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EFFICIENCY FACTOR OF SUPPLEMENTARY CEMENTITIOUS MATERIALS: A STATE OF ART

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ABSTRACT

The use of supplementary cementing materials is gradually increasing due to technical, economical, and environmental benefits. Supplementary cementitious materials (SCM) are most commonly used in producing ready mixed concrete (RMC). A quantitative understanding of the efficiency of SCMs as a mineral admixture in concrete is essential for its effective utilisation. The performance and effective utilization of various SCMs can be possible to analyze, using the concept of the efficiency factor (k-value). This study describes the overview of various studies carried out on the efficiency factor of SCMs. Also, it is an effort directed towards a specific understanding of the efficiency of SCMs in concrete. Further it includes an overview of artificial neural network (ANN) for the prediction of the efficiency factor of SCMs in concrete. It is found that The model generated through ANN provided a tool to calculate efficiency factor (k) and capture the effects of different parameters such as, water-binder ratio; cement dosage; percentage replacement of SCMs; and curing age.

Keywords: artificial neural networks; efficiency factor; supplementary cementitious materials; soft computing techniques.

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1. INTRODUCTION

To preserve the environment and contribute to sustainable development, the construction industry has developed and used materials and technologies that are more energy efficient and environmentally friendly in the building of concrete structures. There is a growing

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realization throughout the world that the raw material resources used in the production of cement are finite and non-renewable and need to be conserved for the future generations. With the objective of attaining sustainable construction, a strong trend favouring the increased use of mineral admixtures, which are basically the waste products of industrial processes, in concrete is emerging throughout the world [1]. Therefore, a quantitative understanding of the efficiency of SCMs as a mineral admixture in concrete is essential for its effective utilisation. Many researchers developed a model know as efficiency factor (k-value) for effective utilization and conservation of SCMs for future generations.

The concept of an efficiency factor may be applied for comparing the relative performance of various SCMs (fly ash, silica fume, slag, natural pozzolans, etc.) as regards to portland cement. The efficiency factor (k) is defined as the part of the SCM in a concrete, which can be considered as equivalent to portland cement. An earlier study was carried out by Smith [2] who was one of the first to define efficiency factor (χ) for an additive with the aim of proposing a rational approach in the mixture proportioning of concrete containing fly ash.

Smith [2] determined efficiency factor (χ) based on the relation between concrete compressive strength and the water cement ratio (w/c) and obtained the efficiency of fly ash using Eq. (1).

$$\frac{w}{c_o} = w/c \times \left\{ \frac{1}{1+\left(\frac{\chi F}{c}\right)} \right\} \tag{1}$$

where χ is the efficiency factor, c_o is the cement content of normal concrete, c is the cement content of the equivalent binder, and F is the fly ash content in a concrete of equal strength.

Ho and Lewis [3] have observed that the k-value of fly ash with respect to 28-day compressive strength varies over a wide range depending on the quantity of fly ash, incorporation of chemical admixture, type of cement and the particular strength level chosen. Fraay et al. [4] have reported that the reaction of fly ash in concrete is only commenced after one or more weeks and during incubation period; the fly ash behaves fairly as an inert material. Hence, the efficiency values of fly ash can be very less or even negative at early ages.

Babu and Rao [5] have reported that k-value has been suggested as 0.25 for replacements up to 25 %, German standards recommend a value of 0.3 for replacements between 10% to 25%, British code refers to a value of 0.4 for replacements up to 25%, CEB-FIP model code proposes a value of 0.4 for replacements between 10% to 25%.

It has been a long time for the industry to wait for 28 days to get the experimental results for the compressive cement strength (CCS). Therefore, faster determination of compressive cement strength is a need for the cement industry and deserves research interest for the researchers. There are mainly two different ways for compressive cement strength, determination one is accelerated strength test methods and second is the use of mathematical models. The focus of this report is on the mathematical model. The most widely used mathematical approach in the past was to use simple regression models [6].

Babu and Rao [7] have reported that the overall efficiency factor of fly ash (k) is the combination of general efficiency factor (k_e) depending on age and an additional percentage efficiency factor (k_p) depending on replacement percentage. It has been reported that the overall efficiency factor ($k = k_e + k_p$) varies from 1.25 to 0.35. The authors have figured out that the efficiency of fly ash increases with decrease in w/c, whereas, it decreases with increase in replacement percentages.

The coefficient "χ" thus represents a measurement of the relative performance of the mineral additives compared to portland cement. The evaluation of this factor can be carried out using various approaches. The mixture "cement + additive" is replaced by the equivalent binder, which introduces the activity index into the evaluation of the efficiency factor [8].

Hanehara et al. [9] have reported that hydration of cement is stimulating with an increase in the water-cement ratio also, it has been mentioned that the pozzolanic reaction of fly ash proceeds from the age of 28 days to 91 days of curing and the reaction ratio of fly ash decreases with an increase in the substitution rate.

The compressive cement strength depends on many different factors, which are chemical and physical in nature. Analytical models including the statistical ones (e.g., regression analysis) used to describe the effects of these factors on strength which can be very complex predictive of CCS [10]. The efficiency factor for Silica fume and Metakoline replaced concrete mixes, shows an increasing trend as the replacement level is increased up to 10%, whereas fly ash replaced mixes shows decreasing trend [11].

Sata et al. [12] used to modify Bolomey's law with linear relationship, for the analysis of the result of compressive strength of concrete, cement to water ratio (c/w), and fly ash to water ratio (f/w), the author also uses the multilinear regression to determine the k factor and other constants in the equations. A remarkable contribution towards a sustainable development of the cement and concrete industries can be achieved by the utilization of cementitious and pozzolanic by-products, such as fly ash (FA) and ground granulated blast furnace slag (GGBS), produced by thermal power plants and metallurgical industries, or natural pozzolanic additions as well as limestone [13].

The use of such supplementary cementitious materials leads to a significant reduction in CO_2 emissions per mass of concrete and, for some additions, it also allows to utilize by-products of industrial manufacturing processes. In a recent years' variety of blending materials are more widely used to improve the performance of cement concrete [14].

Sinha [15], Using the k value, an attempt for the design for the fly ash concrete with different percentages of fly ash replacement is made. The author has observed that by using the k value, there is no need to accept the loss of early strength at different replacement levels. Lollini et al. [16] practices and generally accepted approach to evaluate the contribution of SCMs to the strength of the hardened concrete is through the concept of the SCMs efficiency factor (i.e. k-value concept), which expresses the fraction of Portland cement that can be replaced by an SCM at unchanged strength. In this paper, the efficiency of SCMs on the properties of concretes with different curing times was estimated. In particular, the k-values were evaluated considering compressive strength, carbonation rate and chloride diffusion coefficient with the aim of investigating whether strength can be considered as a proxy criterion for durability properties.

2. ARTIFICIAL NEURAL NETWORKS

ANNs are data-processing paradigms that are inspired by biological nervous systems. They are composed of a large number of highly interconnected processing elements (neurons) working together as shown in Fig. 1.

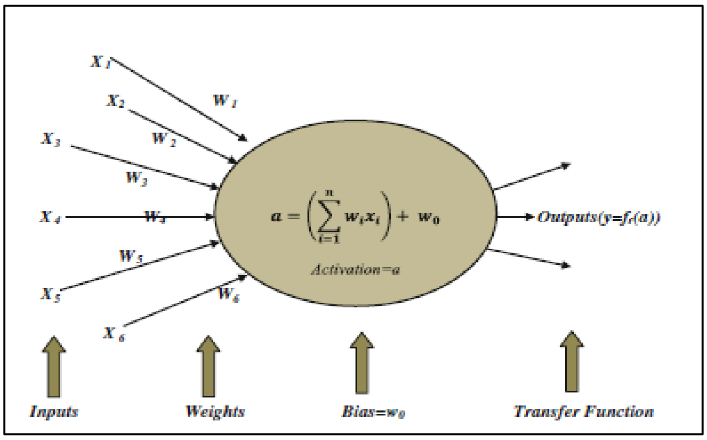

Figure 1. Model of Neuron [17]

Rosenblatt [18] devised a machine called the perceptron that operated in the same way as the human mind. The perceptron is the most popular neural network used in modelling that has an input layer and an output layer, as well as a number of hidden layers that are fully connected to each other [19]. The sum function computes the net input that approaches a neuron. The weighted sums of the input components are calculated by using Eq. (2) as follows:

$$net_j = \sum_{i=1}^{n} W_{ij} X_i + b \quad (2)$$

where, net_j= weighted sum of the j^{th} neuron for the input received from the preceding layer with n neurons; W_{ij} = weight between the j^{th} neuron and the i^{th} neuron in the preceding layer; X_i = output of the i^{th} neuron in the preceding layer; and b = fixed value as an internal addition [20].

Currently, there has been a viable interest in a class of computing programs which known as artificial neural networks (ANNs) that function in a manner analogous to biological nervous systems. The neural network modelling (NNM) approach is very accurate and more direct than other conventional statistical methods, especially when modelling nonlinear multivariate interrelationships [21].

The principal property of ANN in solving civil engineering problems are their learning ability directly from experiments where, Kaveh and Khaleghi [22] compared and trained for one, two and three hidden layers by employing back propagation algorithm, and selected a most efficient network in order to predict the strength of concrete. Inspite of back-propagation algorithm, other significant properties of ANN are accurate or nearly accurate response to incomplete tasks, their withdrawal of information from noisy or poor data, and their creation of generalized results from the novel cases. The aforementioned potentials make ANN a very powerful tool for solving many civil engineering problems where, Nouri et. al [23] developed ANN model to predict soil layering in a specified location, based on the available site investigation data from a 30 square kilometres and concluded that, Artificial Neural Networks are capable of predicting variations in the soil profile with an acceptable level of confidence. Adhikary [24] incorporated ANN technique to overcome with complex or an insufficient data. Based on the review of previous research, experimental results and analysis by using ANN, it can be concluded that the ANN model is an efficient way of predicting physical properties of concrete [17].

Boukhatem et al. [25] developed an ANN model which provided a more accurate tool to calculate χ and to capture the effects of five main parameters, such as age, amount of substitution, and concrete composition (w/b, cement dosage, and replacement level) and mathematical model was also developed based on the ANN model's results for predicting the efficiency factor of Ground granulated blast furnace slag (GGBFS) in terms of percentage replacement (0 to 80%) of GGBFS and concrete testing age (2 to 90 days), as they are considered the most important factors affecting concrete strength.

3. SIGNIFICANCE OF EFFICIENCY FACTOR

Today, supplementary cementitious materials (SCMs) are widely used in concrete either in blended cements or added separately in the concrete mixer. The significance of this investigation is to determine the efficiency factor of SCMs (k-factor) which describes the efficiency of SCMs to act as a cementing material. When $k > 1$, it indicates the SCM used is more efficient than cement, as hydration process is fast compared to OPC. In such a case saving of cement is possible resulting economic mix design of concrete. When $k < 1$, it indicates the SCM used is less efficient than cement as hydration process is slow compared to OPC. In such a case more quantity of SCM should be used to achieve required target strength.

Currently, there is no specific mixture proportioning method available to design SCM concrete for a desired strength and workability. In this review, the efficiency of SCMs with regard to physical characteristics such as compressive strength and workability in concrete may be investigated using a soft computing technique approach.

4. RESEARCH GAPS AND FUTURE SCOPE

From literature survey following research gaps are observed and discussed here as,

1. It is observed from the above studies that the efficiency of supplementary cementitious materials in concrete depends on a number of parameters such as type of cement and fly ash, replacement level, age, water/binder, strength level etc.
2. Efficiency of fly ash should not be considered as an intrinsic or a fundamental property of the material as it depends on a host of parameters. Since, the efficiency value is not a constant one evaluation of the same requires a considerable amount of judgment and understanding on

the part of the designer. Hence, there is a need to develop a model which would be useful for effective utilization/quantity of supplementary cementitious materials in concrete.

3. The previous research has been utilized similar techniques of ANN models proved to be reasonable and feasible, showed a satisfactory performance, and demonstrated its ability to predict the efficiency of fly ash or GGBS.
4. Further work is required to develop neural network models for predicting the efficiency factor of other SCMs, such as silica fume, micro silica, rice husk ash and natural pozzolans. These models will be necessary to establish the reliability of the proposed method, particularly with respect to its incorporation into the design of blended concrete. Hence there is a need to investigate the application of soft computing tools like artificial neural network and genetic algorithm to predict the efficiency factor for time saving and optimization of supplementary cementitious materials for cost saving.
5. It may be expected that the findings of the above literature review, may serve as a useful guideline for judiciously applying the concept of efficiency factors to optimize the content of supplementary cementitious materials in concrete and lead to improvement in the method of mix design of SCMs in concretes. Hence there is a need to investigate the effect of different additives, there optimum content and efficiency of utilization.

5. SUMMARY AND CONCLUSIONS

From the present study the following conclusions are drawn:

1. Several studies independently have shown that concrete strength development is determined not only by the water-to-cement ratio, but that it also is influenced by the content of other concrete ingredients, in which efficiency of SCMs in concrete plays an important role.
2. The reduction of cement content and incorporation of the high volume of supplementary cementitious materials (SCMs) are key factors for the design of environmentally friendly concrete (Eco-Crete).
3. Proper substitution of cement by SCMs can improve packing density of solid particles, reduce water demand, and enhance the mechanical properties of cement-based materials.
4. There is no perfect relation established between various factors, as codal guidelines have a non-numerical structure which is very difficult to quantify and hence they can be better expressed by linguistic values with artificial neural network.

Models generated through software would be helpful for effective utilization of SCMs with respect to percentage of replacements of SCMs in concrete.

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