ji} in Figure 1. Here, indice j represents the number of hidden layer processing units, and indice i represents the number of input layer processing units. The weight between the hidden layer processing units and bias, on the other hand is represented by $w_{j0.}$

In Figure 1, the layer of output is composed of processing units represented by y_k. The output layer processing units transfer the hidden layer processing unit outputs to the network output,. The connection weights between hidden layer, and output layer were represented by $w_{kj.}$ Here, indice k represents the number of output layer processing units, and indice j represents the number of hidden layer processing units. The connection between output layer and bias is represented by $w_{k0.}$ In this study, the estimation of slump value and Bingham parameters of fresh concrete is carried out using a Multi-Layered Perception (MLP) neural network. In literature, the most frequently used algorithm to train a MLP is the back propagation algorithm (Rumelhart et al., 1986). In this algorithm, weight optimization during training process is accomplished using the weight update formulas which are given as a function of output (activation level) of neurons as follows

$$\Delta W_{jk} = -\eta \frac{dY_k}{dnet_k} \Delta Y_k Y_j \tag{2}$$

$$\Delta W_{ij} = -\eta \frac{dY_j}{dnet_j} \sum_k^K \frac{dY_k}{dnet_k} W_{jk} \Delta Y_k Y_j \tag{3}$$

Where, Y_i is the output of ith neuron in the input layer, Y_j is the output of jth neuron in the hidden layer, Y_k is the output of kth neuron in the output layer, and ΔW is the change in the weight strength.

Estımatıon of slump value and bıngham paramaters usıng ANN

Almost all researchers treated fresh concrete as a liquid, and they introduce flow rheology to define concrete flow. As a general approach, it is assumed that the speed of every particle is equal in the microscobic speed of homogeneous fluid in fresh concrete. If the flow is steady, the current is most likely laminar regimed. That is to say, it constitutes Bingham model as pressure gradient that will act on shear stress remains proportional. However, a great deal of methods in this model measures merely one parameter, yield stress. There is not a common method in use though a great many attempts have been made, because predicting flow characteristics is attained from concrete components. Therefore, the most trusted results are collected by experimental methods. Based on finite element analysis of the slump test and on measurement of the yield stress using the rheometer and of the slump, Hu proposed a general formula retating the slump s to the yield stress (Tattersall, 1976; Ferraris and de Larrard, 1998). In his study, he stated that yield stress and slump values are coherent in Bingham model.

Table 1. Fresh concrete mixture parameters and rheological properties.

Dry mixture mass (%)				Composition (kg/m^3)						Slump	Bingham flow	
Gravel	Sand	Fine sand	Cement	Gravel	Sand	Fine sand	Cement	Super Pasticizer SP	Water		Yield stress	Viscosity
45.0	29.0	9.0	17.0	957	617	191	362	--	200	80	1717	174
45.0	29.0	9.0	17.0	952	614	190	360	--	204	100	1489	163
45.0	29.0	9.0	17.0	947	611	189	358	--	208	130	1219	160
45.0	29.0	9.0	17.0	943	607	189	356	--	212	165	881	133
45.0	29.0	9.0	17.0	938	604	188	354	--	216	225	802	84
48.0	30.9	9.6	11.4	1006	648	201	240	--	204	55	1387	285
48.0	30.9	9.6	11.4	996	642	199	237	--	212	125	1037	163
48.0	30.9	9.6	11.4	986	635	197	235	--	220	170	1185	130
24.0	49.3	15.3	11.4	483	993	308	230	--	235	35	1385	258
24.0	49.3	15.3	11.4	478	983	305	228	--	243	60	1206	200
24.0	49.3	15.3	11.4	473	972	302	226	--	251	185	799	127
57.6	19.3	6.0	17.0	1207	405	126	356	--	212	80	1906	147
57.6	19.3	6.0	17.0	1201	403	125	354	--	216	135	1679	209
57.6	19.3	6.0	17.0	1194	401	124	352	--	220	185	1913	223
22.5	46.2	14.3	17.0	460	944	293	347	--	231	95	1008	208
22.5	46.2	14.3	17.0	455	934	290	344	--	239	95	951	172
22.5	46.2	14.3	17.0	450	925	287	340	--	247	160	839	90
0.0	63.4	19.7	17.0	0	1207	375	323	--	284	55	2216	73
0.0	63.4	19.7	17.0	0	1193	370	319	--	292	70	2036	77
0.0	63.4	19.7	17.0	0	1179	366	316	--	300	65	2132	96
52.0	17.4	5.4	25.1	1093	367	114	529	--	220	12	1473	183
52.0	17.4	5.4	25.1	1081	363	113	523	--	228	155	1147	147
52.0	17.4	5.4	25.1	1070	359	111	518	--	236	195	752	117
40.6	26.2	8.1	25.1	851	549	170	527	--	222	105	1688	146
40.6	26.2	8.1	25.1	843	543	169	522	--	230	170	1090	111
40.6	26.2	8.1	25.1	834	537	167	517	--	238	205	888	59
20.3	41.7	12.9	25.1	413	849	264	512	--	244	105	1432	75
20.3	41.7	12.9	25.1	409	840	261	507	--	252	150	1068	73
20.3	41.7	12.9	25.1	405	831	258	501	--	260	225	733	34
0.0	57.2	17.7	25.1	0	1107	344	486	--	282	80	1702	52
0.0	57.2	17.7	25.1	0	1094	340	481	--	290	170	1123	35
0.0	57.2	17.7	25.1	0	1082	336	475	--	298	210	1024	46
0.0	51.1	15.9	33.0	0	984	305	635	--	296	115	1195	48
0.0	51.1	15.9	33.0	0	973	302	328	--	304	175	976	36
0.0	51.1	15.9	33.0	0	961	298	621	--	312	230	731	25
45.0	28.0	8.0	19.0	1015	632	180	429	10.71	155	215	649	499
45.0	28.0	8.0	19.0	1012	630	180	427	10.68	158	180	593	517
45.0	28.0	8.0	19.0	1009	628	179	426	10.65	160	205	473	530
45.0	28.0	8.0	19.0	1003	624	178	423	10.59	165	235	141	439
57.0	18.7	5.3	19.0	1278	419	120	426	10.66	160	150	1216	544
57.0	18.7	5.3	19.0	1270	416	119	424	10.59	165	120	893	437
21.2	43.0	12.3	23.5	468	947	271	519	12.97	181	150	1055	519
21.2	43.0	12.3	23.5	465	941	269	516	12.87	186	225	363	589
21.2	43.0	12.3	23.5	462	935	267	513	12.81	191	260	115	401
0.0	56.0	16.0	28.0	0	1173	335	587	14.67	228	145	200	303
0.0	56.0	16.0	28.0	0	1164	332	582	14.55	234	200	465	424
50.6	16.6	4.7	28.1	1139	373	107	632	15.79	170	245	90	586
50.6	16.6	4.7	28.1	1132	371	106	628	15.69	175	250	61	535
20.0	40.4	11.6	28.0	440	890	254	617	15.42	189	270	47	528

Table 1. Contd.

0.0	49.2	14.1	36.8	0	1050	300	785	19.63	225	280	145	694
0.0	49.2	14.1	36.8	0	1039	297	777	19.43	233	285	204	371
0.0	49.2	14.1	36.8	0	1028	294	769	19.22	241	290	250	155
0.0	42.6	12.2	45.3	0	901	257	957	23.93	244	290	89	695
0.0	42.6	12.2	45.3	0	891	255	947	23.67	252	290	123	429
45.0	28.8	8.8	17.4	952	609	186	369	2.13	205	240	432	121
45.0	28.6	8.6	17.8	966	614	184	383	4.26	194	235	294	205
45.0	28.4	8.4	18.2	980	618	183	397	6.39	182	220	77	295
45.0	28.2	8.2	18.6	995	623	181	412	8.52	171	220	33	394

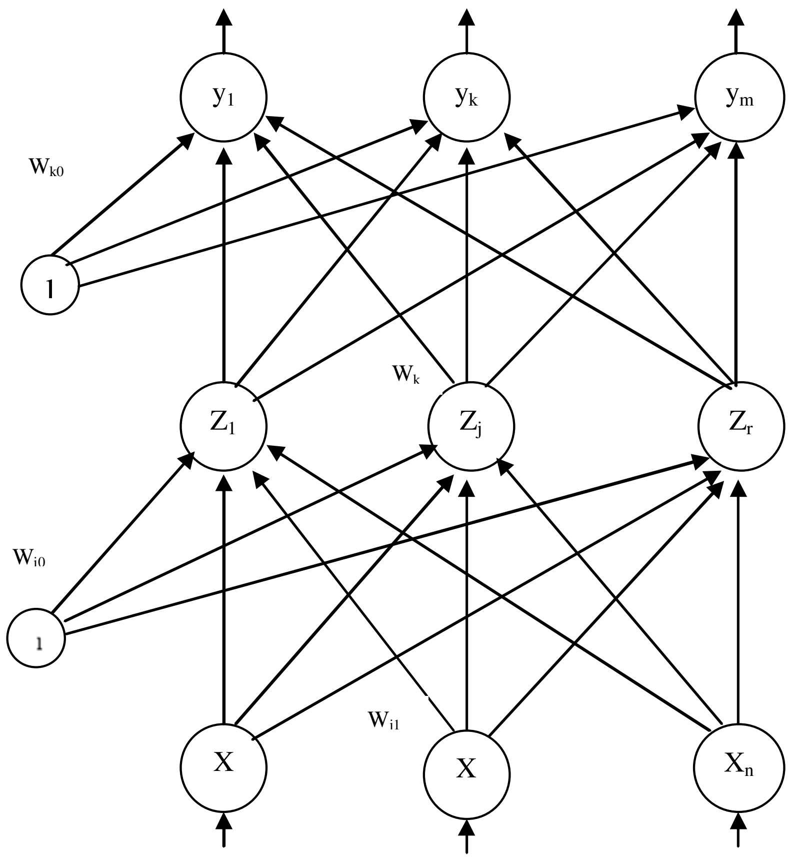

Figure 1. Feed-back artificial neural network model.

In Figure 3, the correlation between experimental slump values and experimental yield stress in Bingham model is easily seen, and it can represent yield stres values of slump values. Ferraris and de Larrard, modifying Hu model, proposed an equation that could predict yield stress in Bingham model with respect to mesured slump values. In Figure 4, the linear correlation of experimental yield stress values, and theoretical yield stress was given. It is the gradient of shear rate of which viscosity was determined with rheometer in fresh concrete. It is not possible to measure with slump values. But Ferraris and de Larrard (1998) proposed viscosity calculation method according to slump values. The linear correlation between theoretical viscosity and experimental viscosity calculated by means of that method was shown in Figure 5. In the correlation, a coefficient as high as 0.71 was obtained.

In this study, the usability of ANN method to determine rheological parameters of fresh concrete was investigated. Accordingly, the correlation of the results of rheological characteristics of fresh concrete, that was attained by means of ANN method and the experimental data were evaluated. The network used in this study is shown in Figure 2. It has a structure with three layers, and it has six inputs and three outputs. The inputs are gravel, sand, fine sand, cement, water, and super plasticizer “SP”. The outputs are slump, yield stress and viscosity. The number of cells in the hidden layer is to ten based on the experiments conducted during training. To test the accuracy of the trained network, the coefficient of determination R^2 was adopted. The coefficient is a measure of how

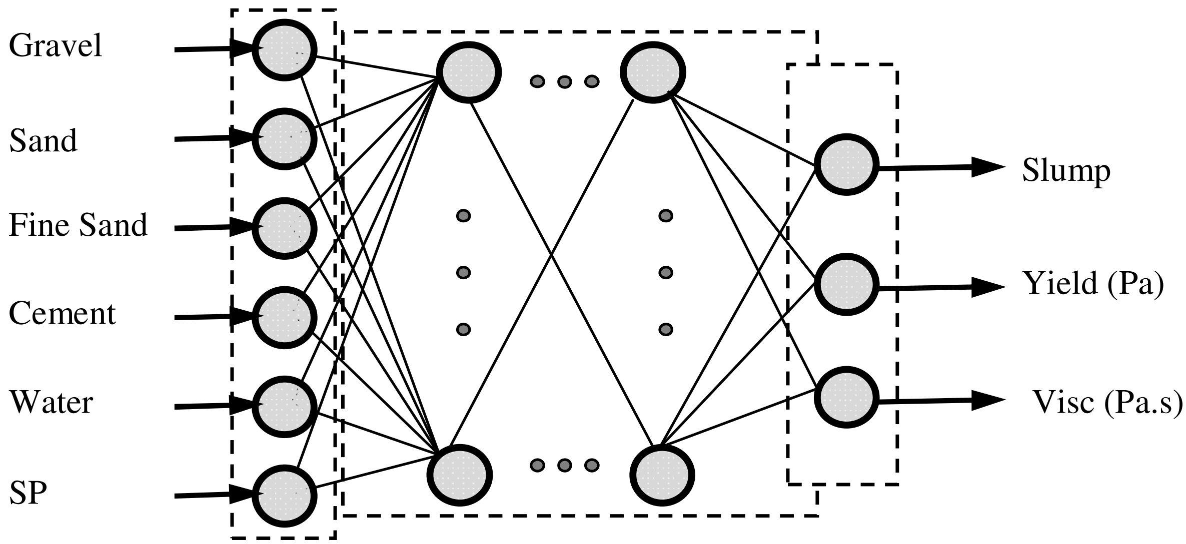

Figure 2. Structure of application artificial neural network.

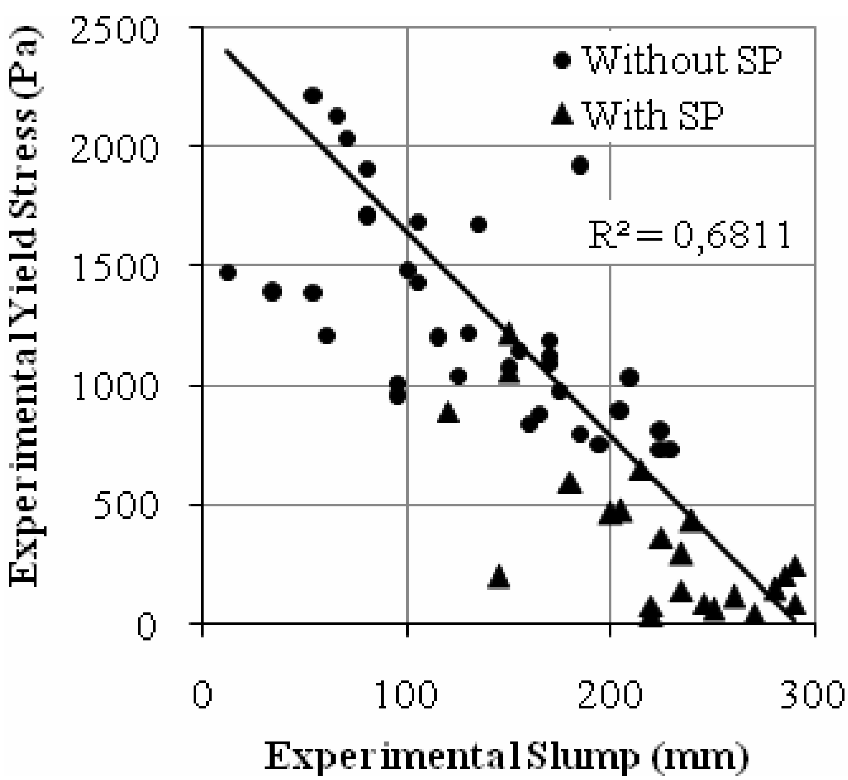

Figure 3. Experimental slump-yield stress correlations.

well the considered independent variables account for the measured dependent variable. The higher the R^2 value is the better the prediction relationship.

DISCUSSION

The ANN has been trained using various training settings. The mixture ingredients that comprised the concrete were sorted into two groups based on their “Dry mixture masses”, and “Compositions” as shown in Table 2. Additionally, from these group of data, three sub-groups have been constructed as shown in Table 2. ANN is trained using Levenberg-Marquardtmethod which is implemented in Matlab as “trainlm” function. This is the

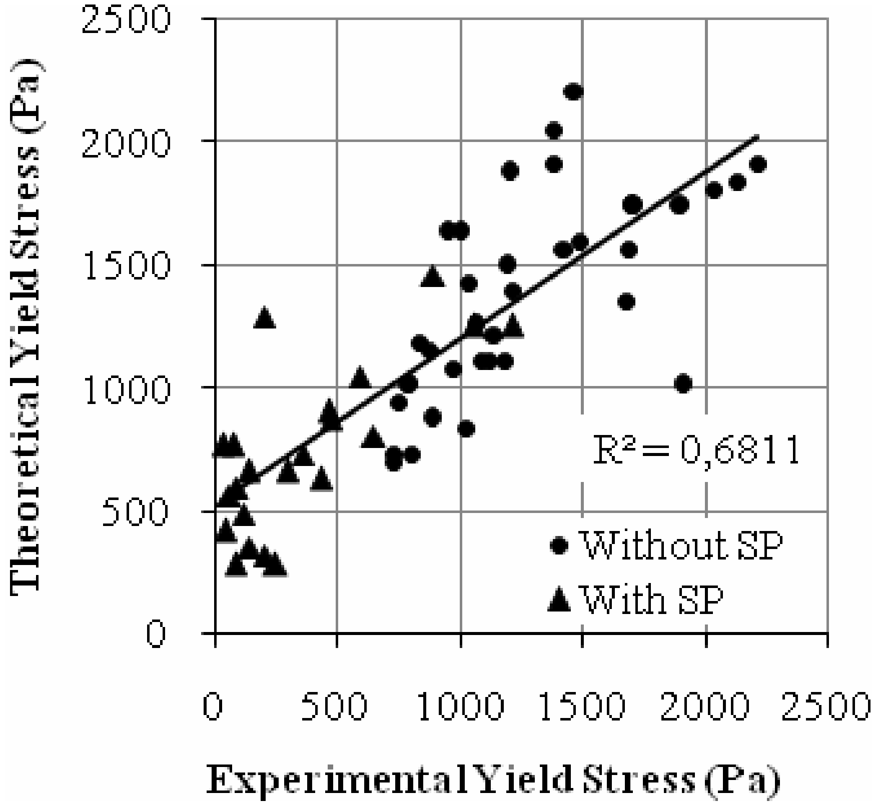

Figure 4. Experimental and theoretical yield stress correlations.

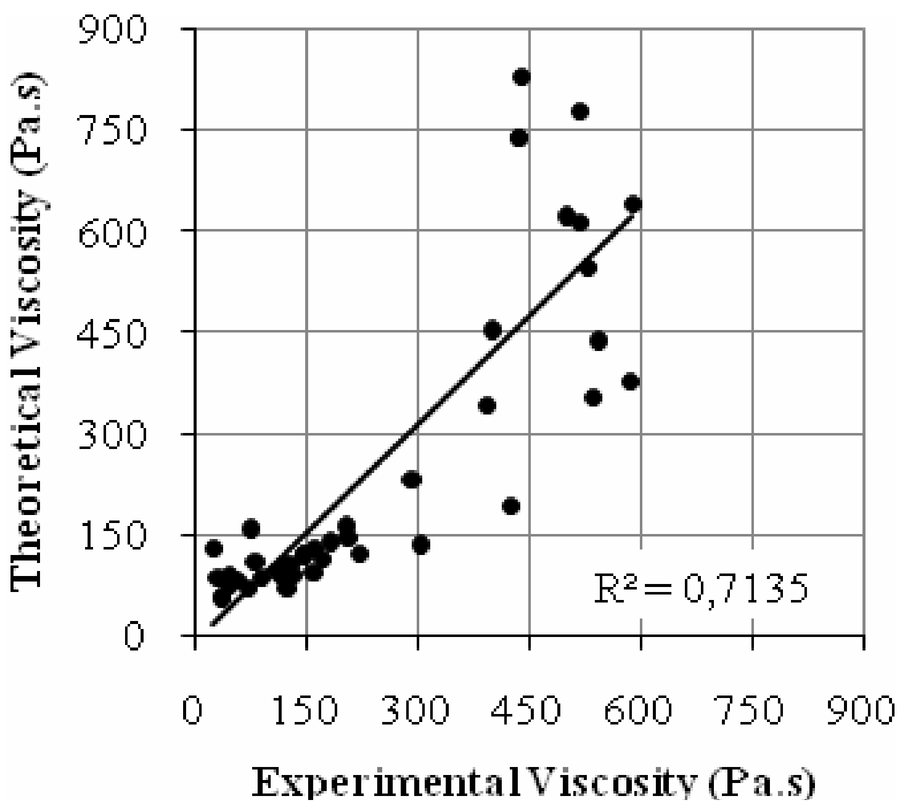

Figure 5. Experimental and theoretical viscosity correlations.

Table 2. Input data groups for ANN.

Group A data			Group B data		
Dry mixture mass (%)			Composition (kg/m^3)		
1	**2**	**3**	**1**	**2**	**3**
Gravel	Gravel	Gravel	Gravel	Gravel	Gravel
Sand	Sand	Sand	Sand	Sand	Sand
Fine sand	Fine sand	Fine sand	Fine sand	Fine sand	Fine sand
Cement	Cement	Cement	Cement	Cement	Cement
Water	Water	Water	Water	Water	Water
	SP	Without SP + SP		SP	Without SP + SP

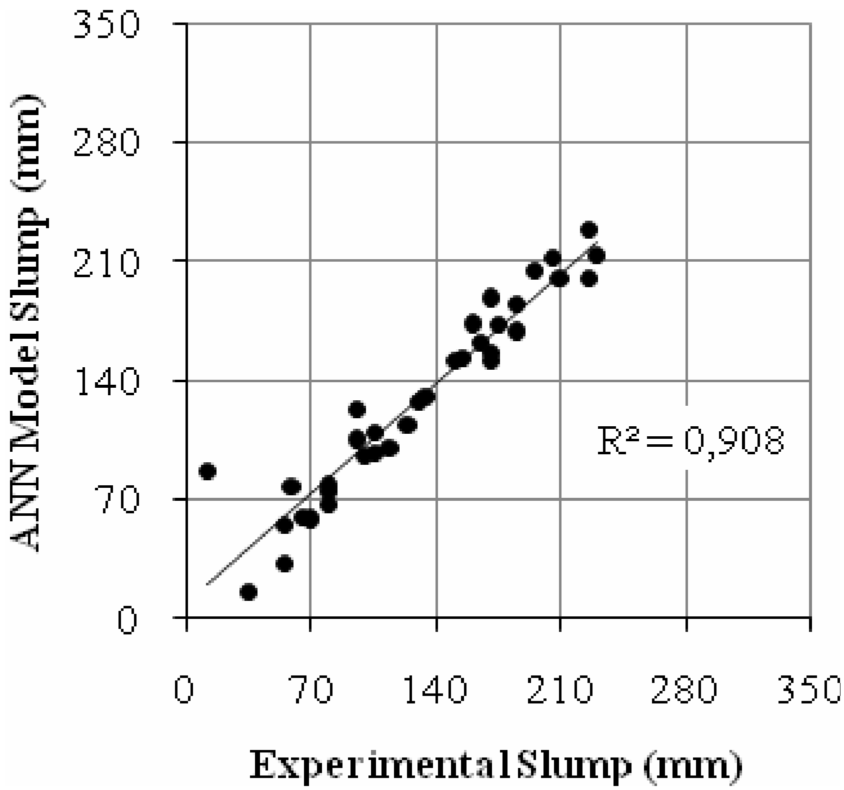

Figure 6. Experimental and ANN model slump correlations (without SP dry mixture mass (%)).

best function which gives the smaller training error compared to the rest of algorithms availabe in Matlab. A part of data shown in Table 1 is used to train ANN. The performance of ANN is evaluated using the rest of data which has not been used in training session. In all training and test processes the groups of data shown in Table 2 were used and results are shown in Figures 6 - 23. As it can be shown from the figure ANN is able to give succesfuly functional relation between input parameters, which are the ingridient factor, and the workability of the concrete.

In this study, the usability of ANN method to determine rheological parameters of fresh concrete was investigated. Accordingly, the correlation of the results of rheological characteristics of fresh concrete, that was attained by means of ANN method and the experimental data were evaluated and shown in Figures 6 - 23. The correlation coefficients of the results obtained were shown in Table 3. Rheological characteristics of fresh concrete determined by ANN method cohered with the experimental data, as shown in Table 3. Rheological properties of fresh concrete could be determined getting quite high R^2 values both in cases the ingredients of the concrete were composed as per their values of dry

Table 3. Correlation coefficients of the data determined by means of ANN method and the experimental data.

Rheological properties	Group A data			Group B data		
	Dry mixture mass (%)			Composition (kg/m^3)		
	Without SP (R^2)	With SP (R^2)	Without SP+SP (R^2)	Without SP (R^2)	With SP (R^2)	Without SP+SP (R^2)
Slump	0.91	0.93	0.92	0.94	0.92	0.87
Yield stress	0.95	0.88	0.97	0.87	0.95	0.95
Viscosity	0.89	0.93	0.91	0.91	0.95	0.91

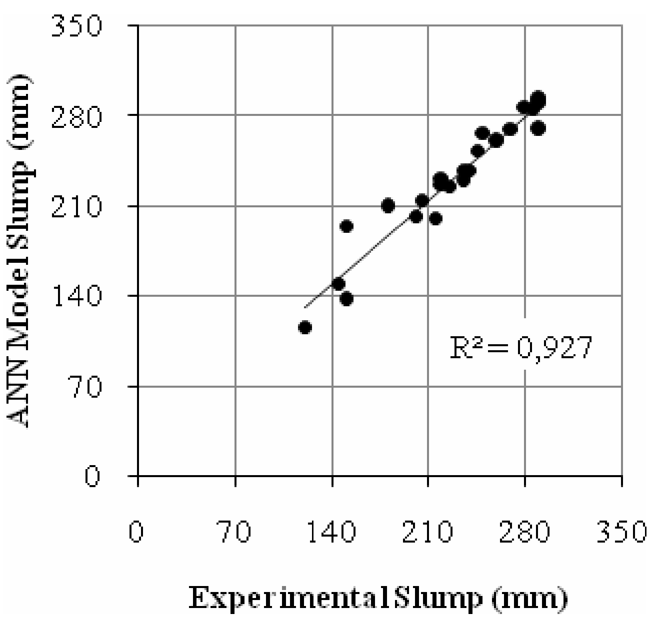

Figure 7. Experimental and ANN model slump correlations (With SP Dry mixture mass (%)).

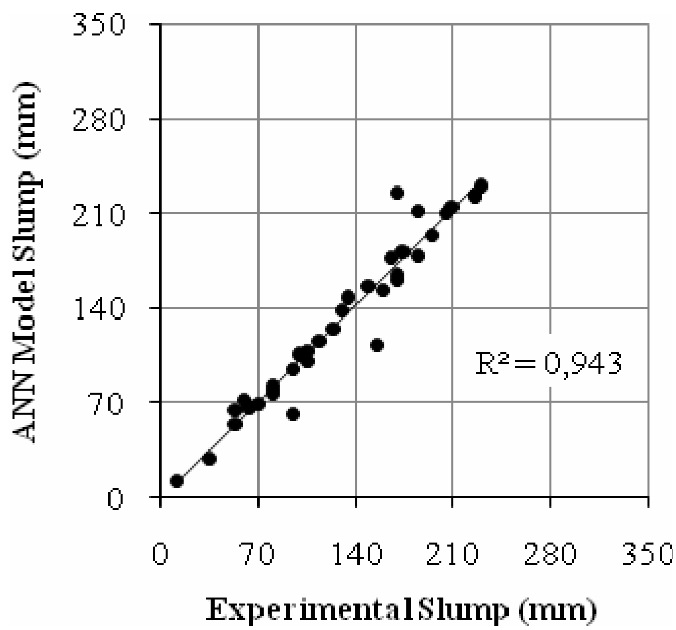

Figure 9. Experimental and ANN model slump correlations (Without SP Composition (kg/m^3)).

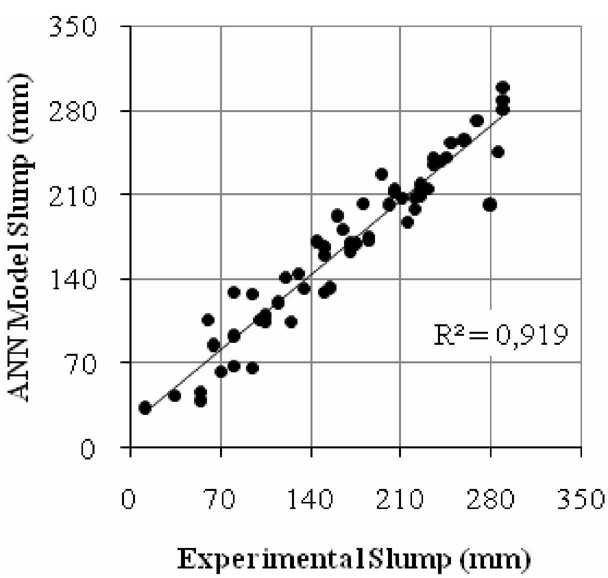

Figure 8. Experimental and ANN model slump correlations (without SP+SP dry mixture mass (%)).

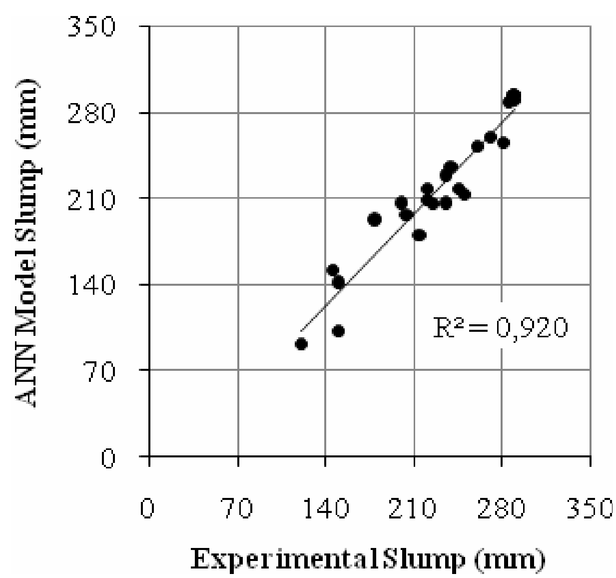

Figure 10. Experimental and ANN model slump correlations (with SP composition (kg/m^3))

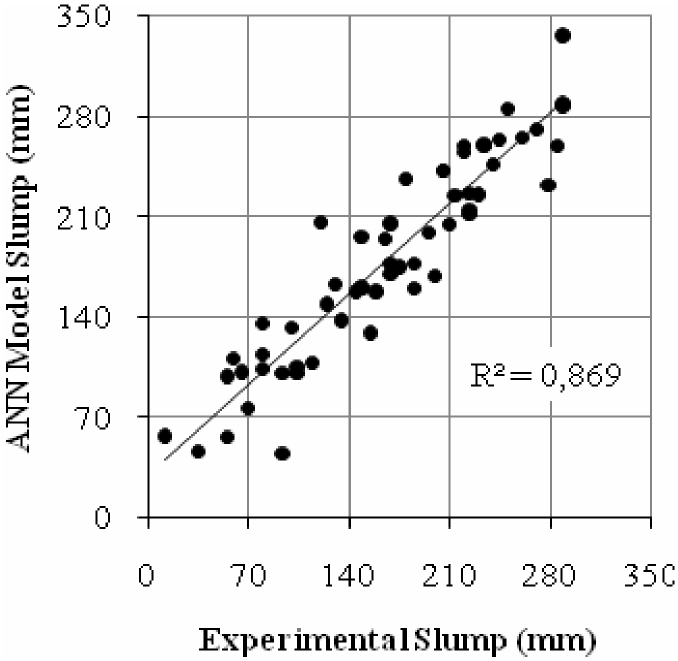

Figure 11. Experimental and ANN model slump correlations (without SP+SP composition (kg/m^3)).

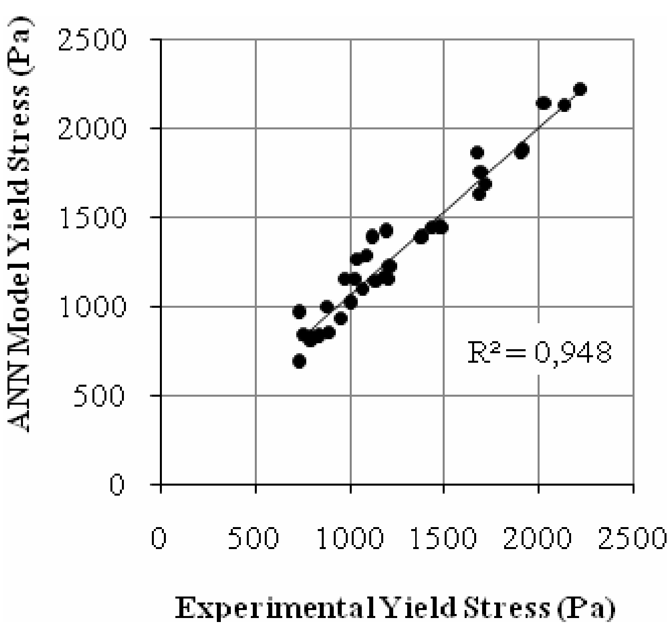

Figure 12. Experimental and ANN model yield stress correlations (without SP dry mixture mass (%)).

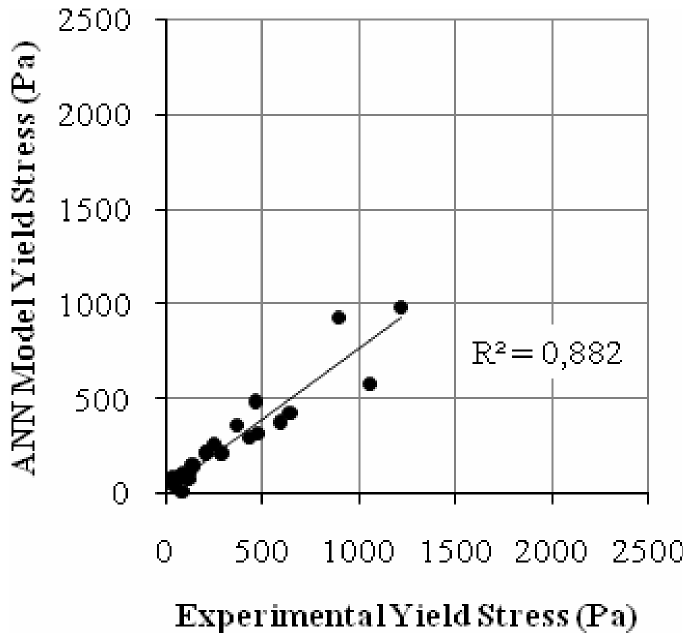

Figure 13. Experimental and ANN model yield stress correlations (with SP dry mixture mass (%)).

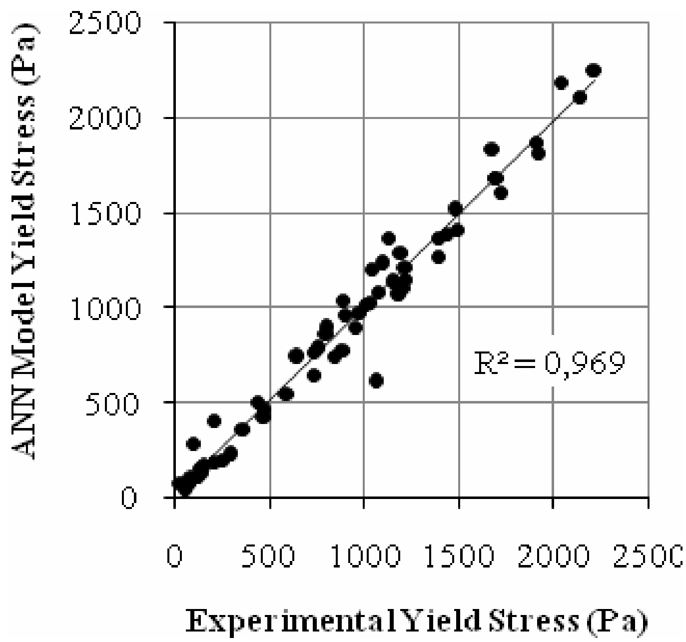

Figure 14. Experimental and ANN model yield stress correlations (Without SP+SP Dry mixture mass (%)).

mixture masses (%), or composition (kg/m^3) values. However, R^2 values of the dry mixture mass group in which the rheological values were evaluated without SP and SP were determined to have been higher that those of the composition group.

Conclusion

In this study, the following results were achieved through the ANN method used to determine rheological characteristics of fresh concrete.

(i) The slump, yield stress and viscosity data of the

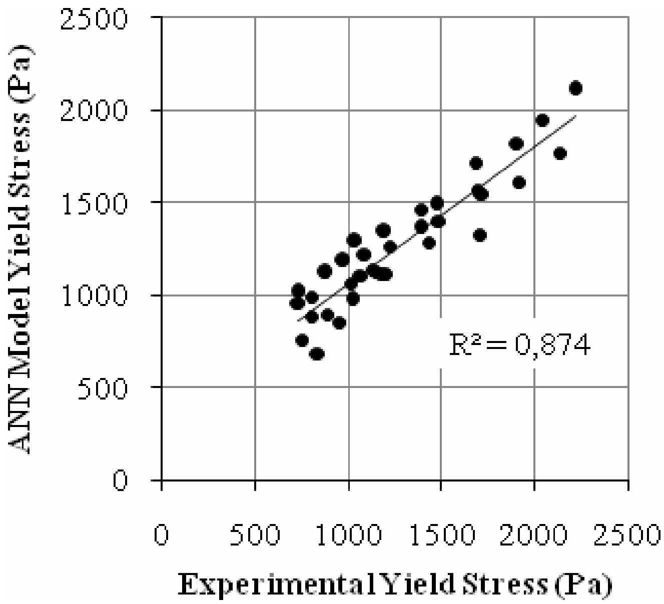

Figure 15. Experimental and ANN model yield stress correlations (Without SP Composition (kg/m^3)).

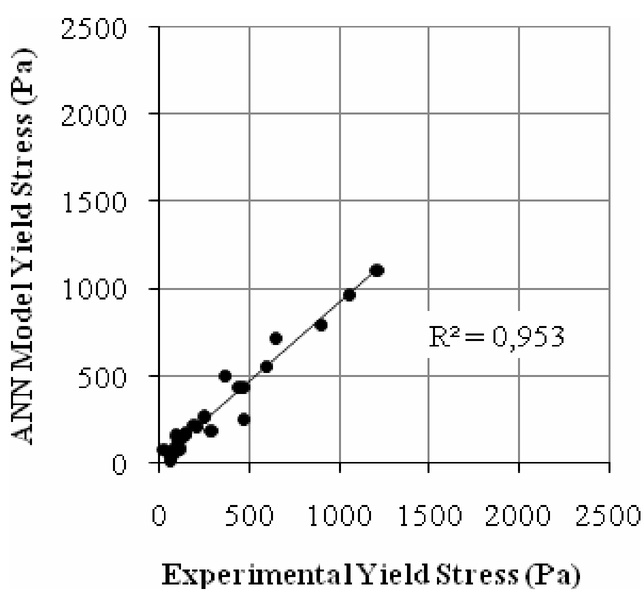

Figure 16. Experimental and ANN model yield stress correlations (with SP composition (kg/m^3)).

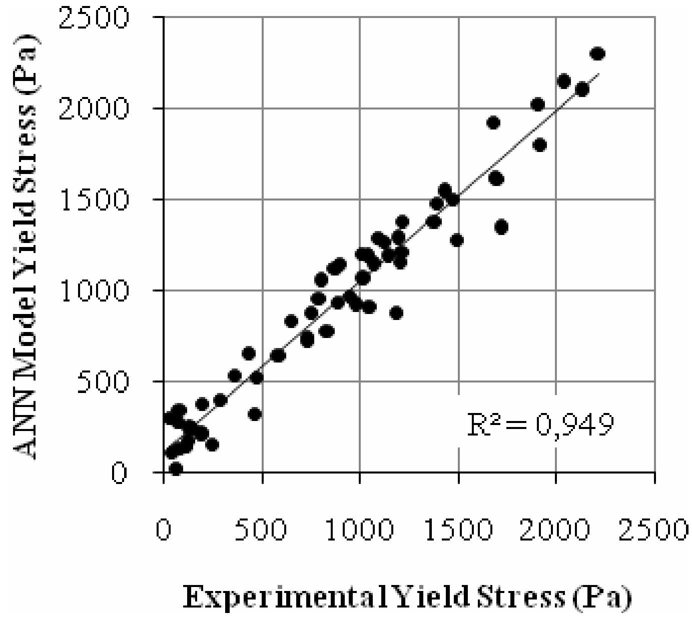

Figure 17. Experimental and ANN model yield stress correlations (without SP+SP composition (kg/m^3)).

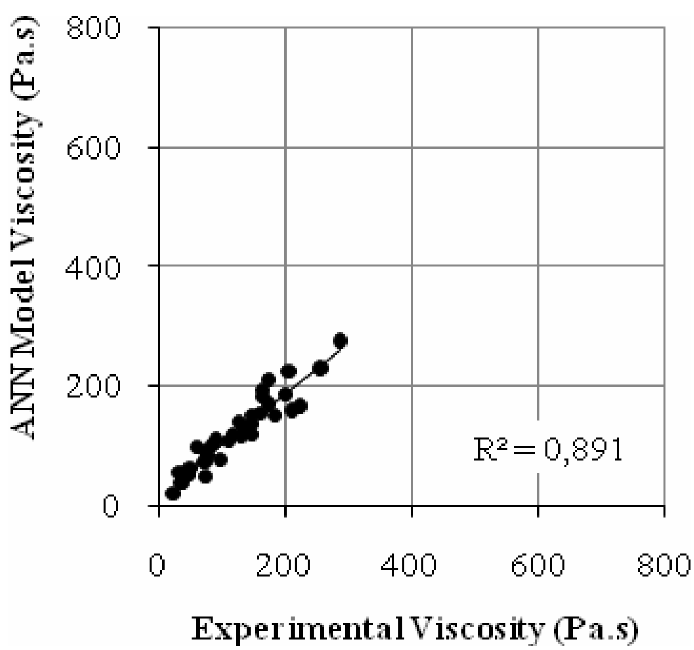

Figure 18. Experimental and ANN model viscosity correlations (Without SP Dry mixture mass (%)).

experimental studies of Ferraris and de Larrard were used as input for this study. Calculations were carried out using the yield stress, and viscosity equations developed by the authors and included in the literature. Their correlations are shown in Figures 4 and 5. According to correlation constants R^2 = 0.68 and R^2 = 0.71 are obtained.

(ii) Dry mixture mass (%) and Composition (kg/m^3) values of ingredient materials of fresh concrete were used as different inputs in ANN method. Higher correlations (R^2 = 0.92, R^2 = 0.97, R^2 = 0.91) were obtained in slump, yield stres, and viscosity values with the outputs when the complete materials (Group A - 3) in the dry mixture masses (%) of the mixture were evaluated, as seen in

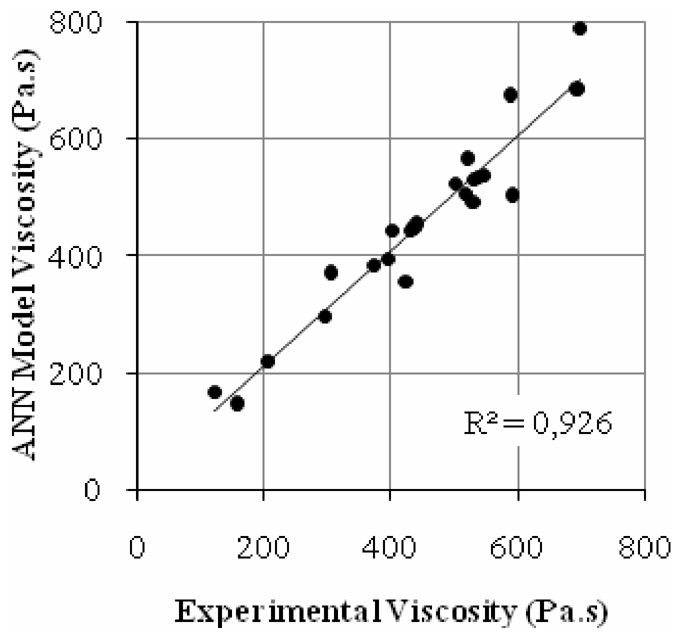

Figure 19. Experimental and ANN model viscosity correlations (with SP dry mixture mass (%)).

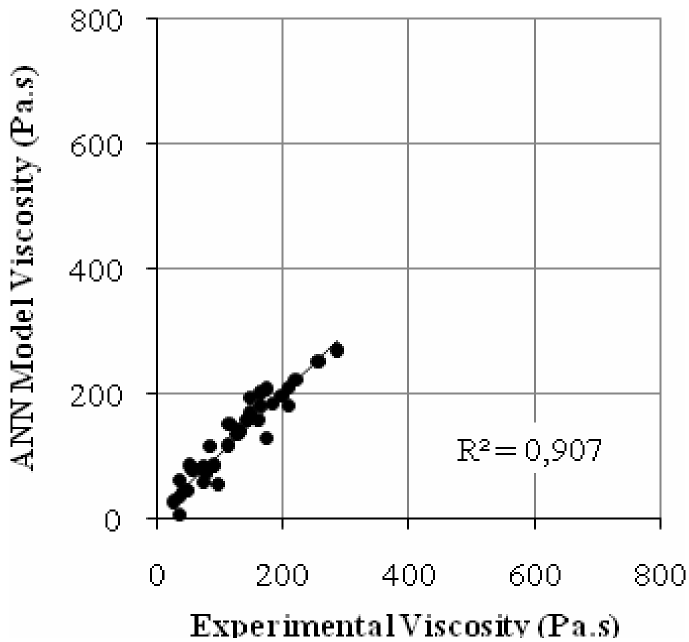

Figure 21. Experimental and ANN model viscosity correlations (Without SP Composition (kg/m^3)).

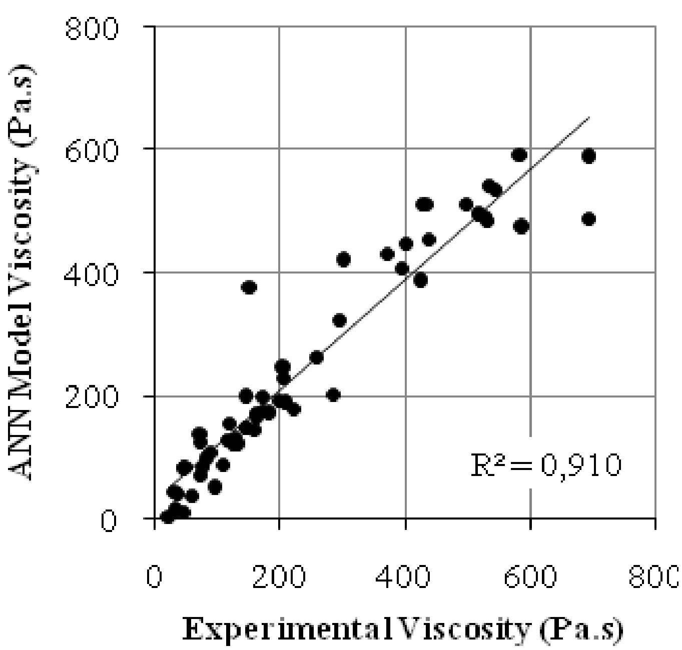

Figure 20. Experimental and ANN model viscosity correlations (Without SP+SP Dry mixture mass (%)).

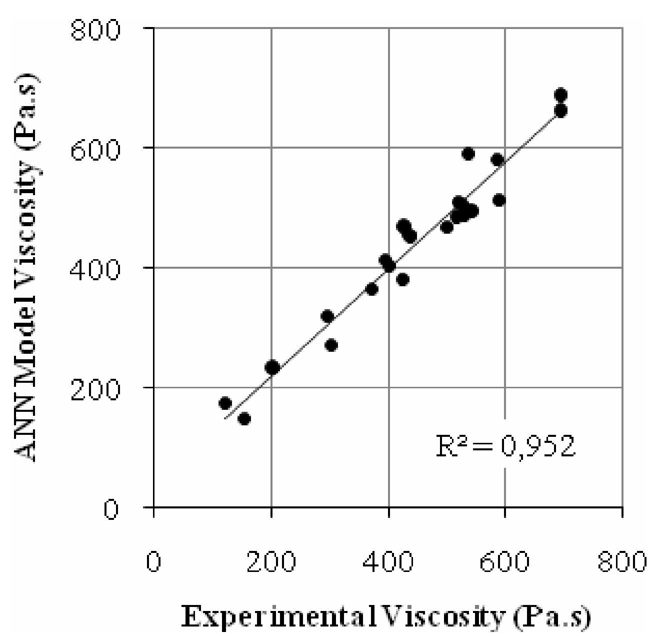

Figure 22. Experimental and ANN model viscosity correlations (with SP composition (kg/m^3)).

Figures 8, 14, and 20.

(iii) Higher correlations (R^2 = 0.87, R^2 = 0.95, R^2 = 0.91) were obtained in slump, yield stres, and viscosity values with the outputs when the complete materials (Group A - 3) in the Composition (kg/m^3) of the mixture were evaluated, as shown in Figures 11, 17, and 23.

(iv) The values of parameters of Bingham model (yield stres and viscosity) can be determined with a high accuracy with correlation coefficients within the interval R^2 = 0.91~0.97.

(v) Regarding the obtained results, it has been decided that the ANN is a viable and usable method in determining rheological characteristics (by Bingham

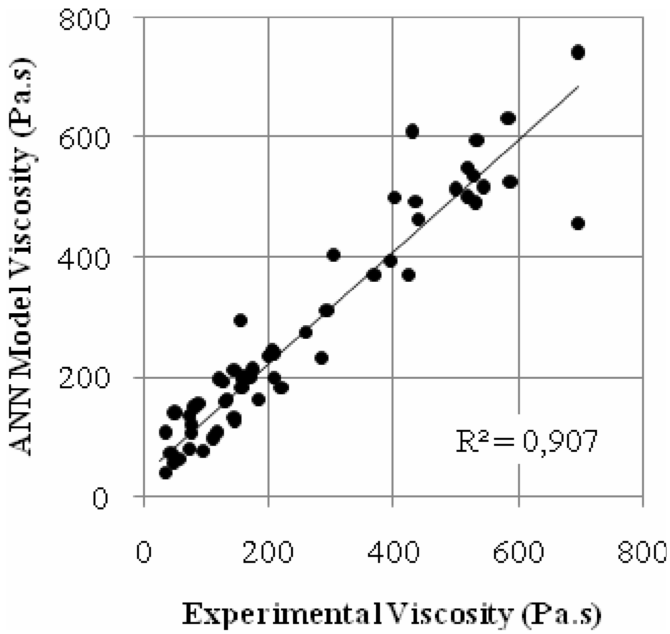

Figure 23. Experimental and ANN model viscosity correlations (without SP+SP composition (kg/m^3)).

model) of fresh concrete.

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