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Research Article

A Neural Network-Based Prediction of Superplasticizers Effect on the Workability and Compressive Characteristics of Portland Pozzolana Cement-Based Mortars

P. Manikandan,[1] V. Vasugi,[1] V. Prem Kumar,[2] S. Duraimurugan,[3] M. Sankar,[4] A. Chithambar Ganesh,[2] and G. Senthil Kumaran[5]

[1]*School of Civil Engineering, Vellore Institute of Technology, Chennai Campus, India*
[2]*Department of Civil Engineering, Sree Vidyanikethan Engineering College, Tirupati, India*
[3]*Regional Concrete Manager, Fosroc Chemicals India Private Limited, Chennai, India*
[4]*Regional Formulator, Fosroc Chemicals India Private Limited, Chennai, India*
[5]*Department of Civil Engineering, Copper Belt University, Kitwe, Zambia*

Correspondence should be addressed to V. Vasugi; vasugi.v@vit.ac.in, V. Prem Kumar; premkumar.v@vidyanikethan.edu, and G. Senthil Kumaran; kumaran.gs@cbu.ac.zm

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Portland Pozzolana Cement (PPC) mortars are predominantly employed in plastering works to achieve better workability, superior surface finish, and higher fineness to offer better cohesion with fine aggregates than the ordinary Portland cement (OPC) mortars. To achieve high performance in the cement mortar similar to cement concrete, the addition of a superplasticizer is recommended. The present study investigates the impact of addition of sulphonated naphthalene formaldehyde- (SNF)-based (0.5%, 0.6%, 0.7%, and 0.8%) and lignosulphate- (LS)-based (0.2%, 0.3%, 0.4%, and 0.5%) superplasticizers on the workability and compressive strength characteristics of PPC mortars. Plastering mortars of ratio 1 : 4 were prepared with natural sand and manufacturing sand (M sand) as fine aggregates. A flow table test was conducted on all the mortar mix proportions, and the effects of the inclusion of superplasticizers on flow properties were recorded at different time intervals (0, 30, 60, 90, and 120 minutes). PPC mortar cubes were prepared, cured, and examined to assess the inclusion of chemical admixtures on compressive strength at different ages (1, 3, 7, 14, and 28 days). The experimental findings from the workability and compressive strength of PPC mortars were analyzed, and the corresponding results were predicted using artificial intelligence. Experimental investigations demonstrated that the desired flow characteristics and higher compressive strength results were achieved from a 0.7% dosage of ligno-based superplasticizer. The predicted workability and compressive strength results at various ages acquired by implementing an Artificial Neural Network (ANN) were found to be in close agreement with the experimental results.

1. Introduction

Cement mortar is considered to be one of the typical and cheaper building materials employed in the field of construction technology. When cement material is utilized for producing mortar for plastering work, it is termed as cement plaster. Cement plaster is essential in bonding internal and external coats between the concrete surface and painting. Cement plaster is the blend of ordinary Portland cement/ Portland Pozzolana cement/Portland slag cement, fine aggregates, and water in adequate proportions that are usually applied to masonry, exteriors, and interiors to obtain a smooth surface finish [1]. Cement mortar finds an extensive application in plastering work, building masonry units, damaged concrete repairing, leveling the floor, patching work, filler materials in ferrocement, and developing precast materials and damp proofing materials [2].

Both OPC and PPC-based mortar mixes are widely employed in construction practices because of their advantages and disadvantages. These days, PPC-based mortar mixes are commonly employed as a replacement for OPC mortars, particularly in plastering works, due to their wide variety of applications like better workability, high fineness, low heat of hydration, and comparatively lower W/C ratio provided for further enhancement in the compressive strength of concrete and better surface finish [3].

Naturally available river sand corresponds to Zones 3 and 4 was generally employed in preparing cement plaster works due to its less water absorption capacity, thereby increasing the plasticity effect [4]. The physical characteristics of river sand, such as particle size distribution, shape, and surface texture, significantly influence the flow and workability properties of mortar mix in the fresh state [5]. Factors such as mineralogical composition, modulus of elasticity, degree of alteration of fine aggregates, and toughness tend to significantly impact the properties of mortar mixes in their hardened state [6, 7].

Overexploitation of the river sand led to the prohibition of sand extraction by the authorities due to the adverse consequences and biological imbalance caused by sand depletion in river beds [8]. Because of the rapidly developing construction industry, the demand for sand has skyrocketed, resulting in a scarcity of sufficient river sand in most parts of the globe [9]. In these conditions, the requirement for a suitable replacement for natural river sand that does not compromise the strength and durability of mortar becomes critical to sustaining infrastructure development and protecting the ecosystem. M sand is the most common alternative material utilized in construction activities for river sand. It is produced by crushing large pieces of granite stone into the sand size aggregates [10].

Compared to river sand, the cost of M sand is 40–45% lesser, and it does not contain the impurities like clay, dust, and silt coatings. Another reason for utilizing M sand is its easy accessibility and lower transportation costs. It is safe to use M sand to alternate river sand in construction practices [11]. When M sand is used in the PPC-based mortar mixes, high water content is required to improve the flow behavior since its particle size is angular and produces high fineness and porosity [12, 13]. Compressive strength issues will occur when the W/C ratio proportion is increased on the utilization of M sand; to overcome this challenge, different types of superplasticizers could be used to reduce the water content [14, 15].

An Artificial Neural Network (ANN) is a quantitative and statistical framework replicating a network of neurons in the human brain. It has the potential to be extensively used in engineering technologies to address highly complicated problems. According to recent studies, the neural network can also estimate the strength properties of building materials accurately. Many critical parameters, such as design mix [16], cement quantity [17], substitution amount of recycled coarse aggregates [18], drying shrinkage of concrete [19], strength characteristics of geopolymer composites containing various source materials [20], and slump values [21, 22], can be predicted using neural network models along with the experimental outcomes in addition to compressive strength [23]. Recent studies have proved that by employing the ANN framework, the compressive strength and flow characteristics of PPC-based cement mortars can be predicted accurately.

From the past literature studies, it was observed that very few literary works had been reported on the investigations on the incorporation of various chemical admixtures on the plasticity effect of PPC-based mortar mixes. Hence, an attempt was made to correlate the impact of the inclusion of various proportions of SNF and LS-based superplasticizers on the workability (flow property) and strength (compressive property) of PPC mortar mixes prepared using M sand against the OPC-based mortar mixes. Furthermore, the ANN model was programmed in MATLAB R2018a with the implementation of the Levenberg Marquardt (LM) algorithm to predict the workability and compressive strength characteristics of PPC mortar mixes in comparison with the experimental results.

2. Materials and Methods

2.1. Materials. A substantial number of cement mortar cube specimens were prepared with varying proportions of W/C ratios, water content, and chemical admixtures proportions to study their impacts on the plasticity (flow characteristics) and strength (compressive) of the mortars. Commercially available Portland Pozzolana cement (PPC) is used as the binding material in the study. Tables 1 and 2 represent the physical and chemical characteristics of the binding material used in this study, respectively. Fine aggregates (river sand and M sand) passing through a 4.75 mm sieve size have been employed in the study, and their physical characteristics are listed in Table 3.

The chemical admixtures used in this study were LS-based and SNF-based, sourced from Fosroc Chemicals India Private Limited, Chennai. In general, ligno-based admixture consists of a small amount of air entrainment agent that makes a smooth finish and creates a capillary portion when added to the mortar/concrete mix. This admixture has 5 to 10% of water reduction capacity as per manufactured recommend value.

SNF-based admixtures are reported to have an effective dispersing impact on concrete and are designed to minimize concrete's water requirement by up to 30% while retaining flow behavior. NSF-based superplasticizers generally contain linear polymers that prefer to adsorb on cement particles, dissipating both cement particles and boosting flowability [24, 25]. According to the literature, the NSF disperses cement particles and decreases attractive interparticle forces (van der Waals forces) through electrostatic repulsion. For NSF, the contribution of electrostatic repulsive force to total repulsive force is very high, resulting in an effective dispersing effect on flow behavior [26, 27]. Water reduction percentage might be changed based on the available solid content in the product. Table 4 illustrates the material characteristics of LS and SNF-based superplasticizers employed in the study provided by the manufacturers.

2.2. Experimental Program. The experimental work was performed in the Regional Concrete Laboratory of the Fosroc Chemicals India Private Limited, Chennai. In this

Table 1: Physical characteristics of binding materials.

Physical characteristics	PPC
Fineness (m^2/kg)	382
Standard consistency (%)	33.5
Initial setting time (min)	190
Final setting time (min)	290
Fly ash addition (%)	31
Specific gravity	2.9
Soundness (mm)	0.50

Table 2: Chemical characteristics of binders used in the study.

Chemical characteristics	PPC (Oxides percentage by mass)
CaO	43.51
Al_2O_3	10.06
SiO_2	30.62
MnO	—
Fe_2O_3	4.34
MgO	1.03
Na_2O	0.54
K_2O	—
Loss of ignition (LOI)	2.80

study, 15 mixes proportions of constant cement: fine aggregate proportion (1 : 4) was prepared in four phases with different W/C ratios (ranging between 0.6 and 0.75), water content, and admixtures (SNF, LS) dosages to determine the plasticity and compressive strength characteristics of PPC mortars. Figure 1 displays the cubic samples prepared for the various PPC mortar mix proportions considered in the study.

In the first phase, PPC was blended with river sand in the ratio of (1 : 4) with different W/C ratios (0.6, 0.65, and 0.70) in three mixes (M1, M2, and M3) without adding chemical admixtures to determine the optimum W/C ratio, which meets the flow characteristics. Phase two involves the preparation of four PPC mortar mixes (M4, M5, M6, and M7) with M sand in the ratio of 1 : 4 by varying the W/C ratios (from 0.65 to 0.75) with a gradual increase in water content from 2.5% to 10% to achieve the plasticity effect in mortar samples as the utilization of M sand creates higher water demand.

In phase three, four PPC mortars (M8, M9, M10, and M11) were prepared by varying the dosages of LS-based superplasticizers (0.5%, 0.6%, 0.7%, and 0.8%) using M sand in the same ratio of 1 : 4 with a constant W/C ratio of 0.65 to obtain cohesive and workable mortar mix with good retention period. In phase four, PPC mortars were prepared using M sand with different SNF-based admixtures (0.2%, 0.3, 0.4%, and 0.5%) in four mixes (M12, M13, M14, and M15) with a constant W/C ratio of 0.65 to achieve the workable mix. In this context, SNF admixture was introduced in the above four mixes to reduce the water capacity as M sand requires huge water content to achieve plastering effect in mortar mixes. Table 5 depicts the details of the 15 mortar mixes adopted in the study.

2.3. Test Methods. The workability characteristics of the mortar mixes can be evaluated by conducting a flow table test. The flow table test in cement mortar is considered an essential parameter in determining the quality of the mortar mix in terms of cohesiveness, consistency, and proneness to segregation. In this study, 15 PPC cement mortar mixes were prepared to determine their workability characteristics in the fresh state using standard flow table apparatus according to IS 5512 provisions [28]. Three mortar cubic samples of dimension $70.6\,mm \times 70.6\,mm \times 70.6\,mm$ in every mix proportion were evaluated under compression load at the end of 28days for compressive strength as per IS 516:2008 provisions [29]. The compressive strength was acquired by evaluating the mortar samples in the universal testing machine (UTM) according to IS 2250:1981 standards, and the load was deployed at the frequency of $2.2\,N/mm^2$ per minute before the failure emerged [30].

3. Results and Discussion

3.1. Flow Characteristics. Table 6 explains the plasticity effects of the fifteen mortar mix proportions adopted in the study. From phase one, it was observed that the M2 mortar mix blended with river sand with a 0.65 W/C ratio yielded a workable mix and was found to be suitable for plastering works compared to the other mixes (M1 and M3). The behavior of flow properties of the three PPC mortar mixes prepared using river sand under the influence of various W/C ratios is shown in Figure 2.

In phase two, four PPC mortar mixes (M4, M5, M6, and M7) were prepared using M-Sand with varying proportions of W/C ratios ranging 0.65 to 0.75 to evaluate its plasticity effect. It is observed that the mortar mix M6 containing a 0.725 (W/C) ratio was workable and suitable for plastering works by meeting the required plasticity effect. Figure 3 depicts the flow properties of the four PPC mortar mixes containing M sand under the influence of various W/C ratios without adding chemical admixtures.

Four PPC mortars (M8, M9, M10, and M11) containing different percentages of LS-based chemical admixtures (0.5% to 0.8%) were prepared using M sand with a constant W/C proportion of 0.65 tested to evaluate the workability characteristics. The slump flow experiment recorded that the mix number M10 yielded a cohesive and workable mortar mix with a good retention period compared to the other three mixes. The flow behavior of four PPC mortar mixes prepared using M sand with various LS-based admixtures is shown in Figure 4.

Phase four experimental trials deal with the effect of adding a variable proportion of SNF-based superplasticizers (0.5% to 0.8%) on the flow properties of four PPC-based mortar mixes (M12, M13, M14, and M15) prepared using M sand with 0.65W/C ratio. From the flow table results, it was observed that all four mortar mixes failed to achieve the normal plasticity effect due to the formation of harsh and segregated mixes [2]. Figure 5 shows the flow properties of PPC-based mortars prepared using M sand with the varying proportions of SNF-based superplasticizers.

Table 3: Physical properties of fine aggregates.

Physical properties	River sand (RS)	Manufacturing sand (MS)
Specific gravity	3.07	3.22
Percentage of water absorption	2.38	3.41
Fineness modulus	2.41	2.05
75 microns passing limits (%)	7.4	10.6

Table 4: Properties of superplasticizers.

Properties	LS-based admixture	SNF-based admixture
Specific gravity	1.16	1.2
Dry material content (%)	34	41
Chloride content	0.003	0.005

From the above flow behavior of 15 mortar mixes, it can be inferred that the PPC mortar mix M10 prepared using M sand achieves better flow characteristics on the incorporation of 0.7% of LS-based superplasticizer by producing a cohesive, workable mortar mix with sufficient retention period, which was found to be best suitable for plastering works [10].

3.2. Analysis of Compressive Strength Characteristics. The compressive strength of PPC mortars is one of the essential features of masonry formations. Figure 6 depicts the compressive strength outcomes at the end of 1, 3, 7, 14, and 28days for the three PPC-based mortar mixes (M1, M2, and M3) prepared using river sand with different W/C ratios (0.60, 0.65, and 0.70). From Figure 6, it can be inferred that the achieves the maximum compressive strength value of 20.5 MPa at the end of 28days due to the low W/C ratio (0.60) but failed to meet the plasticity requirements as the result of poor workability characteristic [31]. On the other hand, M2 produces a workable mortar mix without bleeding/segregation and records the second-highest compressive strength of 18.6 MPa. The M2 mix proportion having a 0.65 W/C ratio is found to produce standard plasticity criteria for the plastering works from the above statement.

The compressive strength analysis at 1, 3, 7, 14, and 28days for the phase two experimental works consisting 4 PPC mortars (M4, M5, M6, and M7) produced using M sand with various percentages of W/C ratios (0.65, 0.7, 0.725, and 0.75) and water contents (2.5%, 5%, 7.5%, and 10%) is shown in Figure 7. According to Figure 7, it can be observed that the M4 reported the highest compressive strength of 18.4 MPa, and the least compressive value of 16.7 MPa corresponds to the M7 mortar mix at the end of 28 days. The gradual increase in the water content from 2.5% to 10% in PPC mixes with M sand had an adverse effect on the compressive strength properties.

The impact of the incorporation of varying percentages of LS-based superplasticizers (to control the water demand due to the usage of M sand) on the compressive strength performance of PPC-based cement mortars at 1, 3, 7, 14, and

Figure 1: Casting of 70.6 mm × 70.6 mm × 70.6 mm cubic samples.

28 days produced with M sand at 0.65 W/C ratio is illustrated in Figure 8. The figure shows that the compressive strength of PPC mortars (M8, M9, and M10) increases monotonically with the increase in LS-based superplasticizers to 0.7%. Further increase in the admixture dosage (0.8%) resulted in a slight declination in compressive strength due to increased workability values [32]. The maximum compressive strength of PPC mortar in phase three trial was 22.4 MPa at the end of 28days for M10.

The effect of addition of different percentages of SNF-based admixtures (0.2%, 0.3%, 0.4%, and 0.5%) on the compressive strength development of PPC cement mortars mixes (M12, M13, M14, and M15) with constant W/C ratio of 0.65 at the different curing periods (1, 3, 7, 14, and 28 days) is demonstrated in Figure 9. From Figure 9, it can be concluded that the M13 mix records the maximum compressive values for 1, 3, 7, 14, and 28days upon the 0.3% addition of SNF-based admixture.

3.3. Prediction of Strength and Flow Properties of Mortars Using Neural Networks. ANN is an extensively parallelly distributed information activity framework that functions like a group of neurons located in the human brain. It has the capability to understand and generalize from the available data and intends to deliver relevant answers even when the set of input parameters contains an error or incomplete [33, 34]. In general, neural networks were employed to resolve and differentiate the experimental results procured from other methods [35]. It contains numerous interconnected artificial neuron-like networks in which every single neuron produces a single output (Y) from all the inputs (X_i) through the given equation (1). Term (f) present in equation (1) denotes the activation function, which deals with the sum of input

Table 5: Details of the 15 mix proportions used in the study.

Mix id	Phase	Cement: FA	Binder	FA	W/C	SP	SP (%)	Water content (%)
M1	Phase I	1 : 4	PPC	RS	0.60	×	×	×
M2					0.65	×	×	×
M3					0.70	×	×	×
M4	Phase II	1 : 4	PPC	MS	0.65	×	×	2.5
M5					0.70	×	×	5.0
M6					0.725	×	×	7.5
M7					0.75	×	×	10.0
M8	Phase III	1 : 4	PPC	MS	0.65	LS	0.50	×
M9					0.65	LS	0.60	×
M10					0.65	LS	0.70	×
M11					0.65	LS	0.80	×
M12	Phase IV	1 : 4	PPC	MS	0.65	SNF	0.20	×
M13					0.65	SNF	0.30	×
M14					0.65	SNF	0.40	×
M15					0.65	SNF	0.50	×

Table 6: Plasticity characteristics of 15 mortar mixes considered in the study.

Mix id	W/C ratio	Admixture	Flow table test remarks
M1	0.60	×	The mix was not workable and unsuitable for plastering
M2	0.65	×	Workable mix observed and suitable for plastering
M3	0.70	×	Workable with surface bleed and not suitable for plastering
M4	0.65	×	Mix was not workable and unsuitable for plastering works
M5	0.70	×	Mix was not workable and unsuitable for plastering works
M6	0.725	×	Workable mix observed and suitable for plastering
M7	0.75	×	Highly workable with surface bleed unsuitable for plastering
M8	0.50	0.5% LS	The mix was cohesive but not workable
M9	0.60	0.6% LS	The mix was cohesive but not workable
M10	0.70	0.7% LS	Cohesive and workable mix with a reasonable retention period
M11	0.80	0.8% LS	Initially, the surface bleed was observed and setting delayed
M12	0.65	0.2% SNF	A very harsh mix observed
M13	0.65	0.3% SNF	A harsh mix observed and unsuitable for plastering
M14	0.65	0.4% SNF	Segregation was observed and not suitable for plastering
M15	0.65	0.5% SNF	A rough mix was observed with bleeding and segregation

parameters acquired from the sum function and influences the output of the neuron. The term (H) represents the weighted sum of the input parameters, which can be derived from equation (2) and (b) is the bias coefficient to influence the function [36, 37].

$$Y = f(H) = \frac{1}{1 + e^{-H}}, \quad (1)$$

$$H = \sum_{i=1}^{n} X_i W_i + b. \quad (2)$$

The ANN framework consists of three distinct layers; hence, it is referred to as multilayer perception (MLP) framework [38]. The first layer is the input layer usually employed for feeding the network with data from outside. The second layer is either a hidden layer or computational layer that connects the input layer with the output layer and processes the data furnished through the input layer. The third component is the output layer, which is responsible for communicating the neural network's predictions in the form of output [39].

The slump flow and compressive strength characteristics of PPC mortars were significantly influenced by two critical factors, such as the W/C ratio and the percentage of chemical admixtures added (Ligno-based and SNF-based superplasticizers). The input layer contains two independent variables (different W/C ratios and various percentages of LS and SNF type chemical admixtures), and the output layer comprises two dependent variables, where ANN predicts the slump flow and compressive strength values. Figure 10 explains the pictorial representation of the process involved in the context of the flow chart explaining the step-by-step process involved in the neural network predictions.

In the present ANN framework, the input and output data sets were categorized into three groups: learning (60%), testing (20%), and validation (20%). Among the 15 experimental trial

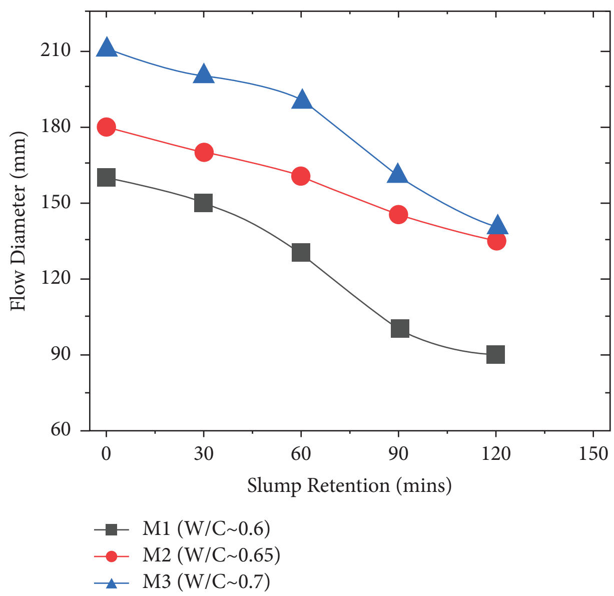

Figure 2: Flow properties of PPC mortars with varying W/C ratios.

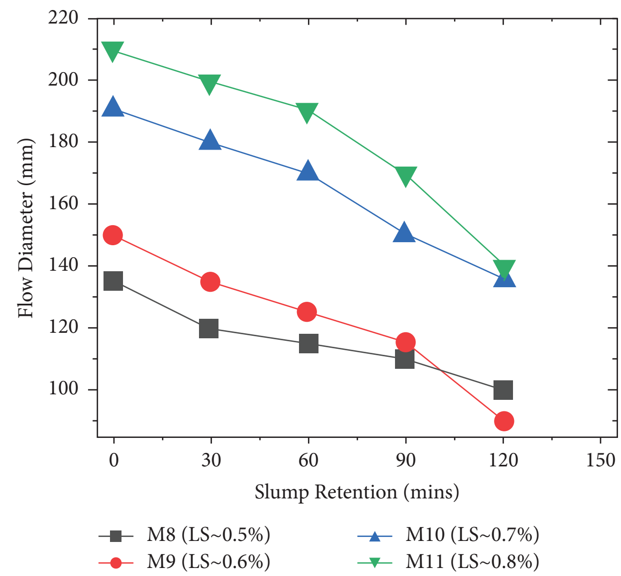

Figure 4: Flow behavior of PPC mortars with different percentages of LS admixture.

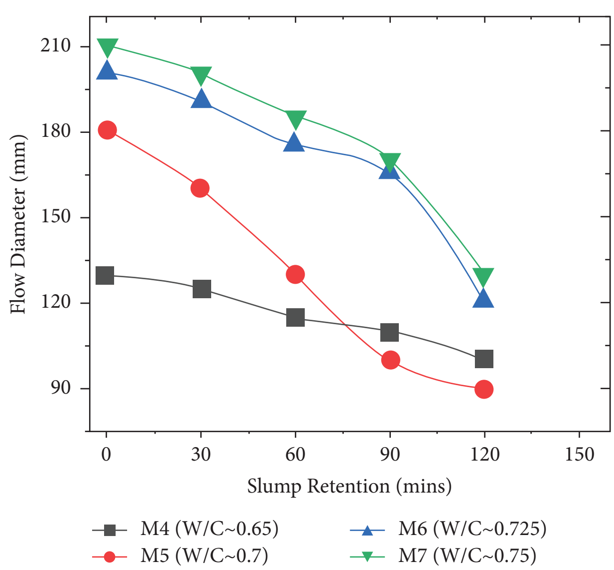

Figure 3: Flow characteristics of PPC mortars with different W/C ratios.

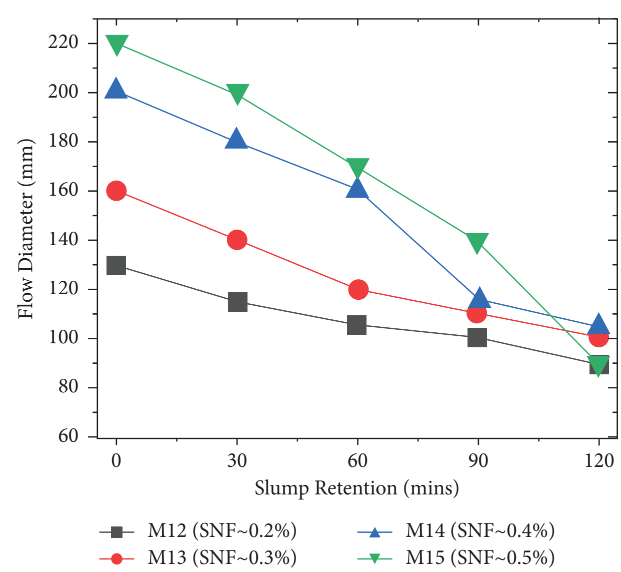

Figure 5: Flow behavior of PPC mortars with varying proportions of SNF admixtures.

results, 9 data sets were considered for the learning phase, 3 data sets for the testing phase, and 3 data sets for the validation phase. The maximum number of hidden layers and the amount of neurons embedded at every hidden layer of the neural network could be determined by performing a certain number of iterations during training, testing, and validation process until the expected results are achieved with limited error values. For the present work, the ANN framework (2-4-4-2) comprising two hidden layers with four neurons in each layer was developed in MATLAB R2018a to predict the slump flow at various periods between 0 minutes and 120 minutes and compressive strength development at the end of 1, 3, 7, 14, and 28days of PPC mortars using feed-forward backpropagation Levenberg-Marquardt algorithm as shown in Figure 11.

Table 7 provides information on the ranges of input and output parameters selected in the ANN database. Following the identification of the framework, the 2-4-4-2 ANN structure was used to implement newly generated learning data for both input and output data. The accuracy of the data obtained from the established neural network can be assessed using the following (3) for error prediction percentage [22].

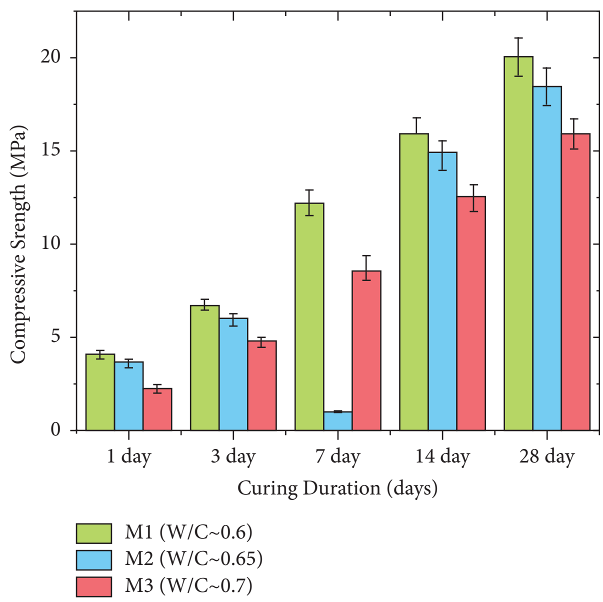

Figure 6: Compressive strength variation for PPC mortars prepared using river sand.

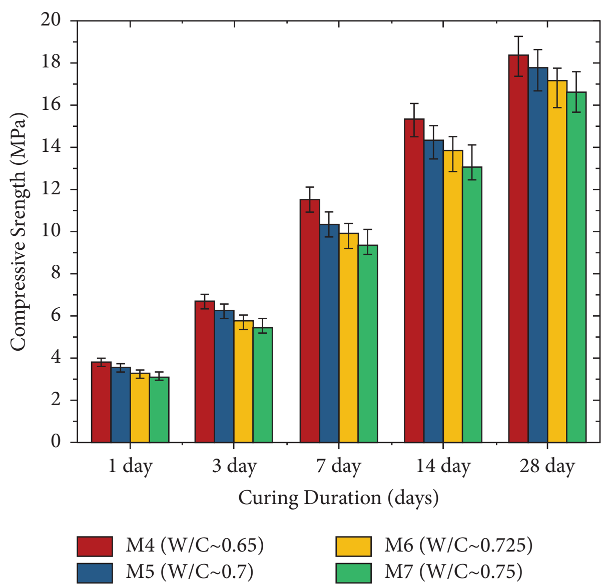

Figure 7: Compressive strength variation of PPC mortars with varying W/C ratios.

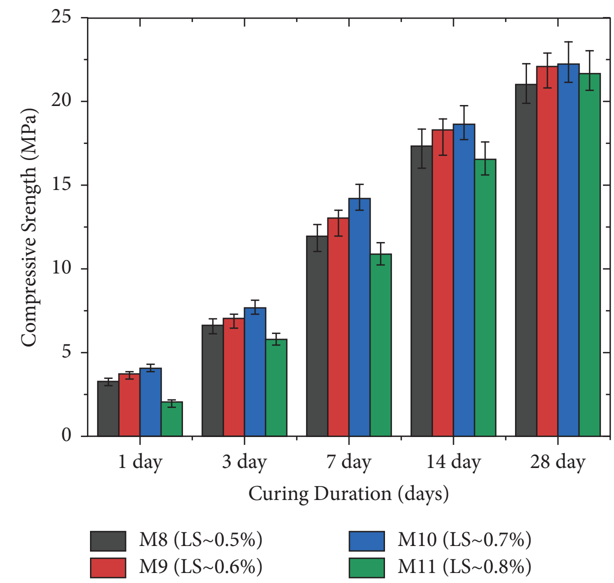

Figure 8: Compressive strength development for PPC mortars with varying LS admixtures.

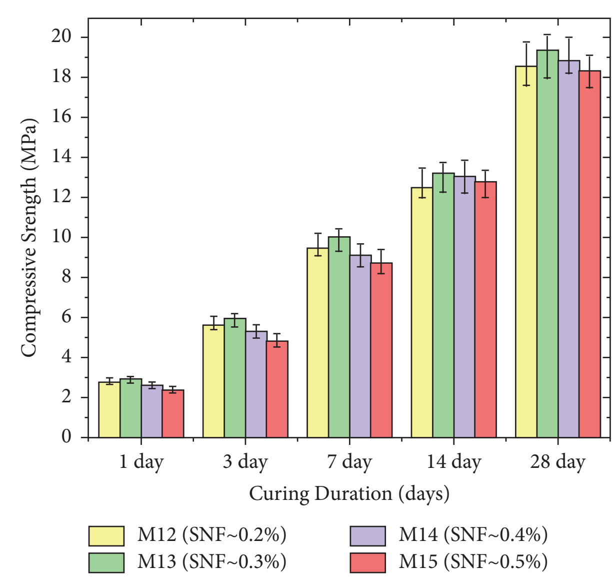

Figure 9: Variation of compressive strength with different percentages of SNF admixtures.

$$\text{Error Prediction}\,(\%) = \frac{\text{Experimental results} - \text{ANN results}}{\text{experimental results}} \times 100. \qquad (3)$$

The percentage error values of PPC-based mortars for the assumed mix proportions under the performance of slump flow (0, 30, 60, 90, and 120 mins) and compressive strength (1, 3, 7, 14, and 28 days) tests with varying proportions of W/C ratios and chemical admixtures are illustrated in Table 8. From Table 8, it can be inferred that the percentage of error values acquired from the ANN framework is marginal as it lies within 10%. The maximum percentage error values for the compressive strength at the end of 1, 3, 7, 14, and 28 days were obtained as 6.76%, 7.46%,

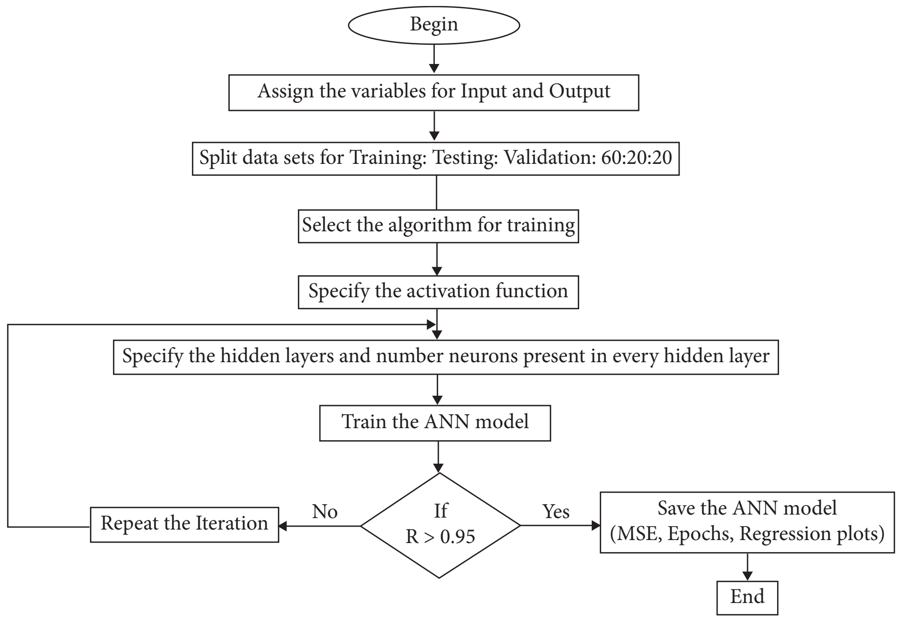

FIGURE 10: Steps involved in the neural network prediction system.

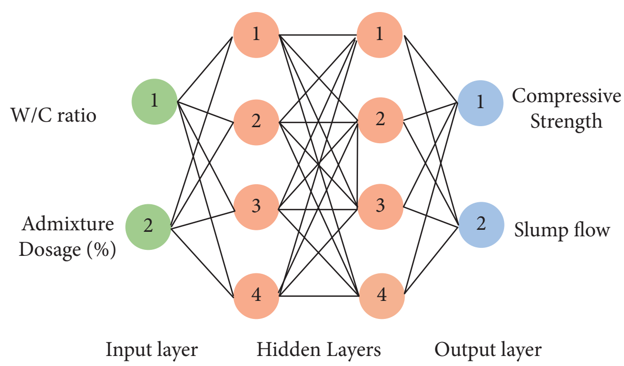

FIGURE 11: ANN framework (4-4-4-2) adopted for the present study.

TABLE 7: Input and target variables accessed in the ANN prediction system.

Variables	Range	Remarks
W/C ratio	0.6–0.75	Input variables
Ligno- and SNF-based admixtures (%)	0.2–0.8	
Slump flow (mm)	90–220	Target variables
Compressive strength (MPa)	2.1–22.4	

6.02%, 8.25%, and 5.39%, respectively. Similarly, the optimum error percentage results for the workability values during 0, 30, 60, 90, and 120 minutes were measured as 2.40%, 3.11%, 3.37%, 4.70%, and 6.23%, respectively.

Figure 12 compares the experimental and predicted compressive strength results of 15 mortar mixes at the end of 1, 3, 7, 14, and 28 days. Similarly, Figure 13 illustrates the comparison between experimental and predicted outcomes of slump flow characteristics for the considered mortar mixes at the end of different time intervals (0, 30, 60, 90, and 120 minutes). From Figures 12 and 13, it can be observed that the compressive strength and slump flow values of the fifteen PPC mortar mixes obtained from the ANN framework and experimental results are nearly equivalent.

For instance, the predictive performance of the compressive strength at the end of 28days obtained from the ANN framework is shown in Figure 14. The overall coefficient of correlation (R) for the 28 day compressive strength outcomes during training, validation, testing, and combination of three phases were recorded as 0.90014, 0.98814, 0.97206, and 0.91566, respectively, is depicted in Figure 14. Furthermore, Table 9 represents the R values for the target variables (compressive strength and workability values) incorporated in the ANN framework at the time of training, validation, testing, and the

Table 8: Percentage error values of the slump and compressive values from the ANN model.

Mix ID	Percentage of predicted error-values from the ANN framework									
	Compressive strength					Slump flow				
	1 day	3 day	7 day	14 day	28 day	0 min	30 min	60 min	90 min	120 min
M1	1.90	0.87	3.63	−5.90	3.17	−0.75	0.10	−0.80	1.51	−3.61
M2	−2.37	0.82	−4.43	−1.48	−0.48	−1.43	−0.73	0.66	0.50	−2.10
M3	0.48	−4.08	−2.05	8.25	−0.56	0.08	0.75	−1.08	−0.36	−0.77
M4	0.54	2.27	0.26	−4.03	−3.64	−1.22	−0.54	−1.10	−0.89	−1.57
M5	0.86	−0.49	6.02	−6.36	5.39	−1.15	−1.47	−0.81	−0.85	−0.23
M6	−1.56	1.03	−5.26	0.36	3.90	−2.13	1.98	−1.85	4.70	−3.78
M7	8.06	0.93	1.76	−2.80	−3.23	−2.38	−2.70	0.54	2.47	1.18
M8	0.61	−2.54	−3.88	−4.14	−1.71	1.96	2.02	−1.72	2.21	4.29
M9	6.76	0.87	3.23	4.15	−2.59	−1.59	3.06	1.17	3.07	2.61
M10	5.12	1.92	1.55	−2.38	−2.72	1.08	0.73	−1.51	3.12	1.31
M11	2.38	7.46	−5.86	5.71	1.11	2.40	0.88	−1.94	3.37	4.51
M12	−6.07	−2.68	−1.61	−3.31	0.70	−1.58	0.67	−1.29	−1.25	6.23
M13	1.72	1.02	−1.49	−4.06	2.19	2.49	−0.96	3.37	0.64	−2.24
M14	−4.23	−2.55	2.93	1.15	−1.75	−1.65	2.58	2.27	1.72	−1.29
M15	0.83	5.29	0.45	0.86	−2.02	−0.49	−3.11	−3.14	3.55	−5.56

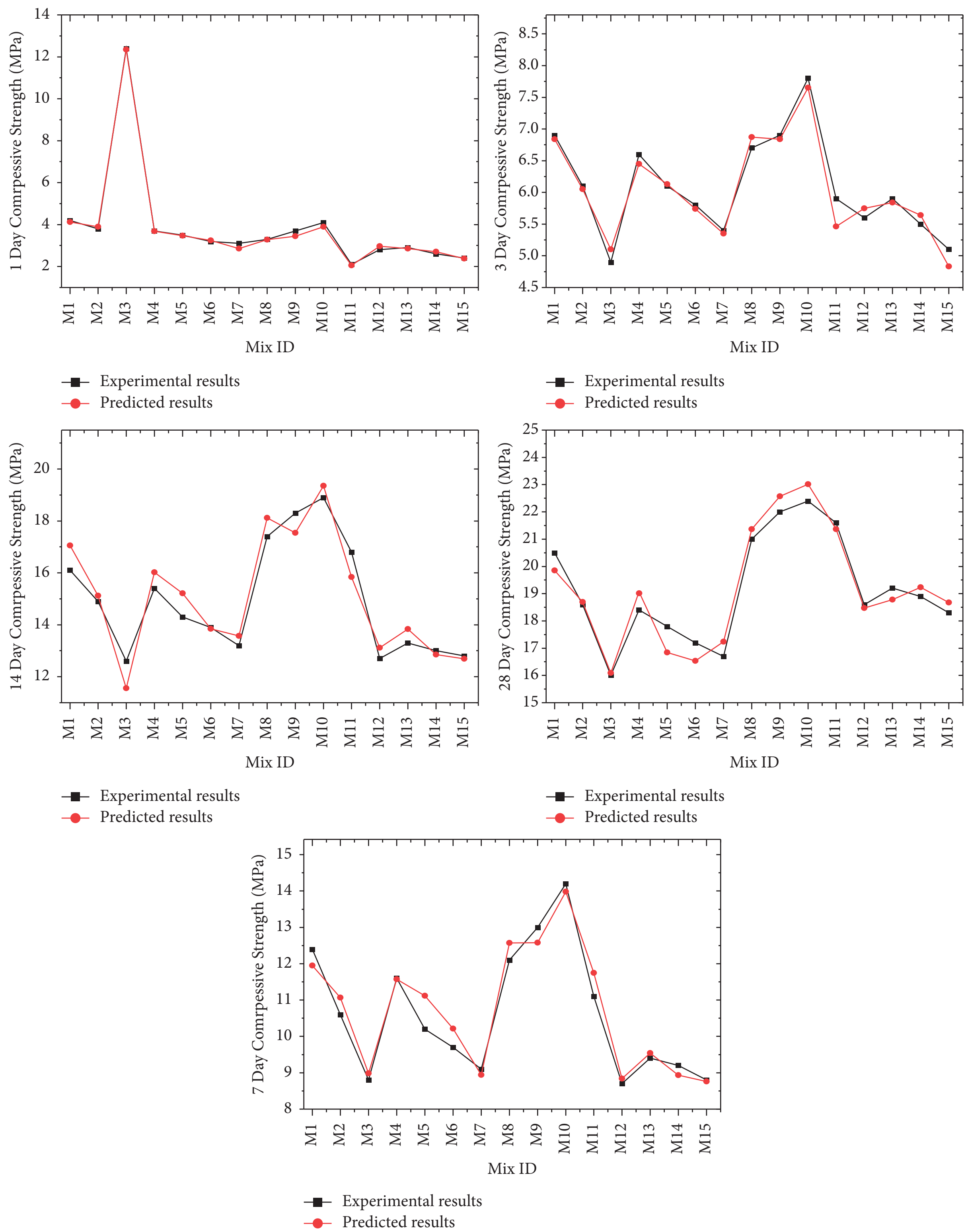

Figure 12: Comparison of actual and predicted compressive strength values at various ages.

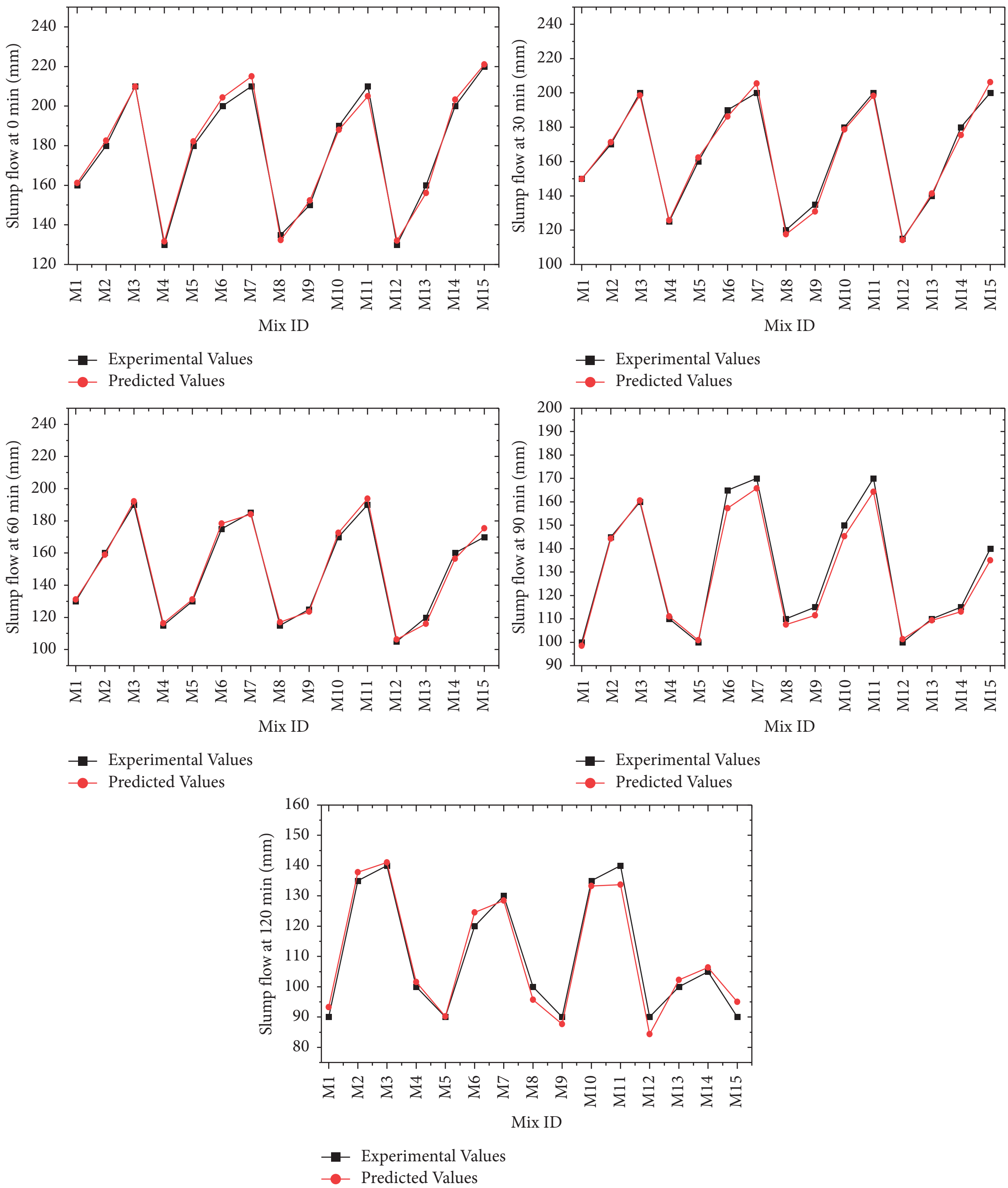

Figure 13: Comparison of actual and predicted slump values at various time intervals.

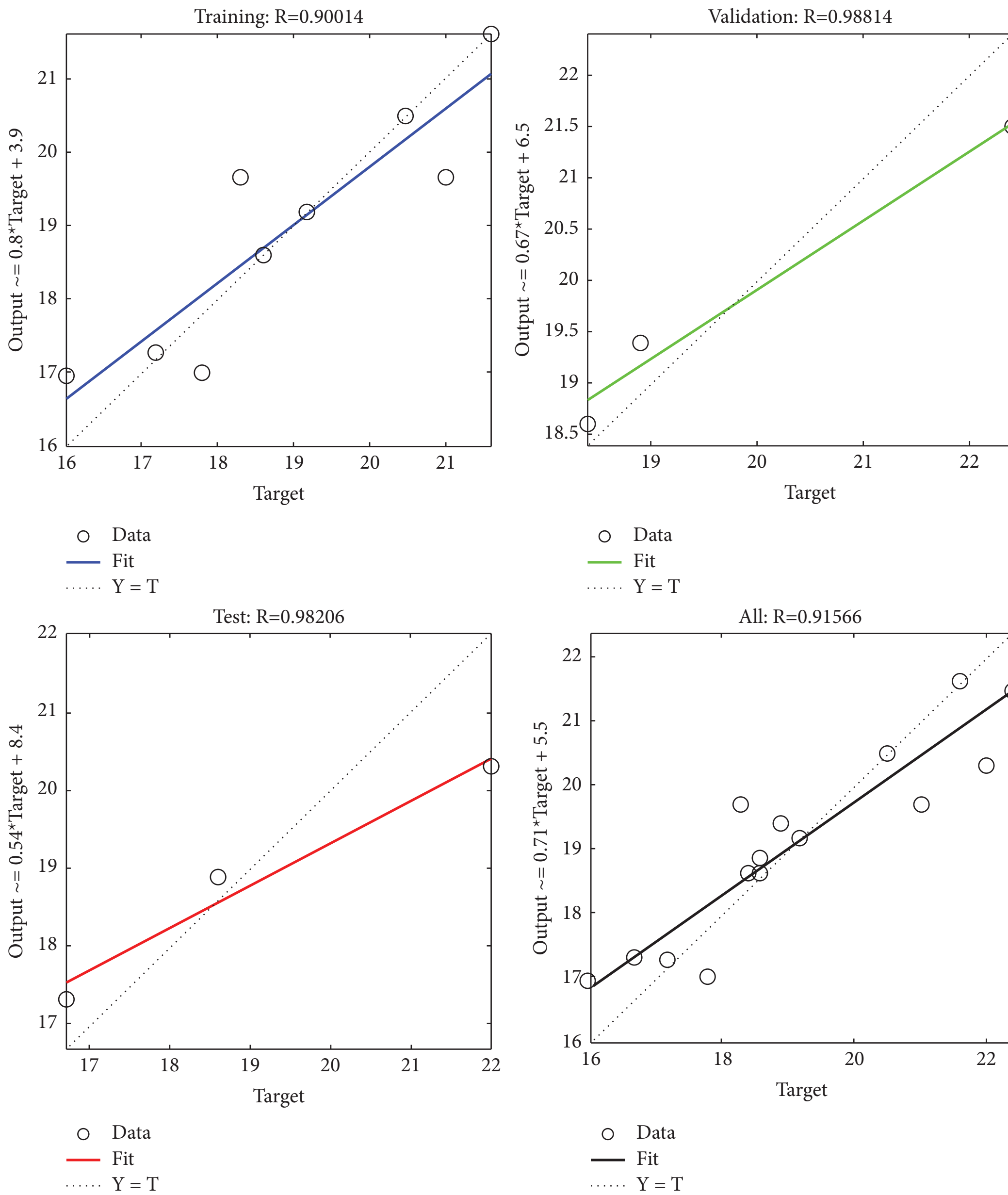

Figure 14: Prediction performance of the output variable (28th day compressive strength).

Table 9: Coefficient of correlation values of target variables.

Target variables	Training	Validation	Testing	Combination
Compressive strength at 1st day	0.98647	0.98514	0.93245	0.95632
Compressive strength at 3rd day	0.99235	0.98745	0.96210	0.97230
Compressive strength at 7th day	0.99412	0.98213	0.95021	0.95542
Compressive strength at 14th day	0.96520	0.96541	0.97854	0.94021
Compressive strength at 28th day	0.90014	0.98814	0.98206	0.91566
Slump flow at 0 min	0.91254	0.97654	0.96542	0.93654
Slump flow at 30 min	0.92541	0.96521	0.97541	0.96541
Slump flow at 60 min	0.93650	0.99754	0.96742	0.98785
Slump flow at 90 min	0.99851	0.98631	0.98745	0.99856
Slump flow at 120 min	0.94632	0.99883	0.98322	0.95120

association of the three levels. Table 9 shows that the *R* values greater than 0.9 for all the target values emphatically exhibit a significant association between recorded and prediction findings throughout all occurrences [22, 39]; the constructed ANN architecture, which has been implemented employing recorded values, predicted the expected outcomes effectively. This reflects the exceptional association among the actual results and ANN outcomes with less error values displayed in Figures 12 and 13.

According to the preceding statement, the ANN structure may be used to forecast the workability and compressive strength parameters of various mortar mixes produced PPC type mortars. Furthermore, the workability and compressive strength values calculated from experimental and predictive studies were constrained by different W/C ratios and the Percentage of chemical admixtures (LS and SNF-based) used in this study.

4. Conclusion

This work used different proportions of LS and SNF-based superplasticizers as water-reducing agents in PPC-based mortar mixes. The following conclusions are drawn based on the flow and compressive strength characteristics of PPC mortars.

(i) The optimum W/C ratio required to achieve the plasticity effect in PPC mortar using river sand without the inclusion of chemical admixtures was recorded as 0.65 for the M2 mix. Moreover, the maximum compressive strength was observed for M1 for all ages containing a 0.6 W/C ratio.

(ii) The plasticity effect on the PPC mortars containing M sand was achieved at a 0.725 W/C ratio with 7.5% extra water without any addition of superplasticizers compared to PPC-based mortars produced with river sand.

(iii) The PPC mortar mix M10 with a 0.65 W/C ratio and 0.7% of LS-based superplasticizer achieved workable plastering with a good retention period and demonstrated the highest compressive value of 22.4 MPa after 28days. M10 develops the highest compressive strength among all the mixture proportions at 28th day with satisfactory workability characteristics.

(iv) The addition of SNF-based chemical admixtures in PPC mortar mixes (M12 to M15) prepared using M sand had a negative effect on the flow characteristics. However, the maximum compressive strength results were observed for M13 at all ages.

(v) The ANN model constructed in this investigation was observed to be acceptable, estimating the workability and compressive strength characteristics of PPC mortar mixes.

Data Availability

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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