Prediction of Concrete Strength Using Microwave Based Accelerated Curing Parameters by Neural Network

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***Abstract*—Prediction of compressive strength of concrete is very useful for economic constructions. The compressive strength can be estimated after 28 days of casting the specimen cubes or may be predicted based on the quantum and quality of ingredients used in making the concrete. When the first one requires a 28-day time, the second one does have problem of accuracy. Hence, a hybrid model is proposed in which the concrete cube is cured using the microwave based accelerated curing procedure and the early strength is used to predict the 28-day strength. Feed-forward neural network model was used to predict compressive strength of the concrete after the microwave curing to ascertain the predictability of neural network models. The results indicate that the neural network models have a good scope for further study and implementations.**

Keyword- Accelerated curing of concrete, microwave curing, neural network

I. Introduction

The strength estimated on the 28-day is used as an important strength characteristics to evaluate. However, it requires waiting period of 28 days which is not convenient in many cases and hence a precise concrete mix design is not possible. Any corrective measure after 28 days is not preferable as is very difficult, costly and time consuming. If the waiting time reduced it will be economically good as optimal mix is possible. Three different types of models can be contemplated to estimate the concrete strength as follows. (1) Using only the physical and chemical properties of varies ingredients of the concrete, the strength may be estimated. (2) As in the conventional practice, a compression test can be performed after moulding a cube and 28-day curing. (3) A hybrid procedure in which, the cube can be moulded, cured for a shorter duration and early strength is estimated using a compression testing and the early strength is to predict the 28-day strength. The first method may be too approximate as (a) estimating the physical and chemical properties are precisely, (b) identifying the properties which influence the strength and (c) the identifying the inter-relationship among these properties in influencing the strength are difficult. Obviously the second method requires more time. Hence, the hybrid method is preferred and being explored by many researchers.

The concrete usually gets about 90% of its strength in about 28 days in ambient atmospheric conditions. When the concrete is not yet attained sufficient strength, fast drying and shrinkage due loss of water results in the development of tensile stresses and thus causes formation of shrinkage cracks. Thus, concrete is kept damp during the curing process. Usually the hydration process is faster at higher temperatures. When the hydration process is faster, the concrete gains the strength faster. However, if the water in the concrete is evaporated due to higher temperature, it will build vapour pressure inside the concrete and will lead to cracks when water vapour escapes from the concrete. Ultimately, the strength of the concrete will get affected due to overheating. Hence, the temperature of curing should be well below the water evaporation temperature. This method by which high early strength is achieved in concrete is called accelerated curing. The accelerated curing techniques are useful in the prefabrication industry, which enables the removal of the reusable formwork earlier which makes business economical. Further, the accelerated curing is useful in special situations like repairing a busy road bridge where the detouring time can be minimized to a great extent by accelerated curing. There are many methods of accelerated curing being practiced. Some of the methods are (1) steam curing at atmospheric pressure, (2) warm water curing, (3) curing in boiling water and (4) autoclaving. Tokyay [1] attempted to find regression relationships for predicting compressive strengths at 7, 28, and 90 days using early strength attained by different accelerated curing methods.

II. Thermal Curing With Microwave Radiation

The usual thermal curing in cement mortar or concrete is due to the application of conductive heat through the surface of the material either in steam, hot-water bath or in autoclaves. Accelerated curing using boiling water or warm water has been investigated and standard codes are available [2], [3]. In conduction, the heat is transferred from water or steam or air to the exterior surface of the cement or concrete block. Due to conduction, a temperature gradient exists in the concrete between surface and central core and this non-uniform heating may cause stress. However, this can be avoided if radiation is used for heating. Microwave heating is due to radiation and further internal energy dissipation associated with the excitation of molecular dipoles in an electromagnetic field causes the heating. Compared to conductive heating, microwave heating is more uniform, that is, the surface and inner core both exist at the same temperature. Since the heating is uniform, a lesser heating duration may also be sufficient.

Materials which have a small but finite electrical conductivity are called dielectric materials. When these dielectric materials are placed in a high frequency electric field, they absorb energy. Consequently, electrically dipole polarization and conduction is generated within dielectric materials, which are composed of polar molecules with positive and negative poles. These orderly dispersed polar molecules vibrate instantaneously and violently in correspondence to the alternative high frequency electric field of microwaves. The friction generated to overcome the resistance of molecular attraction and motion results in the increase of temperature of the material.

The use of microwave energy for curing of concrete or cement mortar has been investigated by few researchers in the last 20 years [4]. However, there have been relatively few new innovations in rapid heat curing technologies over the last few decades [5]. Wu et al [6] and Hutchison et al [7] studied mortar specimens. After casting, Wu et al, [6] applied microwave energy to mortar specimens (made with type I cement) for duration between 15 and 30 min. With this microwave heating, at the end of 3 days, the compressive strength was increased by about 50% and at the end of 28 days, the compressive strength was 5% higher. Initial microwave heating increases the hydration rate and hence there is a strength improvement at the early age of 3 days. The slightly higher strength at 28 days is attributed to the removal of water from the freshly concrete and thus densification of the concrete. This was also verified with the lower permeability of concrete subjected to microwave curing. Hutchison et al [7] measured the degree of hydration at different times with and without initial microwave curing and found that microwave heating significantly increases the hydration in the first day, and later both the microwave curing and conventional curing attain similar degrees of hydration They also reported that the strength of initial microwave cured specimens were more than the conventionally cured control specimen at 1, 7 and 28 days.

Leung and Pheeraphan [8] studied the effect of microwave curing of mortar at very early stage of 3 to 4.5 hours of casting and found that the strength increases with microwave curing. Lee [9] investigated the effects of steam and microwave curing on the strength development of concrete and found that microwave heating increases the early strength of concrete. Study indicated that a 40-min microwave heating duration was optimal curing time. Recently Chindaprasirt et al [10] studied the effect of microwave radiation on the strength and resistance to acid and sulfate solutions of fly ash geopolymer. Microwave radiation was applied along with the convection heat to accelerate the geopolymer formation. This method reduced the curing time, enhanced the geopolymerization, and provided a strong and durable geopolymer leading to a low strength loss under the acid and sulfate attacks.

The broad aim of the present research is to develop a laboratory test procedure for testing concrete cubes by reducing the time required by accelerated curing with the help of microwave energy. However, in this study, only M30 concrete is studied. While the real concrete construction is being cured in a conventional manner, the cube is given the accelerated curing treatment just to identify the 28-day strength in advance. The objective of the study is to identify the predictability of 28-day strength of M30 grade concrete in about a day by microwave heating based accelerated curing procedure.

III. Neural Network Models

In the last two decades, many Artificial Neural Network (ANN) applications were reported for civil and environmental engineering problems as they provide more promising results compared to the other conventional tools [11], [12], [13], 14]. In this line, prediction the compressive strength of the concrete was also attempted using ANNs. The drawbacks of conventional models in terms of accuracy, speed and using more input parameters can be overcome by a great extent by the ANN models.

The popular feedforward neural network model with a error back propagation training algorithm was used to predict the compressive strength of concrete by many researchers [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26]. The application of recent information technology tools such as simulation models, decision support systems, artificial intelligence, and fuzzy logic on concrete mix design is reviewed in detail by Boukhatem et al. [27] and felt the scope for further developments.

Recently, Zarandi et al. [28] used six different fuzzy polynomial neural network models to predict the 28-day compressive strength of concrete. Six input parameters of concrete, namely, the amount of coarse aggregate, fine aggregate, super plasticizer, silica fume, water and cement were considered from 492 records. Root mean square and correlations factors were used as performance indicators. The authors concluded that the results indicated that further studies can be conducted to improve the stability and convergence. Prasad et al. [29] used an ANN model to predict 28-day compressive strength and slump flow of a normal and high-strength self-compacting concrete and high-performance and high-volume-fly-ash concrete. Compressive strength prediction of high performance concrete was analysed by Chou et al. [30] using different techniques such as ANN models, support vector machines, multiple regression, metaclassifier models for the performances of accuracy, training time and overfitting aversion index. Cross-validation was used to avoid biased estimates. Chou and Tsai [31] further used hierarchical classification and regression approach with ANNs and found that the new approach outperforms the other methods. ll paragraphs must be indented. All paragraphs must be justified, i.e. both left-justified and right-justified.

IV. METHODOLOGY

In this study, M30 grade concrete was used. Mix design is made as per the ACI method [32]. Nine numbers of cubes were casted as control cubes. To estimate 7-day, 14-day and 28-day strengths, three cubes each were tested in the compression testing machine. The cubes meant for microwave curing, needs to get a minimum strength before microwave curing. Thus for a period of less than 24 hours, these cubes were left in the mould at a moist environment at room temperature (28°C) and pressure. This period is called delay period. After the delay period, the cubes were cured in the microwave oven and this time is called microwave curing duration. After microwave curing the strength of the cube was tested in the compressive testing machine. The compressive strength was compared with the control strengths. Portland- Pozzolana Cement of 43 grade confirming to IS:1489-1991 [33] was used in the study. The estimated properties of the cement as per IS:4031-1988 [34] are reported in Table I.

TABLE I.
Physical properties of the cement used

Property	Value
Normal Consistency (%)	32
Specific Gravity	3.18
Initial and final setting time (min)	28 and 360
Fineness (%)	9

The physical properties specific gravity, fineness modulus, porosity, void ratio of river sand which was used as fine aggregate and the course aggregate were determined in accordance with IS:2386-1963 [35] and shown shown in Table 2. Potable water was used in the investigations for both mixing the concrete and curing.

TABLE II.
Properties of fine and course aggregates

Property	Fine Aggregate	Course Aggregate
Specific Gravity	2.69	2.94
Fineness modulus	2.4	7.2
Porosity (%)	41.5	40.0
Void Ratio	0.8	0.4

Concrete mix was designed as per ACI method [32] for M30 grade concrete and the mix used was 1 : 2.16 : 2.52 with a water-cement ratio of 0.46. The workability of the concrete was estimated using slump test and compaction factor tests as per IS:1199-1959 [36] and identified as 86 mm and 0.87 respectively. M30 grade concrete cubes of size 100 x 100 x 100 mm size were cast and the cast specimens were removed from moulds at the end of delay period.

To perform microwave heating, a commercial kitchen microwave oven (IFB K024) with internal cavity dimensions of 390 (width) x 268 (height) x 400 mm (depth) was used. Its output power could be adjusted from 20% to 100% of full output power in steps of 20%. The 100% full output refers to 900 W. After microwave curing, the cube was allowed to cool for about 30 min before subjecting it to the compression test. The compression strength of the specimen cubes were found in the laboratory using a digital compression testing machine of 3000 kN capacity as per IS:516-1969 [37] .

The popular backpropagation network [38], [39] which maps the input vectors to output vectors was used in this study with architecture as shown in Fig. 1. Data from input vector provided at the input layer nodes were processed using the weights associated with the connection links and forwarded to the output layer nodes. Errors at the output layer were back-propagated to adjust connection weights. Through an iterative process, weight adjusting and recalculating the outputs were repeated until the errors at the output nodes fall below a desired level. For training of the network (adjusting the weights) the gradient descent search technique was used. In the iterative steps, scaling of the updates to weights was controlled by a learning rate parameter. A momentum parameter was used to add a part of the weight corrections of a previous iteration to weight corrections in the present iteration.

V. Results And Discussions

While curing the cube with microwave energy, the cube was placed in a water bath and kept inside the microwave oven. In all the experiments conducted, the accelerated curing never exceeded 80% of the 7-day compressive strength by regular curing. The experiments were conducted for about 6 hr, 18 hr and 24 hr delay periods.

A back-propagation neural network model was built using the 108 records (Table 3) generated through microwave curing. All the concrete mixes were made using the same material and same mix proportions were used and hence the variables are (1) the delay duration (DD), (2) the microwave curing duration (MD) and (3) Watts (W) set for the microwave curing. These three variables produce compressive strengths varying between 5.68 MPa to 17.50 MPa. Thus, the three inputs are to be mapped to an output which is the compressive strength. Hence, an error back-propagation neural network model was built with an input, a hidden and an output layers. The input layer was formed with three inputs nodes and a bias node. A bias node was also provided along with the hidden layer nodes. The output layer was set with one node, which provides the compressive strength as the output (Fig. 1). The number of nodes in the hidden layer was varied in this study and the kept as minimum as possible while providing reasonable performance. The network was always set fully connected between layers. In table 3, the column titles DD, MD, W and CS represent Delay Duration, Microwave Duration, Microwave oven Watts, and Compressive Strength respectively.

Out of the 108 records, 72 records were used for testing and the remaining records were used for testing. Before splitting the data into training group and testing group, the sequence of records were jumbled so as to avoid clustering and to have fair diversity of records in both the training and testing groups. Initially data in the records were normalized by dividing the by the maximum of the field and thus the data range was rescaled to make all the data lie between 0 and 1. This has been done make the training faster and to avoid getting stuck in local optima.

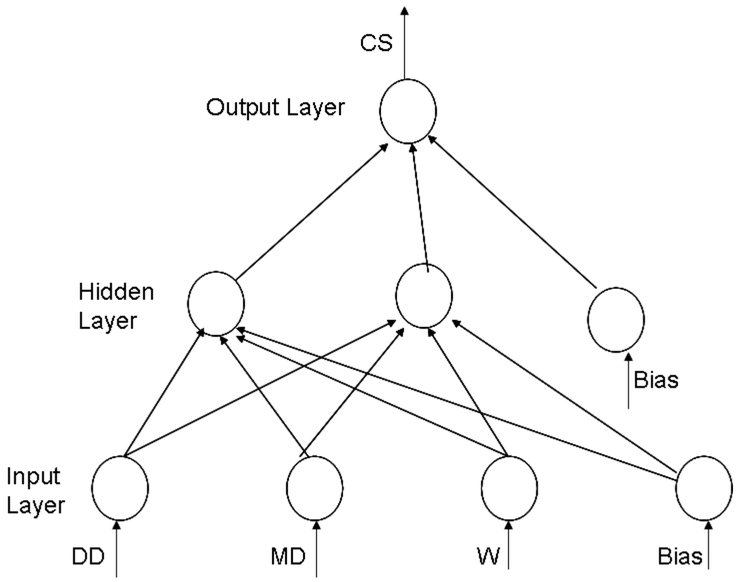

Fig. 1 Feed-forward Neural Network Architecture

TABLE III
Database used for neural network modeling

DD (hr)	MD (min)	W (Watts)	CS (MPa)	DD (hr)	MD (min)	W (Watts)	CS (MPa)	DD (hr)	MD (min)	W (Watts)	CS (MPa)
17.83	20	900	11.43	24.17	30	360	11.29	19.17	40	900	13.50
18.00	20	900	11.98	24.33	30	360	10.95	19.33	40	900	13.52
18.16	20	900	11.95	24.50	30	360	11.21	23.83	50	540	17.42
18.25	20	900	12.82	24.75	40	360	12.41	24.00	50	540	15.39
18.42	20	900	12.52	24.92	40	360	12.59	24.17	50	540	13.24
18.58	20	900	12.79	25.08	40	360	12.45	24.33	50	900	17.50
18.67	20	900	12.41	24.00	30	900	14.95	24.42	50	900	17.04
18.83	20	900	12.31	24.17	30	900	15.14	24.58	50	900	17.09
19.00	20	900	12.01	24.33	30	900	15.08	24.83	50	360	13.87
6.50	20	900	6.49	24.75	40	900	16.56	25.00	50	360	13.99
6.67	20	900	6.11	17.83	20	720	11.82	25.17	50	360	13.72
6.83	20	900	6.38	18.00	20	720	12.04	25.58	60	360	14.95
6.92	20	900	5.68	18.17	20	720	11.96	25.75	60	360	15.16
7.08	20	900	6.11	18.25	30	720	11.99	25.92	60	360	15.01
7.25	20	900	6.25	18.42	30	720	12.20	17.83	20	360	10.32
24.42	20	900	15.28	18.58	30	720	12.17	18.00	20	360	10.32
24.58	20	900	15.87	18.83	40	720	13.00	18.17	20	360	10.32
24.67	20	900	15.42	19.00	40	720	12.48	18.42	30	360	10.97
24.58	40	540	14.78	19.17	40	720	12.53	18.58	30	360	10.97
24.75	40	540	14.65	23.83	20	720	15.20	18.83	30	360	10.97
24.92	40	540	14.85	24.00	20	720	15.31	18.83	40	360	11.25
25.33	30	540	15.07	24.17	20	720	15.24	19.00	40	360	11.09
25.50	30	540	14.71	24.25	30	720	14.96	19.17	40	360	11.32
25.67	30	540	14.89	24.42	30	720	15.01	17.83	50	360	12.90
25.92	20	540	14.64	24.58	30	720	14.78	18.00	50	360	12.58
26.08	20	540	14.42	24.83	40	720	16.29	18.17	50	360	12.74
26.25	20	540	14.53	25.00	40	720	16.02	18.83	50	540	12.95
20.00	40	540	11.29	25.17	40	720	16.08	19.00	50	540	13.28
19.83	40	540	11.61	25.58	50	720	16.34	19.17	50	540	13.25
19.67	40	540	11.39	25.75	50	720	16.72	17.83	50	720	13.83
21.08	20	540	11.61	25.92	50	720	16.41	18.00	50	720	13.58
21.25	20	540	11.78	18.00	30	540	11.73	18.17	50	720	13.45
21.42	20	540	11.32	18.75	30	900	13.29	18.83	50	900	14.42
23.83	20	360	10.66	18.58	30	900	13.01	19.00	50	900	14.64
24.00	20	360	11.78	18.42	30	900	13.06	19.17	50	900	14.38
24.17	20	360	10.66	19.00	40	900	13.72	18.00	35	540	11.25

The number of nodes in the hidden layer was varied from 2 to 4 and no significant improvement was observed when the hidden nodes were increased. Hence, the hidden layer was fixed with 2 nodes. Thus the configuration was set as 3 nodes in the input layer and 2 nodes in the hidden layer and one node in the output layer along with a bias node contributing to hidden layer nodes and another bias node contributing to the output layer node. The initial weights were assumed randomly and simple sigmoid activation function was used. The learning rate and momentum parameters were set to 0.5. Batch learning, which updates the weights after processing all data, was used in this study. A maximum of 100,000 epochs or an average of squared error less than 0.00005 (of the normalized data) was used for stopping the training process. Attempts were made to improve the training by starting from different starting weights. Irrespective of the different starting weights, the training converges to the same weights in many cases, which indicate the response surface is not having many optimal solutions.

TABLE IV
Summary of performance of neural network model

Item	Training set	Test set
Number of records	72	36
Maximum error	1.99	1.48
Minimum error	-2.37	-1.53
Standard deviation of error	0.62	0.64

Table 4 presents the summary of neural network predictions. Fig. 2 and Fig. 3 present the graphs between actual compressive strength and predicted compressive strength in training group and testing group respectively. In each of the cases, the R2 is more than 0.85 and hence the prediction accuracy is good. In the training set, out of the 72 records, 38 records gave error less than 0.3 MPa in prediction. In the test set, out of the 36 records, 17 records gave error less than 0.3 MPa in prediction. In the training set, out of the 72 records, 64 records gave error less than 0.9 MPa in prediction. In the test set, out of the 36 records, 29 records gave error less than 0.9 MPa in prediction. Hence, it can be concluded that the neural network model performance is good.

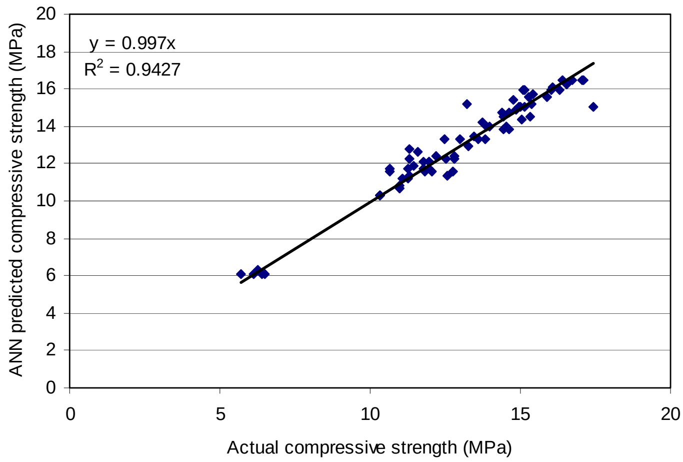

Fig. 2 Relationship between actual and predicted compressive strengths in the case of training records

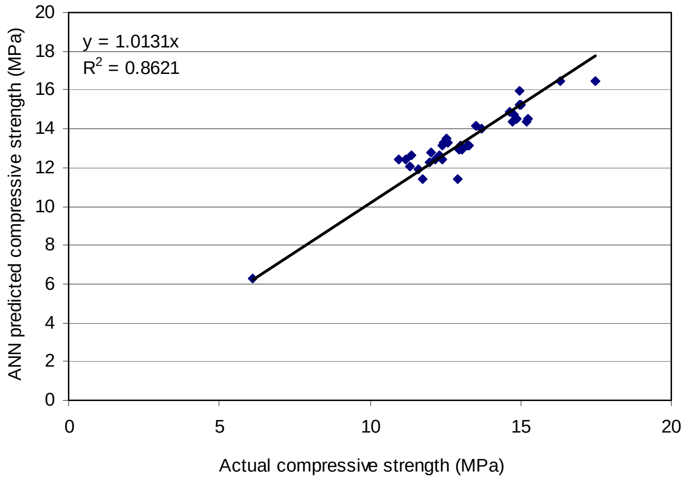

Fig. 3 Relationship between actual and predicted compressive strengths in the case of testing records

VI. CONCLUSION

The microwave curing accelerates the curing process significantly and hence the error in predicting the 28-day strength using the ingredient parameters can be avoided. The improvement in accuracy is at the cost for casting, curing to a short duration (delay time), microwave curing and testing for compression. The high R^2 values clearly indicate that the neural network modeling is well suited. The present neural network model indicates that it captured the process of curing and thus able to predict the strength. In the future research, more data is to be generated for varying 28-day strengths and the neural network model is to be extended. The non-linear neural network model can be better than the simple regression to predict 28-day strength. Hence, the is scope for extending the neural network modeling to capture the microwave curing process; however, it is to be further analyzed with more data so that earlier identification of 28-day compressive strength through microwave curing is possible.

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