Influence of supplementary cementitious materials in the concrete's compressive strength through artificial neural network

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Abstract. Supplementary cementitious materials have been proven to be effective partial cement replacements in concrete to reduce greenhouse gas emissions from the use of ordinary Portland cement. In this study, artificial neural network was used to arrive at a predictive model to assess their effects in the compressive strength of concrete. Collection of 991 datasets from published literatures was done for the development of the best network model with acceptable root mean square error for both training and testing datasets. The supplementary cementitious materials were ranked accordingly using the improved stepwise method and network simulation. From the results, ground granulated blast-furnace slag with 15% cement replacement and silica fume with 30% cement replacement contributed to the highest increase in compressive strength.

1 Introduction

Concrete is used with a utilization rate of three tons per person per year [1]. The common ingredients of concrete are cement, water, coarse aggregates, fine aggregates, and admixtures. The production of ordinary Portland cement (OPC) causes substantial pollutants on air contamination and solid waste. Additionally, the production of OPC accounts to approximately 8% of greenhouse gas emissions globally [2]. Thus, alternative materials must be explored as substitute to cement. To replace cement, the use Supplementary Cementitious Materials (SCM) are introduced. These are pozzolans that possess minimal or no cementitious properties but can act as binder in the presence of water [3]. Some SCMs were found to be abundant or by-products possessing either artificial or natural pozzolans [4]. Two primary forms are hydration and chemical reactivities to provide substantial effect in concrete. Common SCMs like coal fly ash (CFA), rice husk ash (RHA), silica fume (SF), sugarcane bagasse ash (SCB), coal bottom ash (CBA), and ground granulated blast furnace slag (GGBFS) are used for machine learning, specifically Artificial Neural Network (ANN). Machine learnings methods like ANN, are methodologies that can be developed to arrive at acceptable predictive models [5]. The two types of ANN are: unsupervised and supervised learning. Supervised learning is used to develop predictive models from inputs to outputs [6]

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while unsupervised learning finds similarities of the inputs without the outputs. In this study, supervised ANN is considered.

This paper investigated the complex and nonlinear behavior of combined SCMs to arrive at an optimum balance on the use of SCM resources. The outline of the paper are as follows: Section 2 presents the materials and methods from data gathering to ranking; Section 3 are the results and discussions, best model, ranking using the improved stepwise method (ISM), and model simulation to warrant soundness of the best ANN model; and Section 4 summarizes the conclusions and recommendations.

2 Materials and methods

Fig. 1 shows the research design from data gathering collected from published literatures, data processing in the normalization of datasets, data analysis on the use of ANN modelling procedures, and data ranking using ISM.

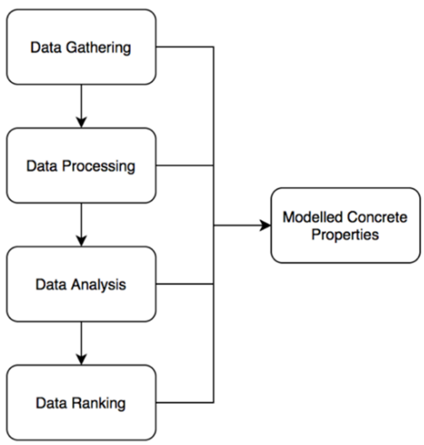

Fig. 1. Research design.

Table 1 is a summary of data collected from literature, indicating the references, number of datasets, and type of SCMs. The total number of datasets initially was 1,130 and then reduced to 991 after data processing, i.e., eliminating the outliers to be included in the ANN modeling. Table 2 shows the number of data, mean, minimum and maximum values, and standard deviation of the 991 datasets.

Data analysis using supervised learning through back propagation ANN was used. The software used was MATLAB R2020b with Statistics and Machine Learning Toolbox™. It consists of three datasets randomly divided to 70% training, 15% testing, and 15% validation datasets. The activation function used was sigmoid function. Sigmoid function is a logistic function with results ranging from zero to one. Normalization of the datasets prior to training is suggested to achieve the best performance [59]. The 13 inputs are: cement, RHA, GGBFS, CFA, SCB, SF, CBA, water, SCM chemical properties, sand, gravel, curing time, and admixture, while the output is the compressive strength (CS) of concrete. The best ANN model is selected based on the root mean square error (RMSE). Ideally, an RMSE close to zero is desired, which indicates that the predicted value using the model is close to the actual value. Thirteen input nodes were used: cement, RHA, GGBFS, CFA, SCB, SF, CBA, water, SCM chemical properties, sand, gravel, curing time, and admixture, with units shown in Table 2. The chemical properties were defined as the summation of SiO_2, Al_2O_3, Fe_2O_3 as per ASTM C618 for SCMs.

Table 1. Summary of data from published literature.

References	Number of data	SCM used	References	Number of data	SCM used
[7]	6	CBA	[35]	8	RHA
[8]	56	CFA	[35]	6	CFA
[9]	8	RHA	[36]	9	RHA
[10]	30	RHA	[37]	56	RHA
[11]	8	SCBA	[38]	16	RHA
[12]	12	SCBA	[39]	10	SF
[13]	24	CFA	[40]	23	RHA
[14]	12	CBA	[41]	8	RHA
[15]	6	CFA	[42]	40	RHA
[16]	27	RHA	[43]	12	RHA
[17]	38	RHA	[44]	24	SF
[18]	8	CFA	[45]	8	GGBFS
[19]	35	CBA	[45]	8	CFA
[20]	16	CBA	[45]	4	GGBFS
[21]	27	RHA	[46]	21	SF
[22]	5	RHA	[47]	4	CBA
[23]	28	SF	[48]	36	CFA
[24]	13	CFA	[49]	18	CBA
[25]	10	SF	[50]	66	RHA
[26]	26	RHA	[51]	3	CFA
[27]	5	CFA	[52]	2	CBA
[28]	10	CBA	[52]	56	SF
[29]	20	RHA	[53]	36	RHA
[30]	42	CFA	[54]	10	CFA
[31]	3	RHA	[55]	28	RHA
[32]	2	RHA	[56]	60	RHA
[33]	21	RHA	[57]	9	RHA
[34]	6	RHA	[58]	6	CBA
[34]	3	SF			

Table 2. Descriptive statistics of the 991 datasets.

Properties	Number of data	Mean	Std. Dev	Max.	Min.
Cement content (kg/m^3)	991	376.3	90.92	783	31
RHA content (kg/ m^3)	455	36.7	49.66	230	0
GGBFS content (kg/ m^3)	15	3.7	31.48	340	0
CFA content (kg/ m^3)	215	20.0	44.70	200	0
SCB content (kg/ m^3)	11	0.5	5.77	100	0
SF content (kg/ m^3)	108	7.0	21.88	102.8	0
CBA content (kg/ m^3)	75	9.4	42.21	562	0
Water content (kg/ m^3)	991	191.6	36.91	300.5	100
Sand (kg/ m^3)	989	687.0	175.00	1293	0
Gravel (kg/ m^3)	991	1051.0	235.09	1600	436
Curing Time (Days)	991	43.6	60.79	400	1
Admixture (kg/ m^3)	552	5.3	15.51	142.8	0
Compressive Strength (MPa)	979	35.9	21.21	106.88	0

A process of conducting sensitivity analysis for data ranking using ISM for the same developed network was proposed [60]. Each input is blocked, with a value equal to zero individually to locate the variable causing the largest error. Fig. 2 describes the process. Row "A" in the figure is when all inputs are turned to zero with the highest error being considered. Once the largest error is achieved, the values are converted to its mean. This is repeated as seen in rows "B" and "C" in the figure until all input nodes are converted to its mean. The order in which the variables are converted to its mean is the ranking influence where the first one is the most influential.

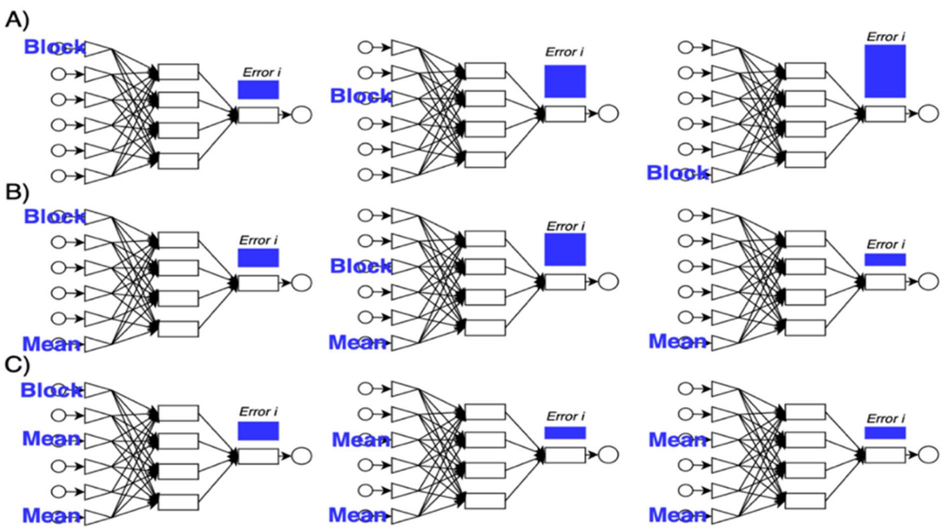

Fig. 2. ISM process.

3 Results and discussion

Data analysis on correlation was made using Python and Jupyter to investigate the collinearity of independent variables to the dependent variable. Fig. 3 shows the collinearity plot using the 991 datasets. The highest collinearity is seen in the cement and SF. This indicated that increasing the contents of the said constituents can increase the compressive strength.

Fig. 4 shows the result of the RMSE for both training and testing data with varying hidden nodes from 1 to 20. It showed that 8 hidden neurons performed best with the lowest RMSE in training followed by the lowest RMSE during validation. The best ANN network of 13 inputs – 8 hidden nodes – 1 output is shown in Fig. 5 with its normalized value of actual compared to predicted values shown in Fig. 6.

https://doi.org/10.1051/e3sconf/202234702004

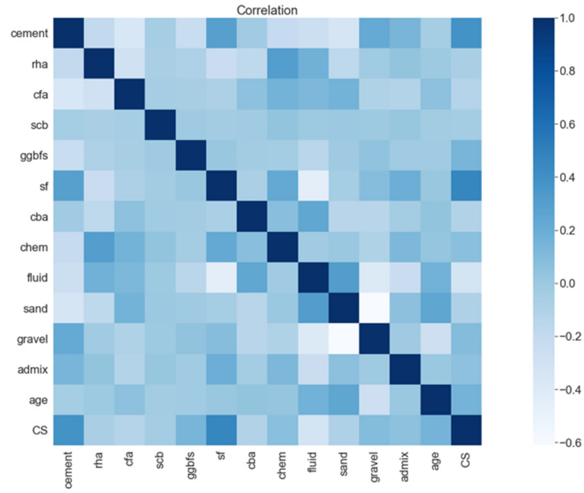

Fig. 3. Collinearity Plot of Compressive Strength Dataset.

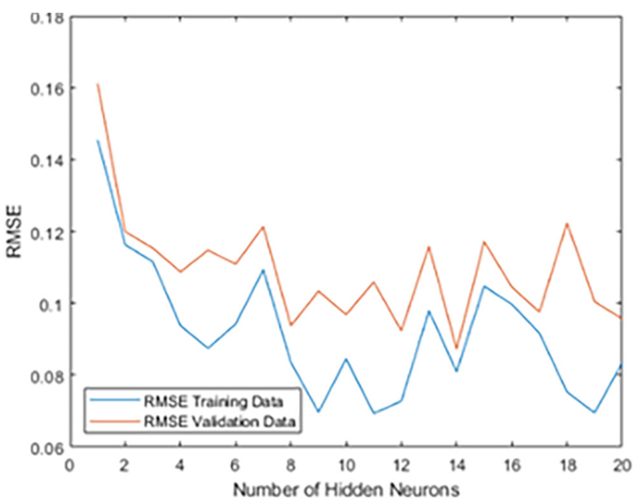

Fig. 4. RMSE Training and Validation Data with varying number of hidden nodes.

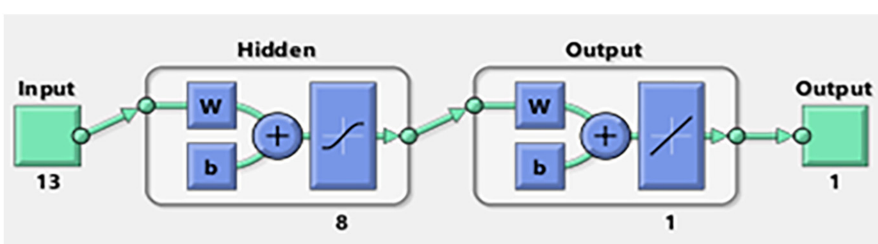

Fig. 5. Best ANN model 13 inputs – 8 hidden – 1 output.

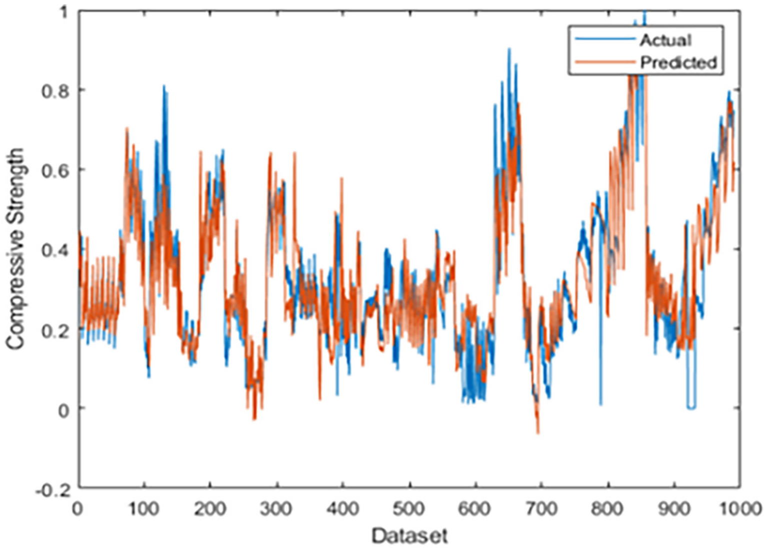

Fig. 6. Actual vs predicted values of normalized compressive strength using the best ANN model.

Using ISM, the ranking of SCMs were determined as shown in Table 3. It showed that SF ranked the first followed by GGBFS. The addition of SF alone decreases compressive strength due to its low content of tricalcium aluminate. However, when SF is mixed with other SCMs, it resulted to favorable results [44]. Simulation was conducted to investigate the combined SCMs interaction with CS of concrete. This was done by making all input parameters as the mean value except for the one parameter that is being investigated. The result of the simulation is shown in Fig. 7. The RMSE of the simulation of the chosen model was 0.1183. It showed that the GGBFS had the highest positive contribution to CS at 15% replacement and had adverse effect afterwards. The replacement of cement using SF was linearly increasing.

Table 3. Sensitivity analysis rankings for compressive strength.

ISM RANK	SCMs
1	SF
2	GGBFS
3	RHA
4	SCB
5	CBA
6	CFA

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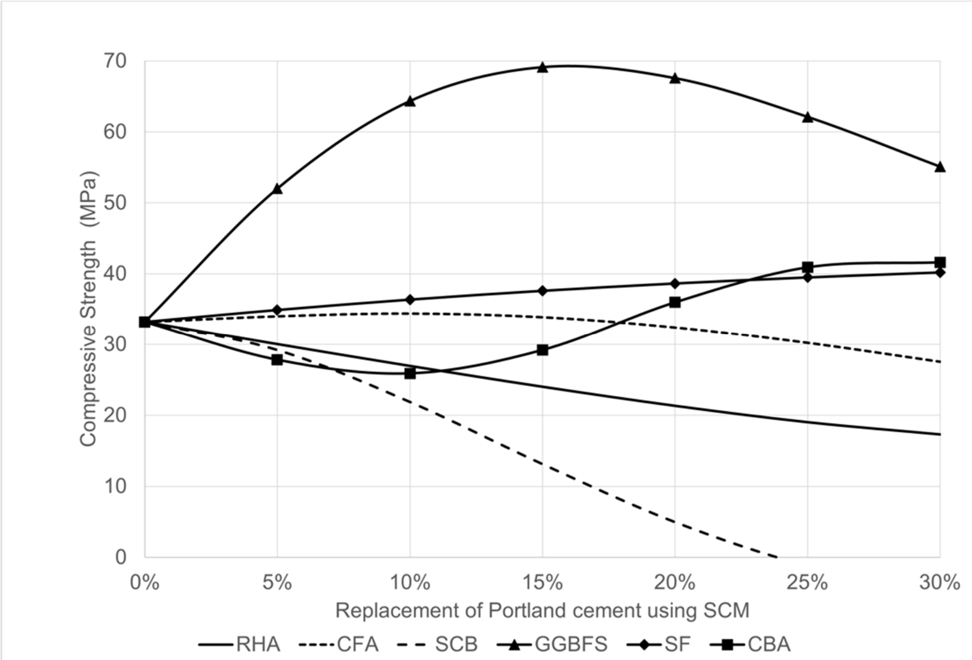

Fig. 7. Concrete's Compressive Strength with varying SCMs.

4 Conclusions and recommendations

The use of SCMs in the construction industry must be encouraged to address the environmental effects brought about by the productions of OPC. With the combination of possible SCMs in concrete, complex and nonlinear relationships were encountered in this study. ANN was used as a machine learning tool, utilizing 991 datasets to arrive at the best predictive model for the compressive strength of concrete. The best network architecture contains 13 inputs – 8 hidden nodes – 1 output. The 13 inputs are cement, RHA, GGBFS, CFA, SCB, SF, CBA, water, SCM chemical properties, sand, gravel, curing time, and admixture, while the output is the compressive strength of concrete. Ranking of SCMs influence was done using ISM to determine the SCMs with the greatest influence. In addition, simulation was done to further investigate the behavior of each SCM to the compressive strength of the concrete. Results showed that the SCMs which contributed to the highest increase of compressive strength in concrete was GGBFS and SF with a replacement of 15% and 30%, that can achieve more than 100% and 18% increase in compressive strength, respectively. Further investigation on the complex interaction of SCMs with each other, additional datasets, and comprehensive understanding of the chemical reactions in the constituents towards concrete properties is recommended.

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