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Identification of Critical Factors Influencing Early Age Creep of High Strength Concrete Using Artificial Neural Networks

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ABSTRACT

Ensuring precise estimation of creep characteristics is critical for the efficient design of structures prone to creep deformation. Creep is an indicator of permanent and gradual deformation that transpires within a material when it is continuously subjected to a burden for an extended duration. In addition to the temperature and duration of load application, the degree of creep in concrete is also affected by the material's inherent properties and the length of time it has been exposed to the load. The enduring consequences of creep might result in significant distortions that give rise to structural deficiencies inside the edifice. Multiple factors, including the concrete's mixing ratios and compressive strength, affect the initial hardening of the material. The data pertaining to the early creep behaviour of high-strength concrete were gathered from relevant literature sources for the purposes of this study. The research utilised artificial neural network methodology and relative importance analysis to ascertain the most influential parameters on the early creep behaviour of high-strength concrete. Understanding the components that contribute to creep is crucial in mitigating the detrimental effects of creep on concrete and concrete structures.

1. INTRODUCTION

The objective of this study is to ascertain, by employing artificial neural network (ANN) models, the pivotal factors that significantly influence the creep behaviour of high strength concrete at an early age [1]. ANN, which is classified as a type of artificial intelligence, determines the correlation between the mean value of a particular variable (e.g., output) and the corresponding values of other variables through the use of regression analysis [2]. This approach allows for the inclusion of multiple variables as inputs to generate a single output or variable. The aim of this research is to investigate the diverse factors that impact the initial creep characteristics of high-strength concrete. This will be achieved by gathering relevant information from existing literature sources [3], employing artificial neural networks as a computational tool, and conducting a relative importance analysis.

During the early phases following the casting procedure, the volume of the concrete is subject to changes due to various environmental influences, including temperature variations, applied stresses, and the drying process [4, 5]. The aforementioned alterations exhibit effectiveness in the early phases of the concrete's lifespan. The influence of creep on the resistance of concrete to cracking is substantial, as it efficiently reduces pressure and, consequently, the probability of early-age cracking in concrete structures. The occurrence of cracking at a young age has the potential to compromise the structural integrity of many materials [6]. Over time, the presence of cracks can facilitate the ingress of hostile substances, hence expediting degrading processes such as corrosion, for instance, through carbonation. The structural integrity of the building is compromised, leading to a decrease in its durability [7]. Consequently, substantial financial resources may be necessary to do the necessary renovations and restore the damaged structure. Furthermore, the act of cracking also serves to amplify the occurrence of leakage, so potentially diminishing the overall effectiveness or efficiency. The topic under consideration is the serviceability of various structures, such as the containment vessel in a nuclear power plant and petrol tanks, among others. Additionally, the presence of weak areas can give rise to the potential for re-tearing if subjected to unintentional loading [8]. The investigation of the effects of coarse aggregate montmorillonite clay content on a range of mechanical properties, including the shrinkage and creep characteristics of early-aged concrete [9]. The present inquiry was conducted utilising an extensive array of experimental methodologies. The potential cause for the observed decrease in mechanical properties, along with the observed increases in shrinkage and creep, is the degradation of the interface transition zone resulting from the coarse aggregate's adhesion to montmorillonite clay. The inquiry undertaken in the research paper was centred on the empirical examination of tensile creep [10]. The early phases of the development process of high-performance concrete (HPC) incorporating mineral admixtures are investigated in this study [11, 12]. In the preliminary phases of examining high-performance concrete (HPC) containing mineral admixtures, a notable fundamental tensile creep rate was observed within the initial twenty hours of loading [13]. Following that, this rate of encroachment exhibited a gradual decline and approached a critical value. High strength concrete (HSC) possesses a notable capacity for resisting compressive forces and exhibits a larger modulus of elasticity, hence endowing it with the ability to endure greater loads [14]. When the force generated by the loads is exerted against the system When concrete is subjected to external forces, it experiences strain. The initial strain exhibits elastic behaviour, characterised by its ability to return to its original state upon removal of applied stresses. The cumulative strain observed in concrete is the result of creep, contraction, and elastic strain acting in concert [15]. The phenomenon of creep in high strength concrete is accountable for the occurrence of cracking and deflection, albeit without a definitive impact on the structural integrity [16]. Consequently, comprehending the various components that influence creep in high strength concrete holds significant importance. The significance of implementing The Human Systems Compatibility (HSC) framework exhibited variation among the heterogeneous group of collaborators engaged in the innovative endeavours [17]. The principal factors that held the greatest significance for the proprietor were an elongated lifespan of the structures, reduced concrete quantities and expenses, a compressed construction period, and improved comfort and luxury in tall edifices via the alleviation of wavering [18]. When it comes to developing a visually enticing and effective design, colour selection is critical. The colour scheme can significantly influence the message and overall aesthetic of a design. Hence, it was determined that the improvement of specific attributes, including compressive strength, E-modulus, durability, and accelerated ultimate creep, in addition to the decrease in dead load, were of considerable importance [19]. Significant considerations for the contractor included cost-effective solutions and expedited construction. With respect to the concrete manufacturer, the implementation of sophisticated technological approaches during production has resulted in heightened profitability and market penetration, as well as advantageous consequences for traditional manufacturing processes [20]. Furthermore, considering the environmental perspective, the conservation of cement and aggregate resources, as well as the extended lifespan of the materials, have made notable contributions towards achieving a more sustainable form of development [21].

2. ARTIFICIAL NEURAL NETWORKS

A domain within computer science and artificial intelligence, artificial neural networks are specifically engineered to emulate the complex operations of a fully developed human brain. These systems possess the ability to store and retrieve data, enabling them to tackle intricate information and acquire knowledge through experiential learning. The system incorporates a symbolic approach to do intelligent computations and employs soft computing techniques for data processing. The field of civil engineering offers a diverse array of advantages and has garnered significant attention as a subject of scholarly investigation [22].

A multitude of studies concerning the application of neural networks in the domains of civil and structural engineering have revealed that the multilayer feed-forward neural network architecture is commonly utilised due to its efficient capacity for generalization [23]. Numerous authors have depicted the organisation and composition The functioning of artificial neural networks (ANNs) has been extensively studied [24]. A common configuration of artificial neural networks (ANNs) comprises many processing elements (Pes), also known as nodes, frequently organised in strata [25]. Typically, these layers consist of an input layer, an output layer, and potentially one or more concealed layers (refer to Figure 1).

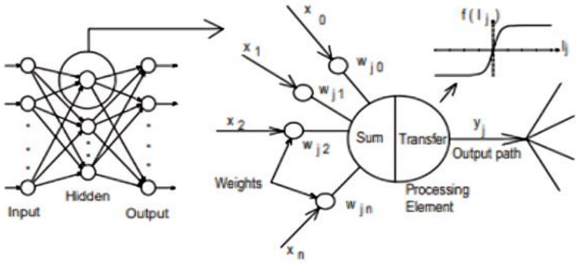

Figure 1. Input layer, an output layer in ANNs

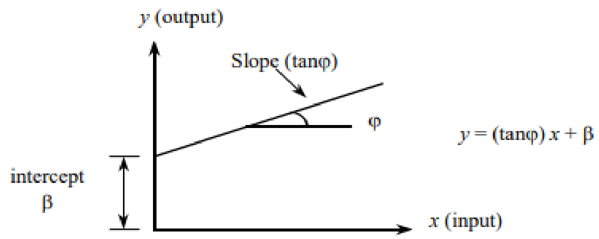

Figure 2. Ever-changing the slope tanö and intercept â of the line

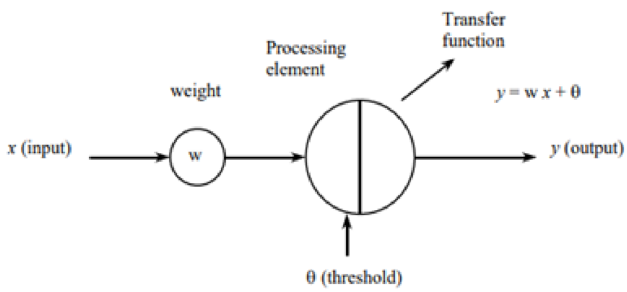

Figure 3. One linear input one linear output

Similar to a number of conventional applied mathematics models, ANN modelling attempts to represent the correlation between a specified collection of past model inputs and their corresponding outputs. To illustrate, let us contemplate a dataset comprising a collection of x-values accompanied by their corresponding y-values in a two-dimensional coordinate system, with y being a function of x. The objective is to locate the illusive function f that relates the input variable x to the output variable y. The function f can be derived within a regression model through the manipulation of the intercept and slope tan of the line illustrated in Figure 2. The purpose of this adjustment is to reduce the deviation between the predicted and actual outputs of the line. An analogous concept is implemented in models of artificial neural networks (ANN). As illustrated in Figure 3, artificial neural networks are a category of regression models distinguished by their singular input and output, absence of hidden layer nodes, and linear transfer function. The affiliation weight, represented in the Artificial Neural Network (ANN) model as w, is comparable to the linear regression model's slope, tan∅. In a similar vein, the intercept, denoted as β, in the linear regression model is equivalent to the threshold, denoted as θ, in the ANN model. By iteratively exposing their weights to samples of input-output pairs, artificial neural networks (ANNs) attempt to minimise a prescribed error function that quantifies the discrepancy between the ANN model's predicted desired outputs and the historical outputs [22].

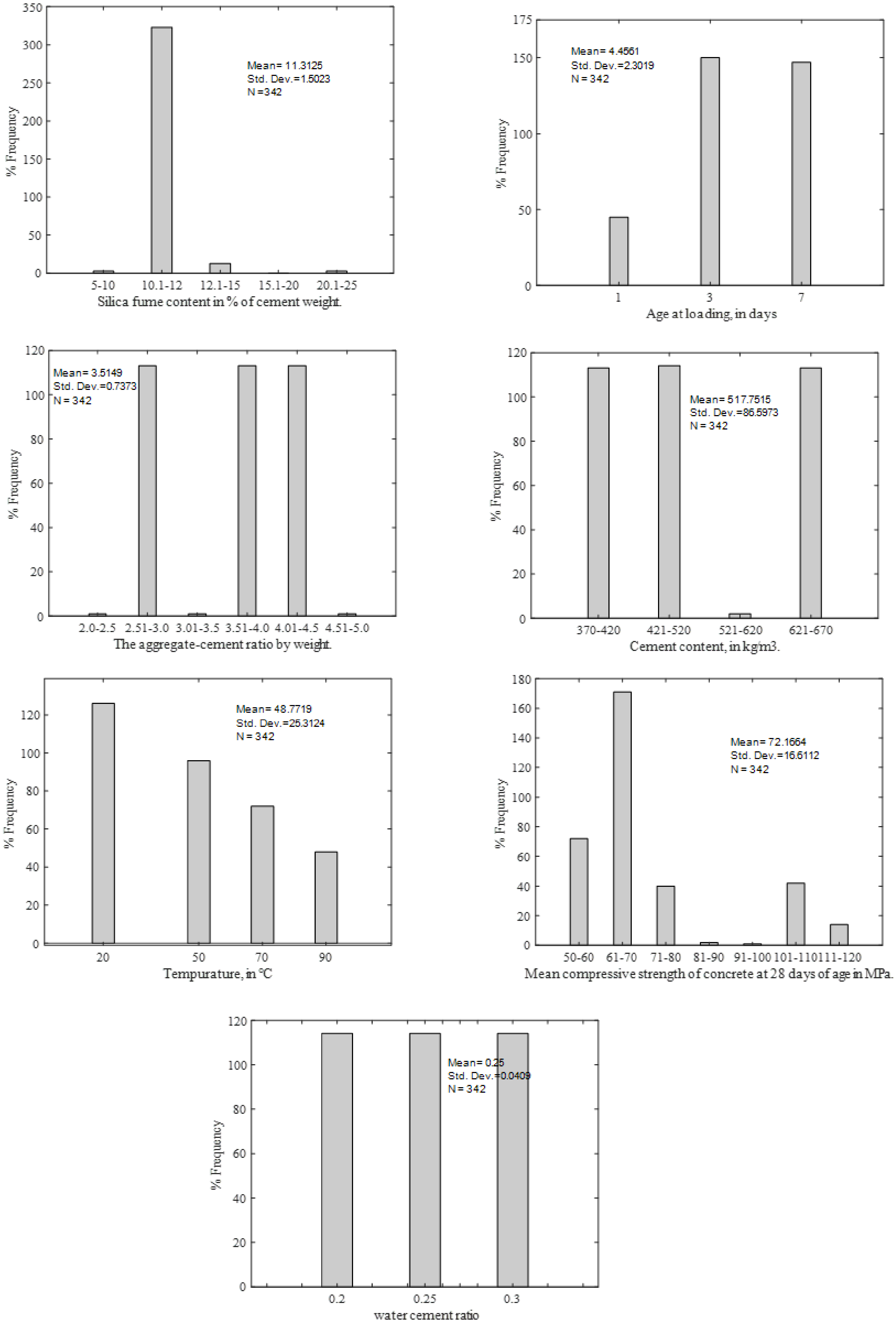

Figure 4. The distribution of the input values

Artificial neural networks (ANNs) possess the ability to exhibit a considerable degree of generalisation based on the patterns they have been trained on. The process of training involves the neural network being exposed to a series of input-output patterns. The information provided pertains to the operation of a multi-layered feed forward neural network exclusively in the forward direction. As data progresses, it undergoes a straightforward procedure within the neurons and along the neural connections. The neural network engages in sequential iterations to adjust the weights of each individual neuron in order to achieve the desired outputs with a specified level of precision. The process of modifying the weights of neurons is employed with the aim of minimising the network error, which is defined as the measure of the discrepancies between the computed output patterns and the desired target output patterns. Once the artificial neural network (ANN) has undergone sufficient training and testing, it demonstrates the ability to extrapolate rules and effectively handle unfamiliar input data in order to make predictions within the domain defined by the training patterns. The data utilised in this study were obtained from the existing literature [26]. A collection of 342 data points was obtained. The artificial neural network (ANN) models were provided with seven parameters as inputs. Table 1 shows all the input parameters that have the potential to influence the creep properties of concrete. The illustration of the input value distribution is presented in Figure 4. As adopted by the majority of researchers, the experimental data for the artificial neural network model was divided into three groups: training data (80%), validation data (10%), and test data (10%) [27]. The Levenberg-Marquardt (LM) method, which was implemented in this study, belongs to the category of conjugate gradient algorithms. In comparison to conventional gradient-type algorithms, the LM algorithm is among the quickest for training artificial neural networks. Prior to utilisation, all input data to the model must be scaled, and the predicted output should reflect the unscaled values. The input values were scaled between -1 and 1. The process of scaling the training datasets was carried out utilising Eq. (1):

$$y = \frac{2(x - x_{max})}{(x_{max} - x_{min})} + 1 \tag{1}$$

On the other hand, the periods of 0 and 1 were used for scaling the output data. The Eq. (2) used to measure the output data:

$$y = \frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{2}$$

In order to achieve a secure model, various neural network architectures were evaluated during model training by adjusting the number of neurons in the hidden layer and the coefficients of the training function. The log-sigmoid function for the output and the tan-sigmoid function for the concealed layer were used as activation functions. The architecture of the used ANN model is shown in Figure 5.

Table 1. Details of the inputs

	Minimum	Maximum	Mean	Standard Deviation
Water-cement ratio by weight	0.20	0.30	0.25	0.0409
Aggregate-cement ratio by weight	2.48	4.88	3.5149	0.7373
Cement content without additives, in kg/m^3	374	665	517.7515	86.5973
Silica fume content in % of cement weight	5.18	25	11.3325	1.5023
Age at loading, in days	1	7	4.4561	2.3019
Temperature, in °C	20	90	48.7719	25.3124
Mean compressive strength of concrete at 28 days of age in MPa	59	118	72.1664	16.6112

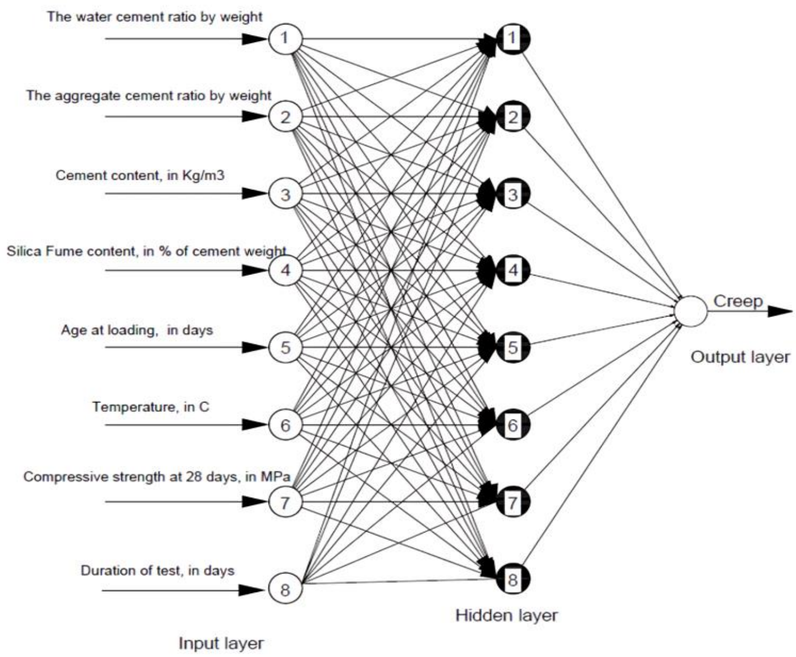

Figure 5. The architecture of the ANN model

The MATLAB software was utilised to generate the code for the neural network model described in this study. The ultimate trained network was utilised to approximate the output. Figure 6 demonstrates a strong positive correlation coefficient (R) between the empirical data and the values projected by the neural network. This indicated a precise correspondence between the results (i.e., for both training and test data) and those computed by a linear regression model. The histogram in Figure 7 illustrates the distribution of errors created by the artificial neural network model. It is evident that the errors cluster around zero, indicating the model's effectiveness in making accurate predictions.

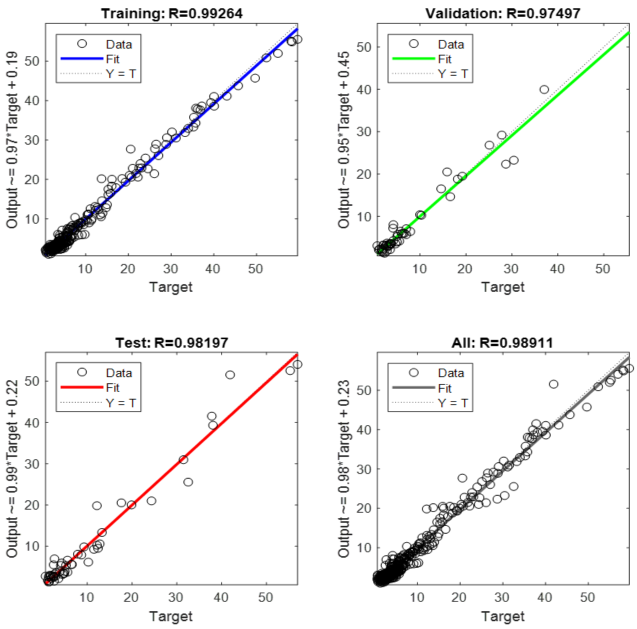

Figure 6. Comparison of experimental and predicted creep

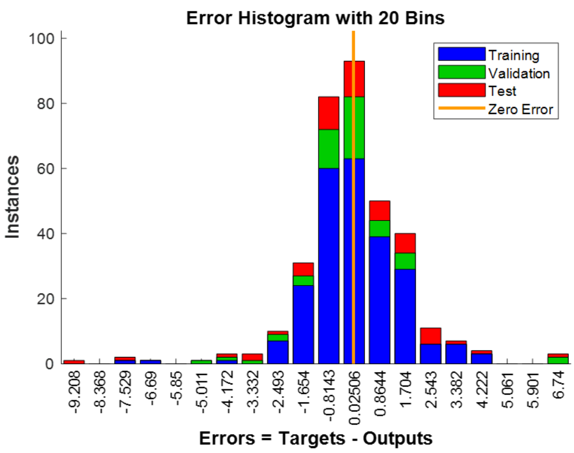

Figure 7. Error histogram for the output

3. RELATIVE IMPORTANCE ANALYSIS (INFLUENCE PARAMETERS IDENTIFICATION)

One notable benefit of artificial neural networks lies in their capacity to do parametric analysis of the inputs through the manipulation of link weights. This study employed parametric analysis of the artificial neural network to ascertain the relative significance of various input parameters. The methodology was initially suggested and was subsequently executed [1, 28]. This methodology involves the partitioning of the synaptic strengths between each hidden neuron in the hidden layer and the neuron in the output layer into relative components that are in accordance with the input neurons. By adhering to the symbolic rule that regulates the weight adjustment process, we shall analyse a neural network consisting of K output neurons, I input neurons, and J concealed neurons, all of which have connection weights.

The computational procedure for the neural network is outlined as follows [1, 28]:

1. The product of connecting weights

For each hidden neuron in the experiment, the absolute value of the connection weight between the input and hidden layer is multiplied by the absolute value of the connection weight between the hidden neuron and the output layer.

i. Compute the value of *Uji* for each input variable *i*.

ii. Determine the products of the connection weights. The equation can be expressed as $Uji = |Wji| |Wkj|$.

2. The proportion of items derived from connection weights *i*.

i. To calculate *Vji*, divide *Uji* by the total of all the input parameters for each hidden neuron. The percentage of items of connection weight:

$$Vji = \frac{Uji}{\sum_{i=1}^{I} Uji} \tag{3}$$

where, *I*=number of input neurons.

3. Sum of percentage of products of connection weights *Ci*

i. For each input neuron, calculate the summation of *Vji* to obtain (*Ci*). Sum of percentage of products of connection weights:

$$Ci = \sum_{j=1}^{J} Vji \tag{4}$$

where, *J*=number of hidden neurons.

4. Relative Importance (*RI*)*i*

i. Divide *Ci* by the sum of *Ci* for each input neuron and express in term of percentage to obtain the relative importance for each input neuron relative importance:

$$(RI)i = \frac{Ci}{\sum_{I=1}^{I} Ci} \tag{5}$$

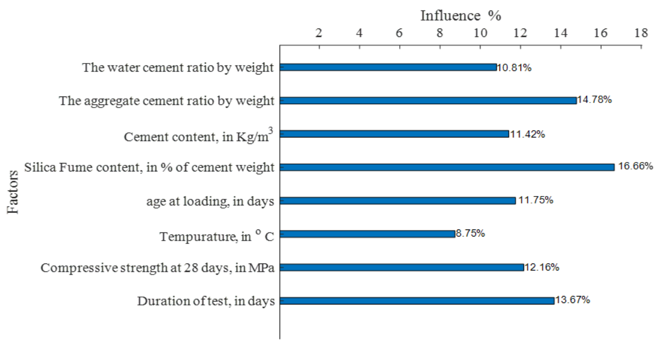

Figure 8. Influence of input factors on the output

The output of this procedure is depicted in Figure 8, which illustrates that the parameters with the greatest impact on early age creep for the high strength concrete utilised in the research are the aggregate cement ratio (14.78%), silica fume content

(16.66%), and duration of test (13.6%). Early-age creep is influenced by the compressive strength of concrete by 12.16%, whereas the combined impact of cement content and age loading is approximately 11.5%.

4. CONCLUSIONS

Using literature-derived data, an artificial neural network (ANN) approach was used to investigate early age encroachment, with the ANN approach employing ANNs. Furthermore, an approach called relative importance analysis was employed to ascertain the influence of high-strength concrete constituents on creep at an early age. The findings derived from this inquiry are outlined below: Following an examination of the impact of seven variables on the early creep characteristics of concrete, it was determined that the proportion of silica haze (16.66%) had the greatest influence on the creep of high-strength concrete. In comparison to the other determinants concerning the creep behaviour of high-strength concrete, the influence of ambient temperature (8.75 percent) was found to be comparatively negligible. The application of artificial neural networks for predicting early-age creep in reinforced concrete has been deemed a viable approach. However, it is imperative to emphasise that relative importance analysis is an exceptionally well-suited technique for examining the impact of ambient conditions and concrete components on creep in early-age concrete.

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