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Predicting Slump Values of Concrete Made by Pozzolans and Manufactured Sand using ANN

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***Abstract:** Large amounts of natural fine aggregate (NFA) and cement are used in building, which has major environmental consequences. This view of industrial waste can be used in part as an alternative to cement and part of the sand produced by the crusher as fine aggregate, similar to slag sand (GGBFS), fly ash, metacaolin, and silica fume. Many times, there are issues with the fresh characteristics of concrete when using alternative materials. The ANN tool is used in this paper to develop a Matlab software model that collapses concrete made with pozzolanic material and partially replaces natural fine aggregate (NFA) with manufactured sand (MS). Predict. The slump test was carried out in reference with I.S11991959, and the findings were used to create the artificial neural network (ANN) model. To mimic the formation, a total of 131 outcome values are employed, with 20% being used for model testing and 80% being used for model training. 25 enter the material properties to determine the concrete slump achieved by partially substituting pozzolan for cement and artificial sand (MS) for natural fine aggregate (NFA). According to studies, the workability of concrete is critically harmed as the amount of artificial sand replacing natural sand grows. The ANN model's results are extremely accurate, and they can forecast the slump of concrete prepared by partly substituting natural fine aggregate (NFA) and artificial sand (MS) with pozzolan.*

***Keywords:** Volcanic Ash Material, Artificial Sand, Slump, Artificial Neural Network. XRD*

I. INTRODUCTION

As the number of construction projects grows, natural sand springs are being used. This haphazard mining of riverbeds for natural sand has caused certain environmental issues. As a result, the usage of synthetic sand has become critical in order to preserve the environment and maintain a reasonable equilibrium.

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[1] The manufacture of massive amounts of cement necessitates a lot of energy, emits CO2, and generates a slew of other issues. As a result, researchers are working hard to identify the best cement substitutes, such as fly ash (FA), metakaolin, silica fume, and risk trays, which provide stronger products with superior cement qualities. [2] The manufactured sand, pozzolanic materials and sand are widely employed in a variety of large-scale applications. The ANN model is designed to produce accurate and rapid findings in order to reduce the time and expenses associated with experimental effort. [3] When compared to other typical regression processes, the ANN model is a well-constructed soft process that produces good results. [4]B. Boukhatem et al. found the use of Neural Networks (NN) and principal component analysis (PCA) in conjunction to forecast concrete qualities. According to the findings, PCA performs more accurately than NN. [5] Vinay Chandwaniet has researched the slump of ready-mix concrete and created an ANN model for slump prediction. According to the findings, the model can accurately predict RMC slump[6]. The neural network model was created by Ahmet O. et al. to estimate the sump and compressive strength of HSC. That neural network model capable of predicting the slump and compressive strength of HSC[7] is really well done. I-Cheng Yeh created two models to predict slump and found that the neural network model is more efficient than the second order regression model in predicting concrete slump[8]. The workability qualities of concrete produced with flies and metakolin were examined by Bai J. et al. The ANN model is effective in predicting the slump and veebe time of concrete containing fly ash and metakaolin, according to a study[9]. Ilker B. et al. investigated the experimental and prediction of ACC aggregate concrete characteristics. Using experimental and anticipated concrete properties, it was established that they are similar[10]. Bekir et al. investigated the characteristics of concrete manufactured from rubber waste. An artificial neural network (ANN) and a fuzzy logic model were created. The experimental and anticipated values are remarkably similar, according to the study[11]. Hosein N et al. have worked on predicting the strength of recycled aggregate concrete. The ANN model produces accurate findings, according to a study[12]. Marek S. investigated the properties of HPCs using three different models. Finely compares and assesses the viability of three models[13]. Keshavarz Z. investigated the prediction of concrete compressive strength using the ANFIS and ANN models, and came to the conclusion that the adaptive neuro fuzzy inference system (ANFIS) is more efficient than the ANN model in predicting concrete compressive strength[14].

The ability of concrete to work with a hint of slump is a highly important quality. Slump is directly related to the pumpability, consistency, flowability, and harshness of concrete. As a result, accurate slump prediction is required. ANN was used to determine the distracted workability metric, i.e. concrete slump, based on the findings of the previous study. The purpose of this study is to apply an artificial neural network method to forecast the slump of concrete prepared with various pozzolans and partially replaced natural fine aggregate (NFA) with manufactured sand (MS).

II.ARTIFICIAL NEURAL NETWORKS (ANN)

The evolution of an Artificial Neural Network (ANN) have three levels: one or more hidden layers ,an input layer and one output layer. Weights, biases, and the transfer function are used to link every hidden layer to the other layers. Observing the intended output values and entry values determines the inaccuracy. By observing the error function, the biases and weight are fine-tuned by an internal process called training to reduce the error. The model is skilled until it achieves the preferred accuracy. And the output values are confirmed using the trained model. [10]

III. DATA

M30 grade concrete was prepared by partially substituting cement with metakaolin, fly ash, silica fume, GGBFS, and natural fine aggregate (NFA) with manufactured sand (MS) in a range of 0 to 100% with a 10% gap, 0.45 water cement ratio, and 0.1 percent superplasticizer. Slump testing was performed in accordance with IS 1199-1959 recommendations. Figure 1 depicts [15,16].

Fig. 1 Slump test

Cement (C), manufactured sand (MS), coarse aggregate (C.A), natural fine aggregate (N.F.A), metakaolin (meta.), Fly ash (F.A), Silica fume (S.F.), GGBFS are the input parameters for the mix design. In all networks, the weights of input parameters were set to the same value; the range of these values is indicated in table 1. Fresh experimentation yielded a total of 131 values. [17,18]

Table1 Parameters for input and output

Sr. no.	Input parameter	Range of values	
		Minimum	Maximum
1	Cement content (C) kg/m³	337.77	422.22
2	Natural sand content (N.S) kg/ m³	0	612.21
3	Manufactured sand content(M.S.) kg/ m³	0	612.21
4	Course aggregate content (C.A.) kg/ m³	-	1258.21
5	Fly ash content (F.A.) kg/ m³	0	84.85
6	Silica fume content (S.F.) kg/ m³	0	84.85
7	GGBFS content kg/ m³	0	84.85
8	Metakaolin content (Meta.) kg/ m³	0	84.85
	Output parameters		
1	Slump (mm)	72	100

To forecast flexural strength, input data was communicated in a feed forward process with no cycle creation in three layers, and the model was trained until it had a very low error rate. The number of neurons in hidden layers was fixed using the trial and error method. The Levernberg-Marquaedt approach was utilised for training. And the values were kept between 0 and 1. Eighty percent of the values were trained, and the remaining twenty percent were validated. [9.10,] Instead of using a single experiment for each material combination, the neural network was trained using different (5 types) of combinations at a time as input data values, resulting in 25 input layer models as shown in Figure 3. The maximum number of hidden layers is set to 30, out of which the neural network consumes as needed, with a maximum of 10 hidden layers employed during the experiment. The collection of goal values, which represent genuine intended results in terms of practical experimentation values, must be accomplished in a maximum of 10,000 iterations, with a 1e-25 convergence target. The learning rate is 0.01 with step 0.01 as the network's and values, respectively. The network's whole configuration is set and may be understood from table 2. [8]

Table2 Parameters for configuring neural networks

Parameter	Configuration value
Input layers	25
Hidden layer	10
Output layer	1
Convergence	$1e^{-25}$
Learning rate (α)	0.01
Step size (μ)	0.01

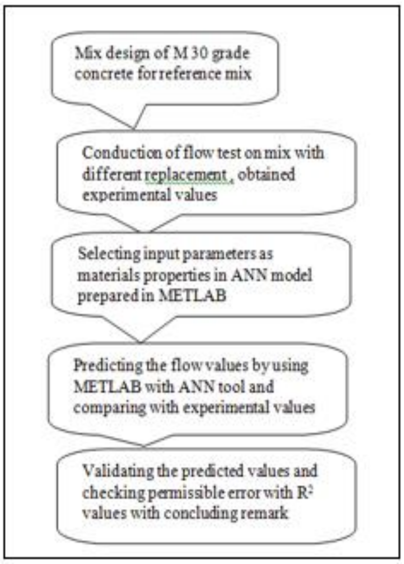

Fig. 2 Block diagram

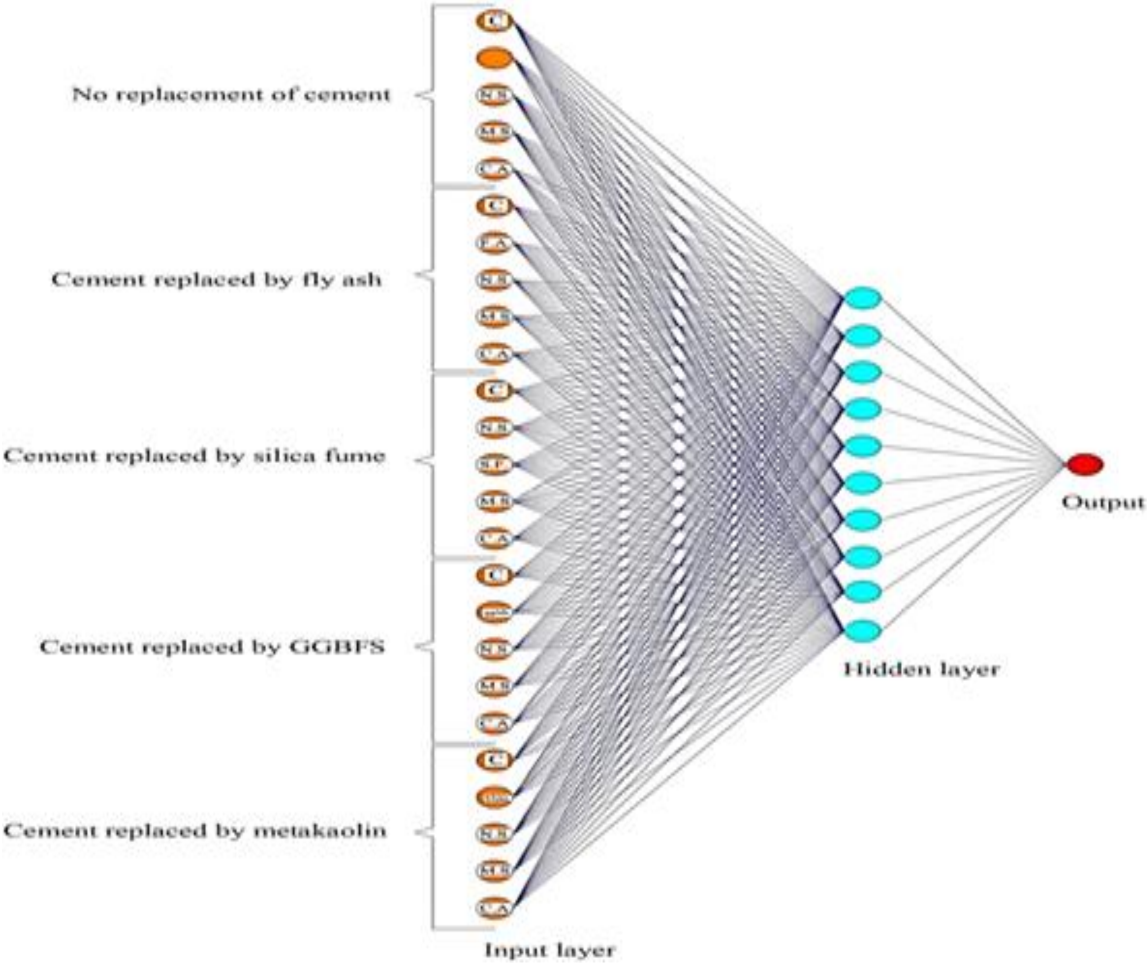

Fig. 3 Neural network

Table 3 Values of overall experimental and anticipated slump (mm)

The percentage of natural sand that is replaced by manufactured sand.	Slump (mm)									
	There will be no cement replacement.		20%Fly ash has taken the place of cement.		20%silicaf ume has taken the place of cement.		20% GGBFS has taken the place of cement.		20%metakaolin has taken the place of cement.	
	R^2 = 0.932		R^2 = 0.953		R^2 = 0.967		R^2 = 0.891		R^2 = 0.959	
	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted
0	100	103.01	98	98.12	98	97.02	98	98.29	99	99.82
10	95	97.84	96	96.61	95	95.13	94	94.28	96	96.13
20	94	97.09	95	95.08	94	94.59	94	94.3	95	95.69
30	90	92.7	93	93.87	92	92.27	93	95.79	94	94.59
40	85	84.31	85	84.92	92	91.92	92	91.19	92	91.92
50	85	86.95	85	85.78	88	88.11	90	90.21	89	89.01
60	84	84.83	85	85.59	82	82.17	88	88.87	84	84.83
70	80	79.19	82	81.92	80	80.08	82	81.51	82	81.54
80	80	82.39	80	80.74	78	78.72	82	84.46	82	82.76
90	75	77.24	76	76.07	76	76.09	80	80.23	78	78.72
100	75	74.17	76	75.39	74	73.24	74	72.65	72	71.87
	Max. variation = 3.19%		Max. variation = 0.92%		Max. variation = 0.92%		Max. variation = 2.91%		Max. variation = 0.98%	

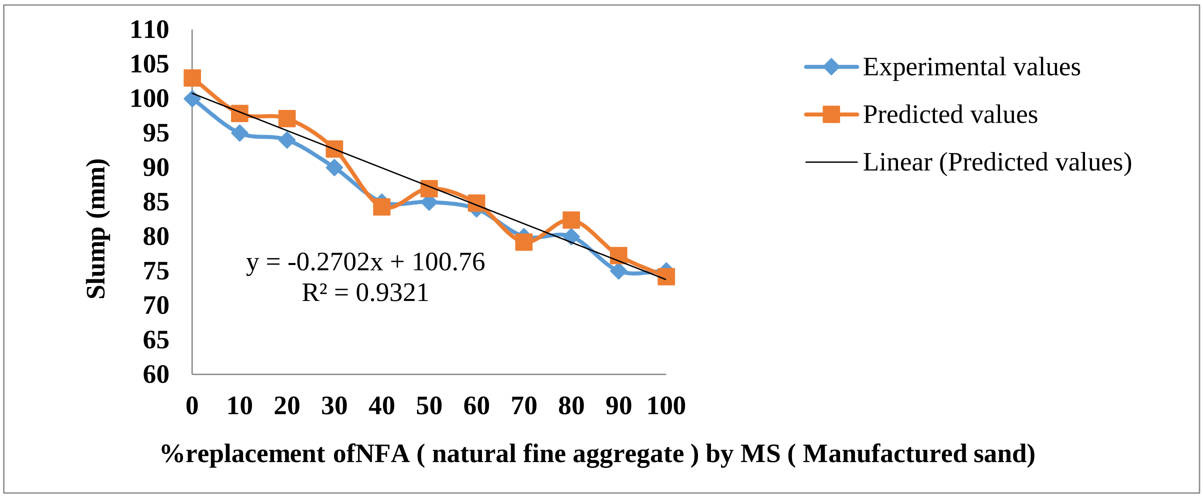

Fig. 4 Variation in experimental and anticipated slump when no pozzolans in cement.

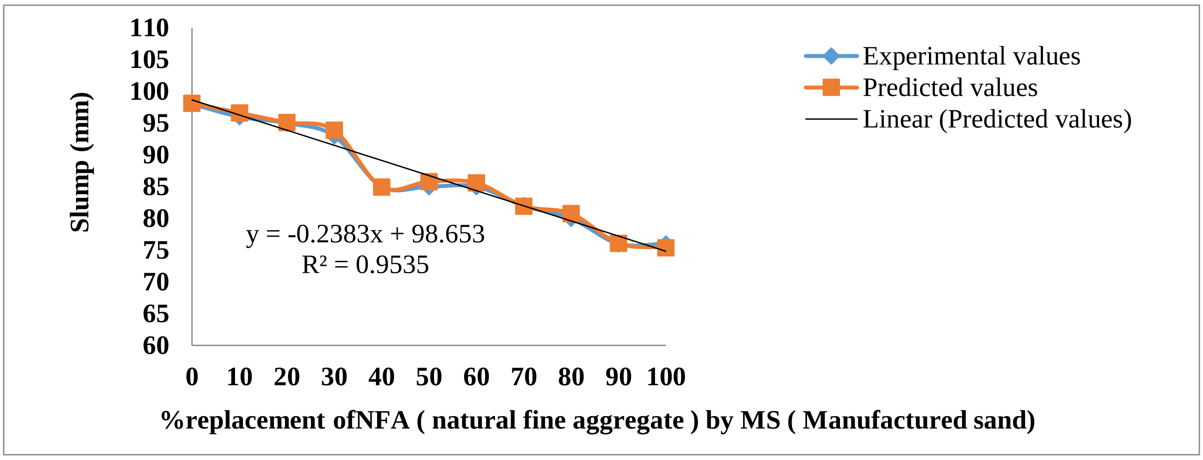

Fig. 5 Variation in experimental and anticipated slump when fly ash is used to partially replace cement.

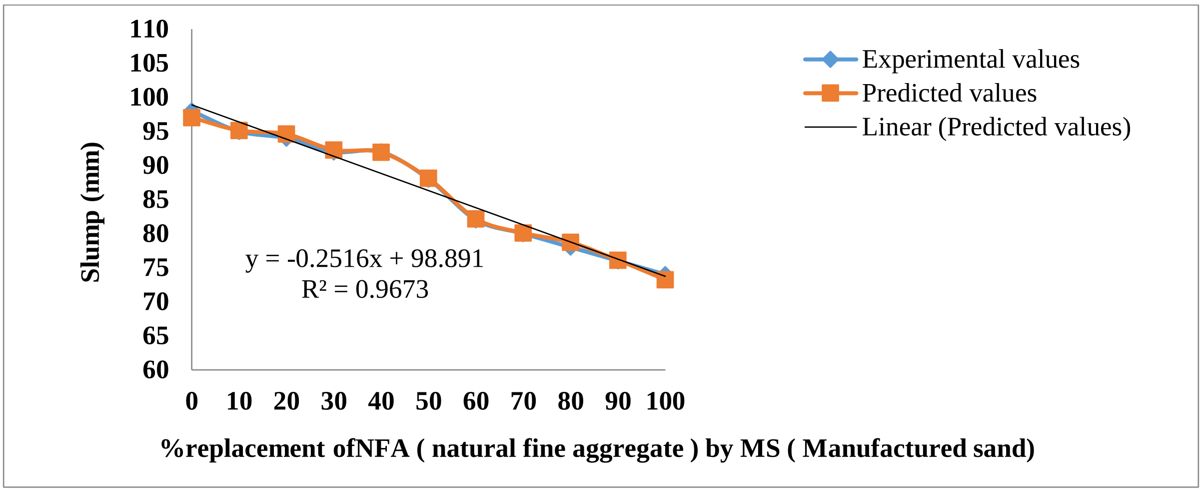

Fig.6 Variation in experimental and anticipated slump when silica fume is used to partially replace cement.

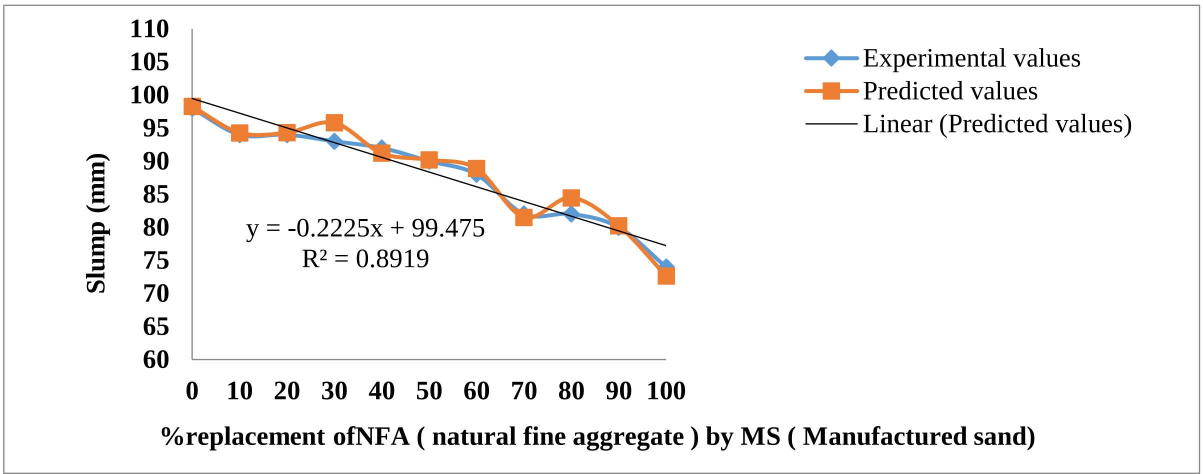

Fig.7 Variation in experimental and anticipated slump when GGBFS is used to partially replace cement.

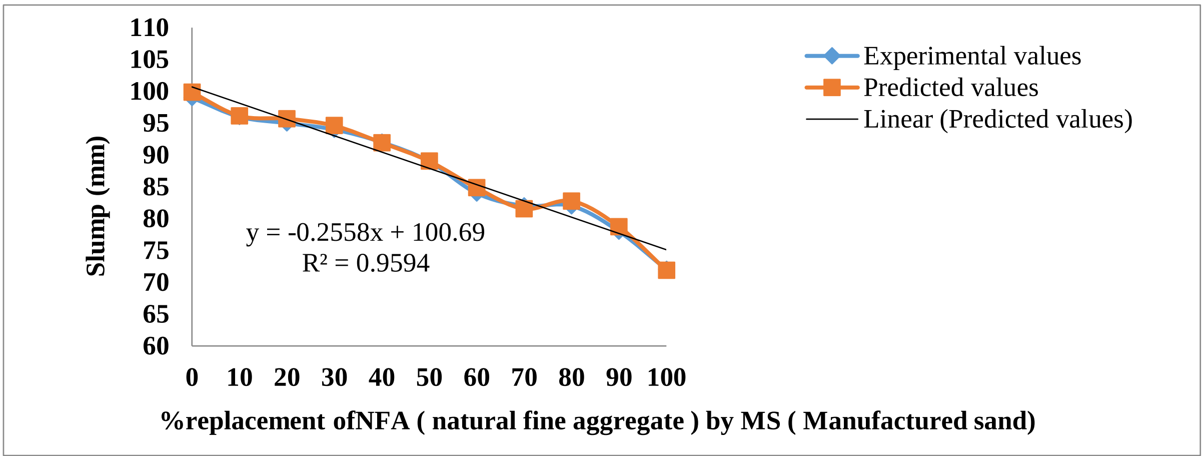

Fig.8 Variation in experimental and anticipated slump when metakaolin is used to partially replace cement.

IV.X-RAY DIFRACTION (XRD) ANALYSIS

X-ray difraction is a nondestructive technique for identifying different phases in hardened concrete. The difraction angle was set to 2. Figure 9 shows the comparable X-ray difraction pattern. The difraction peak intensity of the reference concrete specimen constructed with 60% manufactured sand and no pozzolanic ingredients was found to be higher. In comparison to reference concrete, difraction peak intensity is clearly lower for 60 percent replacement of natural sand by synthetic sand and partly cement replacement by silica fume [22]. According to a structural investigation, the peak intensity drops from reference concrete to concrete constructed with manufactured sand replacing 60 percent of natural sand and cement partially replaced with silica fume. Due to the peak of 27° (JCPDS), it was obvious that the predominant component in the sample is silica content, and all of the samples are crystalline in form [23].

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V.RESULTS AND DISCUSSION

Table 3 shows the workability obtained from slump testing with various percentages of natural fine aggregate (NFA) replaced by manufactured sand (MS) and 20 percent cement replaced by various pozzolanic materials, as well as the variation in slump degree illustrated in figures 4 to 8. Following the test results, the fraction of natural fine aggregate (NFA) replaced by manufactured sand (MS) was increased, resulting in a fall in slum value. The angular shape and rough surfaces of produced sand particles cause a reduction in workability by imparting increased inner friction and so lowering the flow properties of concrete

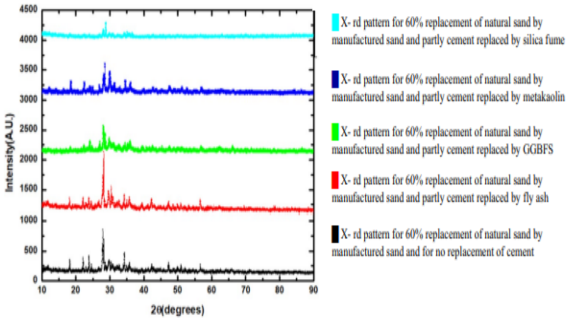

Fig. 9 Comparative X Ray diffraction pattern

As a result, it's reasonable to argue that workability suffers as the amount of natural sand replaced by synthetic sand rises. [16] Table 3 shows the experimental and anticipated slump values for NFA (natural fine aggregate) replacement with MS (manufactured sand) and partly cement substitution with GGBFS, silica fume, fly ash, and metakaolin in concrete. Figures 4,5,6,7, and 8 exhibit a graphical representation of experimental and projected slump values. The slump values generated from the model and the experimental values are found to be fairly similar. For this model, the percentage variance did not exceed 3.19 percent for a combination without pozzolans. 0.92 percent for cement that has been partially replaced by fly ash. There is an allowable variance of 0.92 percent for cement partly replaced with silica fume, 2.91 percent for cement partly replaced with GGBFS, and 0.98 percent for cement partly replaced with metakaolin. It's also worth noting that the coefficient of correlation values range from +1 to -1. A +1 corresponds to the right positive correlation, whereas a -1 corresponds to the fit's negative correlation. [19,20]. In table 3, the R values are shown.The R square for no replacement is 0.932, 0.953 for cement partly replaced with fly ash, 0.967 for cement partly replaced with silica fume, 0.891 for cement partly replaced with GGBFS, and 0.959 for cement partly replaced with metakaolin, all of which are acceptable. The R^2 number indicates that the obtained values from the model and the experimental values have a close relationship. When it comes to R values, the model performs well in all of the figures. The results of constructing an artificial neural network show that the target and output values are in good agreement. As a result, the slump of concrete may be predicted reliably and easily using an ANN model. [21].

VI. CONCLUSIONS

- Workability decreases as the percentage of NFA (natural fine aggregate) replaced by MS (manufactured sand) increases.
- The model is successful in forecasting the slump of concrete. The model's maximum percentage of error is acceptable when tested using input parameters.
- The developed ANN model predicts quick workability of pozzolans and manufactured sand concrete in terms of slump in a very short period.
- As a result, the ANN model is capable of predicting a slump.
- The ANN model was created with the goal of being able to forecast concrete slump values.

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