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Adaptive Network-Fuzzy Inferencing to Estimate Concrete Strength Using Mix Design

S. Tesfamariam[1] and H. Najjaran[2]

Abstract

Proportioning of concrete mixes is carried out in accordance with specified code information, specifications, and past experiences. Typically, concrete mix companies use different mix designs that are used to establish tried and tested datasets. Thus, a model can be developed based on existing datasets to estimate the concrete strength of a given mix proportioning and avoid costly tests and adjustments. Inherent uncertainties encountered in the model can be handled with fuzzy based methods, which are capable of incorporating information obtained from expert knowledge and datasets. In this paper, the use of adaptive neuro-fuzzy inferencing system (ANFIS) is proposed to train a fuzzy model and estimate concrete strength. The efficiency of the proposed method is verified using actual concrete mix proportioning datasets reported in the literature, and the corresponding coefficient of determination r^2 range from 0.970-0.999. Further, sensitivity analysis is carried out to highlight the impact of different mix constituents on the estimate concrete strength.

CE Database subject headings: Fuzzy logic, Adaptive neuro-fuzzy inferencing; Compressive strength; Concrete mix proportioning.

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Introduction

Concrete is one of the oldest materials in the construction industry. The concrete mix

proportioning method has evolved from a simple arbitrary volumetric method (1:2:3 –

cement:sand:coarse aggregate) to the present-day mass and absolute-volume method (ACI 211.1-

91 1991). A four-step mix design procedure is illustrated in Fig. 1. *Step 1* entails specifying

exposure condition, workability of freshly mixed concrete, and strength and durability

requirements of hardened concrete. Once this is specified, *Step 2* follows code specified design

procedures to satisfy *minimum/maximum* requirements, i.e. maximum water cement ratio (*w/c*

ratio), minimum 28 days specified strength ($f_c^{'}$), minimum entrained air (*EA*), maximum slump,

and maximum coarse aggregate (*CA*). *Step 3* entails computing the required unit water content,

coarse aggregate and consequently the fine aggregate (*FA*). Finally, *Step 4* specifies the final

water, cement, coarse aggregate, fine aggregate and admixture content. Typically, the mix design

is verified in the laboratory through trial mix, and adjustments are made accordingly. The final

proportioning of the mix design has to be verified through concrete mix made in the field, since

variation may arise due to different mixers, pumping properties and wall effect (Neville 1997).

Moreover, the quality of the final in-place concrete is determined by the prevalent construction

quality. Hence, from batching to concrete placement, stringent control has to be exercised as any

deviation may compromise the structural integrity and durability of the structure. As shown in

Fig. 1, there is an infinite possibility of obtaining the desired mix design specification, however,

the desirable one is the one that satisfies the design constraints at *minimal cost*.

The mix design involves a complex and nonlinear procedure that is influenced by the material interaction and culture of construction quality. Hence, it is difficult to develop a comprehensive analytical model by considering all design variables. Typically, concrete mix companies have extensive records of their past mix proportions, which can be used to develop a model for the design procedure. Automation of the mix proportioning can be carried out with different soft computing techniques. Soft computing is a conglomerate of computing techniques that include fuzzy-based methods, neuro-computing, genetic computing, probabilistic reasoning, genetic algorithms, chaotic systems, belief networks, and learning theory (Zadeh 1997). The soft computing techniques effectively explore the relationship among independent and dependent variables without any assumptions about the relationship (e.g., a linear relationship) between the various variables.

Various authors have used a standard multilayer feedforward artificial neural network (ANN) to predict the compressive strength of concrete (e.g. Lai and Serra 1997; Yeh 1998; Oh et al. 1999; Ni and Wang 2000; Hong-Guang and Ji-Zong 2000; Lee 2003; Kim et al. 2004; Chiang and Yang 2005) where a back propagation algorithm (BPNN) is used to train the network existing datasets. Kim et al. (2005) have further enhanced the previously reported (Kim et al. 2004) ANN using probabilistic neural network method to handle uncertainty and save computational time. Jain et al. (2005) forwarded further insight into the implementation and discussions on the efficiency of neural network models for concrete mix.

The main advantage of using ANN is their flexibility and ability to model nonlinear relationships. However, the ANN models have often been criticized for acting as a "black box." The knowledge contained in an ANN model is maintained in the form of a weight matrix that is

hard to interpret and can be misleading at times. In other words, the ANN models do not have the ability to incorporate additional knowledge or expertise into the model. Although qualitative modeling methods can be used to capture human knowledge, such models will naturally suffer from subjective human judgments. One way to overcome many of these shortcomings is to use fuzzy models or fuzzy inference systems (FIS) that can handle the uncertainties arising from insufficient knowledge, partial truth and vagueness (Zadeh 1973). These models combine the transparent linguistic representation of expert knowledge with the ability to learn from datasets. Various fuzzy modeling techniques have been presented in the literature (e.g., Sugeno and Yasukawa 1993, Klir and Yuan 1995, and Emami et al 1998). Jang (1993) proposed an adaptive network-based fuzzy inference system (ANFIS) to constructs a fuzzy inference system (FIS) in which membership functions is adapted using a back propagation algorithm in combination with the least-squares optimization.

ANFIS has recently been used in civil and environmental engineering applications. Akbuluta et al. (2004) used ANFIS for data generation of shear modulus and damping ratio in reinforced sands. Chau et al. (2005) used ANFIS and ANN for comparison of flood forecasting models and reported that ANFIS obtained optimal results. Chang and Chang (2005) utilized it to build a prediction model for reservoir management. Vernieuwe et al. (2005) applied it to the modeling of rainfall–discharge dynamics. Nayak et al. (2004) applied it to model hydrologic time series, and reported that ANFIS was superior to ANN and other statistical methods.

In this study, ANFIS is introduced as a tool to develop a fuzzy model that can estimate compressive strength of concrete given its mix proportioning. Previously reported data (Kim et al. 2004, 2005) are used to train and validate the fuzzy model. The estimated strengths are

compared with the reported concrete strengths. The results highlight the utility of ANFIS in the construction industry. The outline of the paper is as follows. First, the concept of fuzzy based methods, including fuzzy inference systems and fuzzy modeling is explained briefly. Second, the implementation and derivation of an ANFIS based model is discussed. Third, ANFIS is used to develop a FIS model for estimation of concrete strength. The results are verified using actual concrete mix proportioning datasets reported in the literature, and the corresponding coefficient of determination r^2 are computed. Finally, sensitivity analysis is carried out to highlight the impact of each mix constituents on the estimate concrete strength.

Fuzzy modeling methods

Fuzzy logic was initially used to formulate linguistic information (Zadeh 1965). Later its potential to model complex multi-input-multi-output systems, where classical mathematical methods failed, is realized. This is followed by the use of fuzzy inference system (FIS), also known as fuzzy rule-based systems or fuzzy models, in control and modeling problems in which there is usually some numerical information available, although incomplete and uncertain. A key feature of the FIS is that it can readily integrate expert knowledge in the form of linguistic information and uncertain numerical data in the form of input-output records into a model and then use it for approximate reasoning. According to Zadeh (1973), the FIS contains three features:

- linguistic variables instead of, or in addition to numerical variables;
- relations between the variables in terms of IF-THEN rules; and
- an inference mechanism that uses approximate reasoning algorithms to formulate complex relationships.

These features can be explained using the notion of fuzzy sets. A fuzzy set is a collection of ordered pairs that describe the relationship between an uncertain quantity and a membership function $\mu(x)$, where $0 \le \mu(x) \le 1$. A fuzzy number is a normal and convex fuzzy set in a continuous universe of discourse in which the variable is defined. Figure 2 shows the commonly used fuzzy numbers including triangular, trapezoidal, and Gaussian shape fuzzy numbers. Finally, a linguistic variable can be regarded as a variable whose value is a fuzzy number, but fuzzy numbers can also represent numerical variables without being firmly connected to linguistic terms. An excellent introduction to the fuzzy set theory and fuzzy logic can be found in (Klir and Yuan, 1995; Lee, 1990a, b). In this section, the components of the FIS and the methods for constructing a FIS are explained.

Fuzzy inference system (FIS)

The information of the FIS is encapsulated in two modules: a fuzzy knowledge base and an inference mechanism. The former is a model developed based on expert knowledge and/or input-output data. The inference mechanism then uses the knowledge base to estimate the output of the system for given inputs. A modularized design of the FIS enables it to maintain a generic processing structure that is capable of dealing with various systems in different application domains (e.g., physical, medical, financial) as long as a relevant knowledge base is defined. Also, the FIS can be readily updated by modifying the knowledge base using new information as it becomes available.

Knowledge base - The knowledge base defines the relationships between the input and output parameters of a system. The most commonly used representation of the input-output

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relationships is Mamdani type fuzzy models (after Mamdani, 1977). In this type of fuzzy models, linguistic propositions are used both in antecedent and consequent parts of the IF-THEN rules.

Another type of representing the input-output relationships is Takagi-Sugeno-Kang (TSK) (Takagi and Sugeno 1985) fuzzy models in which the antecedent part of the rules is composed of linguistic propositions, but the consequent parts is defined by either a constant number (0th order) or linear equations (1st order). A 1st-order TSK model of a multi-input-single-output system may be represented by a set of linear subsystems (rules) each of which defined by a linear consequent statement,

$$R_i : \text{IF } x_1 \text{ is } A_{i1} \text{ AND } \ldots x_m \text{ is } A_{im} \text{ THEN } y_i = b_{i0} + b_{i1}x_1 + \ldots + b_{im}x_m, \ i = 1, \ldots, n \tag{1}$$

where R_i represents the ith rule, n is the total number of rules, x_j $(j = 1, \ldots, m)$ are the input variables, y_i is the output variable, A_{ij} is an input fuzzy set defined in the input space U_j, and b_{ij} are the consequent parameters. Thus, every rule is a local fuzzy relationship that maps a part of the multidimensional input space U into a certain part of the output space V.

It has been demonstrated (Sugeno and Tanaka 1991) that the TSK models can accurately represent complex behavior with a few rules. Although the TSK fuzzy models are computationally less involved than the Mamdani type fuzzy models, the difficulty in defining a numerical function for the output propositions has often made them less attractive in fuzzy applications. This problem is resolved when the model is constructed automatically based on input-output data acquired from the systems. Another problem with the TSK models is that it is difficult to assign an appropriate linguistic term to the consequence propositions of the TSK models, but this will not be a problem if a qualitative model of the system is not required.

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The rule base of a complex system usually requires a large number of rules to describe the behavior of a system for all possible values of the input variables. This is referred to as the "completeness" of a fuzzy model. The aggregation of the rules described in (1) forms a rule base that is valid over the entire application domain. The aggregation is obtained using the union of the rules or subsystems as,

$$R = \bigcup_{i=1}^{n} R_i = R_1 \text{ ALSO } R_2 \text{ ALSO } \ldots \text{ ALSO } R_n \tag{2}$$

Inference mechanism – The inference mechanism of Mamdani type and TSK fuzzy models are slightly different. Mamdani's inference mechanism (Fig. 3a) consists of three connectives: the aggregation of antecedents in each rule (AND connectives), implication (i.e., IF-THEN connectives), and aggregation of the rules (ALSO connectives). The operators performing the connectives distinguish the type of fuzzy inferencing. The AND and ALSO connectives are chosen from a family of *t-norm* and *t-conorm* operators, respectively. Comprehensive discussions on *t-norm* (e.g., minimum and product operators) and *t-conorm* (e.g. maximum and sum operators) can be found in (Lee, 1990a, b). The implication (IF-THEN connective) also uses *t-norm* operators, but not necessarily identical to the ones used for the AND connectives.

The inference mechanism of TSK models (Fig. 3b) is more straightforward than the more common Mamdani's type because the outputs of individual subsystems are crisp numbers. An algebraic product operator is usually selected to perform the *t-norm* to simplify the computations further. The result of implication of each rule is a weight factor that indicates the rule degree of firing (*dof*), w_i. The aggregation of the rules is simply adding the weighted average of the output of the individual rules. Thus, the crisp output y^* of a TSK model is given by,

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$$y^* = \sum_{i=1}^{n} \frac{w_i}{\sum_{k=1}^{n} w_k} y_i \qquad\qquad (3)$$

Fuzzy modeling

There are two basic approaches for developing a FIS: direct approach and system identification (Yager and Filev 1994b). In the direct approach, the information extracted from the expert knowledge is used to:

- specify the input, state, and output variables;

- determine the partitions of input and output variables in their universes of discourse, and optionally label the partitions with appropriate linguistic terms;

- define a set of IF-THEN statements (rules) that represent the relationships between the system variables;

- select an appropriate reasoning method; and finally,

- evaluate the model adequacy.

Direct approach is essentially simple and intuitive, but it has inherent limitations. The main limitation is due to the fact that quantitative observations provide an overview of the performance of the system, but do not explicitly determine the structure or parameters of the model. Also, it is often the case that an expert cannot tell linguistically what kind of outcome he expects or what kind of action he takes in a particular situation. As a result, the adequacy of the direct approach is restricted to the boundaries of the expert knowledge. In other words, if the expert knowledge about the system is incomplete and subjective, then so will be the model.

Another approach for developing a FIS is system identification. In this approach, the FIS is developed based on the input-output data (training data) obtained from the actual system. System identification is predominantly useful when a predetermined model structure based on characteristics of variables is not available. Therefore, system identification can increase the objectivity of fuzzy modeling by introducing new knowledge to the model (Zadeh 1991). System identification is divided into two parts: structure identification and parameter identification (Sugeno and Yasukawa 1993). Similar to the direct approach, the objective of structure identification is to determine the input and output variables, partitions of the input and output spaces (i.e., fuzzy sets), relationships between the input and output variables (IF-THEN rules), and finally the number of rules. Parameter identification involves adjusting the parameters of the model obtained in the first part so that a performance index such as the root mean square of the output errors is minimized. The parameters of a TSK type fuzzy model define the input fuzzy sets A_{ij} and the output coefficients b_{ij} of (1).

Structure identification - The input variables are selected from a pool of input candidates that most likely affect the output. Typically, there is no systematic way to specify the input candidates, and hence selection is primarily carried out based on experience or common sense. Subsequently, given a finite number of input candidates and the training data, the input variables can be selected using the combinatorial algorithm described in (Tagaki and Sugeno 1985). In the latter, first a combination of input variables is selected from of a number of input candidates. Next, the optimum premise and consequent parameters are identified according to the input-output data and a performance index (e.g., mean square of differences between the model output and output data) is calculated. The optimal combination of input variables is the one that yields the minimum performance index.

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The selection of the input variables is generally a complicated problem requiring iterative

algorithms, if *a priori* knowledge of the system is not available. At this point, a general

understanding of the system performance or a sensitivity analysis of the input candidates prior to

modeling can help reducing the number of input candidates.

The most important step of structure identification is the rule generation. Clustering of the input-

output data is an intuitive approach to rule generation. The idea of clustering is to produce a

concise representation of a system's behavior by dividing the output data into a certain number

of fuzzy partitions. The fuzzy C-Means (FCM) clustering algorithm (Bezdek 1981, Bezdek et al.

1987) has been widely studied and applied in many applications.

The convergence of the FCM optimization similar to most optimization problems depends on the

choice of initial values (i.e., the number of clusters c and initial cluster centers v_i). Yager and

Filev (1994a) proposed a simple and effective clustering algorithm, called the mountain method,

for estimating the number and initial location of cluster centers. In this method, a grid is

generated for data space of each input and output variable, and then a potential value for each

grid point based on the distances to the actual data points is calculated. The grid points with high

potential values correspond to the cluster centers. The problem with this clustering method is

that the computational load increases exponentially with the number of input variables. Chiu

(1994) proposed a modified form of the mountain method, called subtractive clustering, which

significantly decreases the computational load, especially for systems with a large number of

input variables. In this method, the potential value P_i^1 is calculated with respect to the actual

data points not some inscribed grid points. The potential of a data point x_i is given by,

$$P_i^1 = \sum_{j=1}^{n} e^{-\frac{4\|x_i - x_j\|^2}{r_a^2}} \quad, \quad i = 1,\ldots,n \tag{4}$$

where r_a is a positive constant. The first cluster center is at v_1 that has the highest potential

value $\pi_0 = \max(P_i^1)$, $i = 1,\ldots n$. Subsequently, the potential values of the remaining data points

are updated with respect to the first cluster by,

$$P_i^k = P_i^{k-1} - \pi_{k-1} e^{-\frac{4\|x_i - v_{k-1}\|^2}{r_b^2}} \quad, k = 2,\ldots,c \quad i = 1,\ldots,n-1 \tag{5}$$

where r_b is a positive constant and c is the total number of clusters. The procedure is repeated

until all cluster centers are obtained. The parameters r_a and r_b are used to adjust the distance

between the clusters. Typically, the clusters stand in an appropriate distance when $r_b = 1.5 r_a$. In

this paper, subtractive clustering is used to partition the input space and find the initial structure

of the FIS.

The number of rules is an important parameter of the FIS. Clearly, the appropriate number of

rules depends on the complexity of the system. According to Sugeno and Yasukawa (1993), the

number of fuzzy rules corresponds to the order of a conventional model where an optimal model

minimizes both the order and the output error. A statistical analysis for evaluating the optimal

order of a model is discussed by Akaike (1974). A large number of rules, similar to a high order

of a model, will bias the model towards specific data that can be imprecise or even erroneous. On

the other hand, less number of rules will likely increase the output error, which is essentially

equivalent to disregarding the effect of some of the data points containing valuable information.

Thus, the optimal number of rules n can be obtained from a tradeoff between the number of rules and the output error.

The number of rules will be automatically determined through clustering the input and output spaces. Each cluster center is used as the basis of a rule that describes the system behavior. Thus, the neighborhood radii r_a and r_b can be selected such that an optimal number of rules is achieved.

Parameter identification – Parameter identification concerns the adjustment of the antecedent and consequent membership functions. In general, parameter identification is more straightforward than structure identification, especially when an initial structure of the model is determined based on expert knowledge or through clustering. In this paper, parameter identification is carried out using Adaptive Network-based Fuzzy Inference System (ANFIS) (Jang 1993), which is also called Adaptive Neuro-fuzzy Inference System. The ANFIS algorithm basically provides a learning technique for extracting information from an input-output dataset viz., *training data*, and setting up the antecedent and consequent parameters of a fuzzy inference system, accordingly.

The ANFIS is essentially an adaptive multilayer feedforward network whose mathematical functionality is equivalent to a fuzzy inference system (FIS). The network is composed of a number of nodes connected through directed links. Each node is a processing unit that performs a node function on its incoming signal and yields the node output. The links only specify the direction of signal flow from one node to another. If a node function depends on certain parameter values (i.e., node's parameter set is nonempty), the node is an *adaptive node*. If a node function is fixed (i.e., node's parameter set is empty) then it is a *fixed node*. The output of the

nodes as well as the overall behavior of the adaptive network can be modified by changing the node function parameters. Thus, these parameters can be updated according to the training data to achieve a desired input-output mapping.

The ANFIS network consists of the following five layers:

Layer 1: Every node i in this layer is an adaptive node with a node output $O_{1,i}$ given by

$$O_{1,i} = \mu_{A_{ij}}(x_j), \quad i = 1,\ldots,n \quad j = 1,\ldots,r$$

(6)

where x_j is the input to the node, A_{ij} is a fuzzy set associated with the node, m is the number of inputs, and n is the number of rules. The use of Gaussian-shaped fuzzy sets is usually preferable from a computational point of view. A Gaussian fuzzy set with a maximum membership equal to 1 and minimum membership equal to 0 is given by,

$$\mu_{A_{ij}} = exp\left\{-\frac{\left(x - c_{ij}\right)^2}{2a_{ij}}\right\}$$

(7)

where a_{ij} and c_{ij} are the antecedent parameters of the FIS.

Layer 2: Every node i in this layer is a fixed node, labeled Π, which multiplies the incoming signals and sends the product out.

$$O_{2,i} = w_i = \prod_{j=1}^{m} \mu_{A_{ij}}(x_j)$$

(8)

where w_i is the degree of firing strength (*dof*) of rule i. Any *t-norm* operator that performs AND connective can be used as the node function in this layer.

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ration of the ith rule's firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{\sum_{k=1}^{n} w_k} \tag{9}$$

where $\overline{w}_i$ is called the normalized *dof* of each rule.

Layer 4: Every node i in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w}_i y_i = \overline{w}_i (b_{i0} + b_{i1} x_1 + \ldots + b_{im} x_m) \tag{10}$$

where $\overline{w}_i$ is the output of layer 3, and b_{ij}, $j = 1, \ldots, m$ are the consequent parameters of the FIS.

Layer 5: The single node in this layer is a fixed node labeled Σ that composes the overall output as the summation of all incoming signals, i.e.,

$$O_{5,1} = \sum_{i=1}^{n} \overline{w}_i y_i = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{11}$$

The above 5-layer network is functionally equivalent to a TSK type fuzzy inference system.

The parameter identification of the TSK models involves the determination of antecedent parameters a_{ij} and c_{ij} and consequent parameters b_{ij} using a given input-output dataset. A basic approach for identifying the parameters of an adaptive network is based on gradient method (Werbos 1974). The learning rule concerns how to recursively obtain a gradient vector in which

each element is defined as the derivative of an error measure with respect to a parameter. In gradient method, the learning rule is a chain rule, generally referred to as "back propagation" (Rumelhart et al. 1986) because the gradient vector is calculated in the direction opposite to the flow of the output of each node.

Although the gradient method seems a straightforward approach for the determination of the parameters of an adaptive network, this method is generally slow and likely to become unstable or trapped in local minima. The ANFIS constructs a fuzzy inference system (FIS) using a hybrid of the least squares estimate (LSE) and gradient descent proposed by Jang (1993) (see also Jang and Sun 1995). Specifically, the learning procedure uses the least squares estimate in a forward pass and gradient descent in a backward pass. In the forward pass, the network is simulated till layer 4 and the consequent parameters are identified by the least squares estimate under the condition that the antecedent parameters are fixed. In the backward pass, the error rates propagate backward and the antecedent parameters are updated by the gradient descent. The learning process is continued based on a learning rule, usually represented by the discrepancy between the desired output and the network output under the same input conditions. This discrepancy is called the error measure, which is usually defined as the sum of the squared differences between the desired and network outputs.

ANFIS model development for concrete strength estimation

The efficiency of the proposed ANFIS modeling technique is illustrated using the mix proportioning and material characterization data reported in Kim et al. (2004) and Kim et al. (2005). A three step procedure on the implementation of ANFIS to estimate concrete strength

using mix design is illustrated in this section. Fig. 4 shows the flowchart of the proposed modeling approach.

Step 1: Preparation of training data

The concrete mix constituents used in the model development are similar to those used in Kim et al. (2004) and Kim et al. (2005). The reported data were gathered from actual mix proportions of two companies, Company A and Company B. The overall basic material properties between the two companies are similar, with the exception of sand used. Company B uses only natural sand whereas Company A mixes both natural and crushed sand. Sample input data of the specified concrete mix proportions of Company A and B are presented in Tables 1a and 1b, respectively. Further, the main difference between the reported Kim et al. (2004) and Kim et al. (2005) data is the units assigned to the mix proportions. Kim et al. (2004) use kN/m^3 for water, cement, fine aggregate and coarse aggregate contents, whereas Kim et al. (2005) use kg/m^3 for those proportions Consequently, to combine the two datasets, the kN/m^3 units (shown in Tables 1a and 1b) are converted into kg/m^3.

The Company A and B data were combined for model training under the assumption that the data are commensurate. Hence, the final training data for Company A and B consist of 45 data points each. Further, a combined model of Company A and B, henceforth described as Company A-B is generated using a total of 90 training data points. It is noted that Company A and B have different fine aggregate constituents. Thus, for combined Company A-B data, the natural and crushed sand of Company A are combined and represented with a single fine aggregate (*FA*) label. For brevity, data are not repeated here; curious readers are referred to Kim et al. (2004) and Kim et al. (2005).

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Kim et al. (2004) and Kim et al. (2005) have considered nine different concrete mix proportioning parameters to model the 28-day compressive strength. The efficiency of a given model can be demonstrated using minimal input parameters to capture the desired model output. Hence, in this paper, initial screening is carried out to eliminate any redundant input parameter. For example, the simultaneous use of water-cement ratio and the corresponding water and cement contents as input parameters is redundant. Hence, the input parameters are divided into two groups, *absolute variables* and *relative variables* (Table 2). The absolute value modeling includes absolute values, input parameters entail, where possible, parameters without any relative ratios, e.g. using only unit water content and unit cement content, without the w/c ratio, specified concrete strength, slump, etc. The input of the relative value modeling includes relative ratios where possible (e.g., w/c ratio, fine aggregate percentage, etc…).

Step 2: Structure and parameter identification

ANFIS is used for structure and parameter identification as outlined in the previous section. The models are generated using datasets of Company A, Company B and the combination of Company A and B that are referred to as Model A, Model B and Model A-B, respectively. Moreover, each of the three models is implemented for *absolute variables and relative variables*, which are referred to as absolute model and relative model, respectively. In this way, a total of six models are generated. Initial sensitivity analysis is carried out to observe if there is any significant difference between the actual concrete strength and those predicted using the six models. The analysis showed that the results are only slightly different. Nevertheless, for a pragmatic model application, where a more generic model with the minimum number of inputs is

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typically more desirable, Model A-B is preferable. The ensuing discussion is only for the relative

Model A-B, but the derived conclusion is equally applicable to the other five models.

The FIS generated for the five relative input parameters (Table 2: *slump*, *w/c ratio*, *FA*, *CA*,

Amix) has four rules. Each input parameter is modeled using a Gaussian type membership

function (7). Result of coefficients of the Gaussian type membership function, for *slump*

(μ_{Slump}), *w/c ratio* ($\mu_{w/c}$), *FA* (μ_{FA}), *CA* (μ_{CA}), and *Amix* (μ_{Amix}) are summarized in Table 3.

For example, from Table 3, the μ_{Slump} associated with Rule 1 is:

$$\mu_{Slump}(x) = e^{-\frac{1}{2}\left(\frac{(x-4.5386)^2}{14.9938}\right)}.$$

The ANFIS equivalent of the TSK model is illustrated in Fig. 5. As discussed in the previous

section, the ANFIS is represented in five layers. Layer 1 corresponds to the membership

functions (Table 3). Layer 2, is a product layer, which illustrate the firing strength of a rule.

Hence, the ith rule firing strength (w_i) of input parameters associated with Rule *i* is (8):

$$w_i = \mu_{Slump}(Slump) \times \mu_{w/c}(w/c) \times \mu_{FA}(FA) \times \mu_{CA}(CA) \times \mu_{Amix}(A_{mix}).$$

Layer three entails normalization of the ith rule strength to the sum of all rules firing strength (9):

$$\overline{w}_i = \frac{w_i}{w_1 + w_3 + w_3 + w_4}.$$

Hence, $\overline{w}_i$ is called normalized firing strengths. Layer four computes the corresponding output

O_i strength estimation of Rule *i* (10):

$$O_i = \overline{w}_i y_i = \overline{w}_i \left(b_1 \times slump + b_2 \times w/c + b_3 \times FA + b_4 \times CA + b_5 \times A_{mix} + b_0 \right).$$

The parameters, $\{b_1, b_2, b_3,$ and $b_4\}$ are referred as *consequent parameters* (Table 4). For example, the model output from Rule 1 can be shown as

$$O_1 = \overline{w}_1 \left(-0.0471 \times slump - 0.4684 \times w/c + 0.4255 \times FA\% + 0.000988 \times CA - 8.866 \times Amix + 34.46 \right).$$

Finally, the estimated concrete strength, $f_c^{'}$, is obtained by summing the model output of the four rules (11):

$$f_c^{'} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Step 3: ANFIS Model Validation

Model validation must be carried out using the input-output data that are not used for training to evaluate the efficiency the FIS in predicting concrete strength. The reported (Kim et al. 2004 and Kim et al. 2005) testing data points are combined in the model validation, which resulted in total of 24 data points for each of Model A and B, and 48 data points for Model A-B. The FIS model predicted and actual concrete strength are used for model validation. The results are plotted in Figs. 6a to 6e. Figures 6a, 6c, and 6e show result of the absolute model validation of Model A, B, and A-B, respectively. Similarly, Figs. 6b, 6d, and 6f show result of the relative model validation of Model A, B, and A-B, respectively. A linear regression fit is performed between the actual and predicted concrete strength. The corresponding absolute and relative model coefficient of determination r^2 values are as follows: Model A (0.999, 0.984), Model B (0.970, 0.995) and Model A-B (0.999, 0.998).

Discussion

Concrete mix proportioning is a highly nonlinear process that is also subject to experimental error (Kim et al. 2004). Reliable prediction of concrete strength necessitates the development of models which are tolerant of various manifestations of uncertainty. Identification of dominant parameters can help to implement stringent monitoring and quality control during mix proportioning (Jain et al. 2005). A sensitivity analysis is commonly carried out using random sampling (Monte Carlo-type simulations) where the probability distributions for input data can either be assumed or derived from observations. Thereafter, the rank correlation method (Cullen and Frey 1999) is applied to the results of the Monte Carlo simulations to identify input data/parameters that dominate the output. The rank correlation method involves the determination of coefficient of determinations, which measure the strength of the linear relationship between two variables. The procedure utilized for the sensitivity analysis is as reported in Tesfamariam et al. (2005) and the basic steps are outlined here. For n_s number of realization,

For i = 1 to n_s,

- *Generate a uniformly distributed random numbers for the five input parameters (ranging between the min and max values), x_j*

- *Compute the corresponding membership function (6) and (7), $\mu_{A_{ij}}(x_j)$*

- *Compute the dof (8) and normalized dof (9)*

- *Compute the output of each layer (10) and normalized output (11)*

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Next i

   ▪ *For the n input-output results, rank order the results and perform rank correlation*

   ▪ *Normalize the rank correlation results and show the result on a tornado graph*

Sensitivity analysis of the FIS model is carried out for 3000 realizations from the relative Model A-B, and the results of the rank correlation are normalized to the sum of one and are plotted in a tornado graph (Fig. 7). Figure 7 shows that an increase in *CA* (16% contribution) and *w/c ratio* (72% contribution) decreases the concrete strength. Clearly, the contribution of *Slump* is not considerable. On other hand, an increase in *FA* (11% contribution) and *Amix* (1% contribution), albeit to a smaller degree, is followed by an increase in the concrete strength. It is interesting to note that impact of *CA, w/c ratio, Amix* and *FA* is in agreement with the results reported in Neville 1997. Overall the *w/c ratio* is the most dominant parameter towards the variability of the concrete strength. This reinforces our intuitive understanding that stringent quality control of the *in situ w/c ratio* should be implemented.

Further, two parameters at a time simulation is carried out for the three most dominant variables; *w/c ratio, CA* and *FA*. Figure 8a shows the simulation between *w/c ratio* and *CA*. At a higher *CA* content, e.g., 60%, there is a linear decrease in concrete strength with an increase in *w/c ratio*. At a lower *CA* content, e.g. 10%, the variation of *w/c ratio* from 40% to roughly 65% show negligible variation. However, at CA = 10%, significant decrease in concrete strength is observed with increase in the *w/c ratio* from 65% to 80%. At a lower *w/c ratio,* e.g. <50%, an increase in *CA* content (from 10% to 30%) is followed by a decrease in concrete strength. However, with further increase in *CA* content (from 30% to 60%), the concrete strength increases. This relation is in agreement with a reported (Neville 1997) relationship and Neville

underlined that the reason for this effect is not clear. At a higher *w/c ratio*, an increase in *CA* content (beyond 35%) reaches minima and the variation is not significant.

Figure 8b shows the relationship between *FA* and *w/c ratio*. In general, an increase in *FA* and a decrease in *w/c ratio* are followed by a linear increase in concrete strength. Figure 8c shows the variation of *CA* and *FA* in the estimated concrete strength. At any level of the *FA* content, increase in *CA* is followed by a decrease in concrete strength; however, after 35% *CA* content, it reaches minima. Similarly, and increase in *FA* is followed by an increase in concrete in strength, however, after 48% *FA*, it reaches a maxima.

The accuracy of the ANFIS model generated from the input parameters may be compromised outside the range of the training datasets. The inputs parameters for the proposed ANFIS model discussed in the paper are bounded within the following ranges: Slump, mm [5, 18]; unit water content [160, 185]; unit cement content, kg/m^3 [228, 524]; unit fine aggregate content, kg/m^3 (663, 1004); unit coarse aggregate content, kg/m^3 [882, 1060]; admixture, % [0.7, 2.6]; specified strength, MPa [10.8, 39.2]. Extrapolating the model outside these limits should be carried out with caution.

Conclusions

Concrete mix proportioning is a nonlinear process, for which developing a comprehensive and reliable analytical model is rather challenging, if not impossible. Typically, concrete manufacturing companies have extensive datasets of past mix proportions, which can be used for modeling and validation. Hence, the concrete industry can benefit from their historical datasets in conjunctions with soft computing techniques to automate mix proportioning and predict the

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strength of the final product, reliably. This study presents ANFIS modeling for concrete strength

estimation from concrete mix proportioning. The open architecture of the ANFIS model is

appealing as it captures the designer's intuitive experience as well as the numerical information

included in the datasets. The ANFIS modeling also allows post-modeling adjustment and fine

tuning based on the new datasets as they become available. The ANFIS modeling has a

significant potential in the concrete industry. Sensitivity analysis is carried out to identify critical

parameters that impact the concrete strength. Results of this analysis can be used to develop *in

situ* construction quality. The ANFIS model is developed for absolute input parameters where

necessary (e.g. unit water content (kg/m^3), unit FA content (kg/m^3), etc…). However, to

minimize the number of input parameters, relative input parameters (e.g. w/c ratio (%), FA

percentage (%), etc…) are taken into account where possible. The proposed model is tested and

validated with actual reported data in the literature. The coefficients of determination r^2 of the

corresponding absolute and relative models are as follows: Model A (0.999, 0.984), Model B

(0.970, 0.995) and Model A-B (0.999, 0.998).

The proposed ANFIS modeling method is a step forward toward the development of a

comprehensive model for the concrete industry. In any future development, the concrete strength

modeling should incorporate external factors that impact the concrete strength, such as

construction quality, environmental condition, etc. Further, this modeling approach can be used

at different stages of the concrete industry. These stages include, but not limited to, mix design

proportioning, simulation of concrete strength using mix design proportioning, estimation of *in

situ* concrete strength given the history of construction quality and *in situ* construction quality

monitoring using the a measured slump and air content. Finally, the use of soft computing

techniques such as ANFIS modeling allows the concrete industry avoid the risk of faulty or

deficient concrete that often entails durability and safety problems.

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LIST OF NOTATION

A_{ij}	Input fuzzy set
ANFIS	Adaptive Network-based Fuzzy Inference System
a_{ij}, c_{ij}	Parameters of Gaussian-shaped function
b_{ij}	Consequent parameters
c	Subtractive cluster, total number of clusters
CA	Coarse aggregate
dof	Degree of firing strength
i, j	Counters
ε	Error measure
FA	Fine aggregate
FIS	Fuzzy inference system
f_c'	minimum 28 days specified strength
n	Total number of rules
$O_{1,i}$	Node output of the ANFIS network
P_i^1	Subtractive cluster, potential value
R_i	i^{th} rule
r_a, r_b	Subtractive cluster, adjustment parameters
TSK	Takagi-Sugeno-Kang
U_j	Input space
V	Output universe of discourse
v_i	Subtractive cluster, cluster centers
w_i	Degree of firing strength
$\overline{w}_i$	Normalized dof of each rule
$w/c\ ratio$	water cement ratio
x_j	Input variables $(j = 1, \ldots, m)$
y_i	Output variable

y^*	Defuzzified crisp value
$\mu(x)$	Membership function
π_0	Highest potential value
Σ	Summation of all incoming signals

List of Figures

Table 1a. Sample Input Data, Specified Concrete Mix Proportions of Company A for Training[§]

Specified strength (MPa)	Slump (cm)	Water-cement ratio (w/c)	Fine aggregate percentage (%)	Unit water content (kN/m³)	Unit cement content (kN/m³)	Unit fine aggregate content (kN/m³)		Unit coarse aggregate content (kN/m³)	Admixture (%)
						Natural sand (s_1)	crushed sand (s_2)		
15.68	10	64.2	46.6	1.75	2.73	3.28	4.93	9.67	0.84
15.68	15	64.2	47.6	1.86	2.90	3.27	4.92	9.26	0.89
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
39.20	15	32.1	41.2	1.76	5.50	2.53	3.79	9.26	1.68
39.20	18	32.1	41.8	1.82	5.67	2.51	3.77	8.99	1.74

[§]from Kim et al. 2004

Table 1b. Sample Input Data, Specified Concrete Mix Proportions of Company B for Training[§]

Specified strength (MPa)	Slump (cm)	Water-cement ratio (w/c)	Fine aggregate percentage (%)	Unit water content (kN/m³)	Unit cement content (kN/m³)	Unit fine aggregate content (kN/m³)		Unit coarse aggregate content (kN/m³)	Admixture (%)
						Natural sand (s_1)	crushed sand (s_2)		
15.68	10	63.1	50.9	1.68	2.66	9.23	-	9.08	1.36
15.68	15	63.2	50.4	1.76	2.79	8.98	-	9.01	1.43
⋮	⋮	⋮	⋮	⋮	⋮	⋮		⋮	⋮
39.20	15	33.2	44.4	1.71	5.14	7.11	-	9.08	2.62
39.20	18	33.2	44.1	1.75	5.28	6.96	-	9.00	2.70

[§]from Kim et al. 2004

Table 2. Datasets of Specified Concrete Mix Proportions

Absolute value modeling	*Relative value modeling*
Specified concrete strength (MPa)	Specified concrete strength (MPa)
Slump (cm)	Slump (cm)
Unit water content (kg/m^3)	Water-cement ratio (w/c)
Unit cement content (kg/m^3)	Fine aggregate percentage (%)
Unit fine aggregate content (kg/m^3)	Coarse aggregate percentage (%)
Natural sand (s_1), crushed sand (s_2)	Admixture (%)
Unit coarse aggregate content (kg/m^3)	
Admixture (%)	

Table 3. Membership function of the Model A-B input parameters

Rules	Slump, μ_{Slump}		w/c ratio, $\mu_{w/c}$		FA, μ_{FA}		CA, μ_{CA}		Amix, μ_{Amix}	
	c_{i1}	a_{i1}	c_{i2}	a_{i2}	c_{i3}	a_{i3}	c_{i4}	a_{i4}	c_{i5}	a_{i5}
R1	4.5386	14.9938	14.9342	53.3991	4.1284	45.4977	14.4901	56.0001	0.5983	1.0611
R2	4.5242	15.0009	14.9346	35.7003	4.1316	41.9012	14.4901	59.6099	0.5704	1.5168
R3	4.5236	15.0006	14.9342	45.2000	4.1297	46.7999	14.4902	16.7901	0.5888	1.9525
R4	4.5217	12.0046	14.9333	66.3006	4.128	51.4011	14.4901	49.4499	0.5793	1.3134

Table 4. Datasets of Specified Concrete Mix Proportions

Rules	b_1	b_2	b_3	b_4	b_5	b_0
R1	-0.0471	-0.4684	0.4255	0.000988	-8.866	34.46
R2	-0.4072	0.2037	1.329	-0.9398	18.57	-59.22
R3	-0.06809	-1.013	1.298	1.09	3.304	-51.54
R4	-0.4016	-0.9981	1.512	-0.6199	-0.6334	48.12
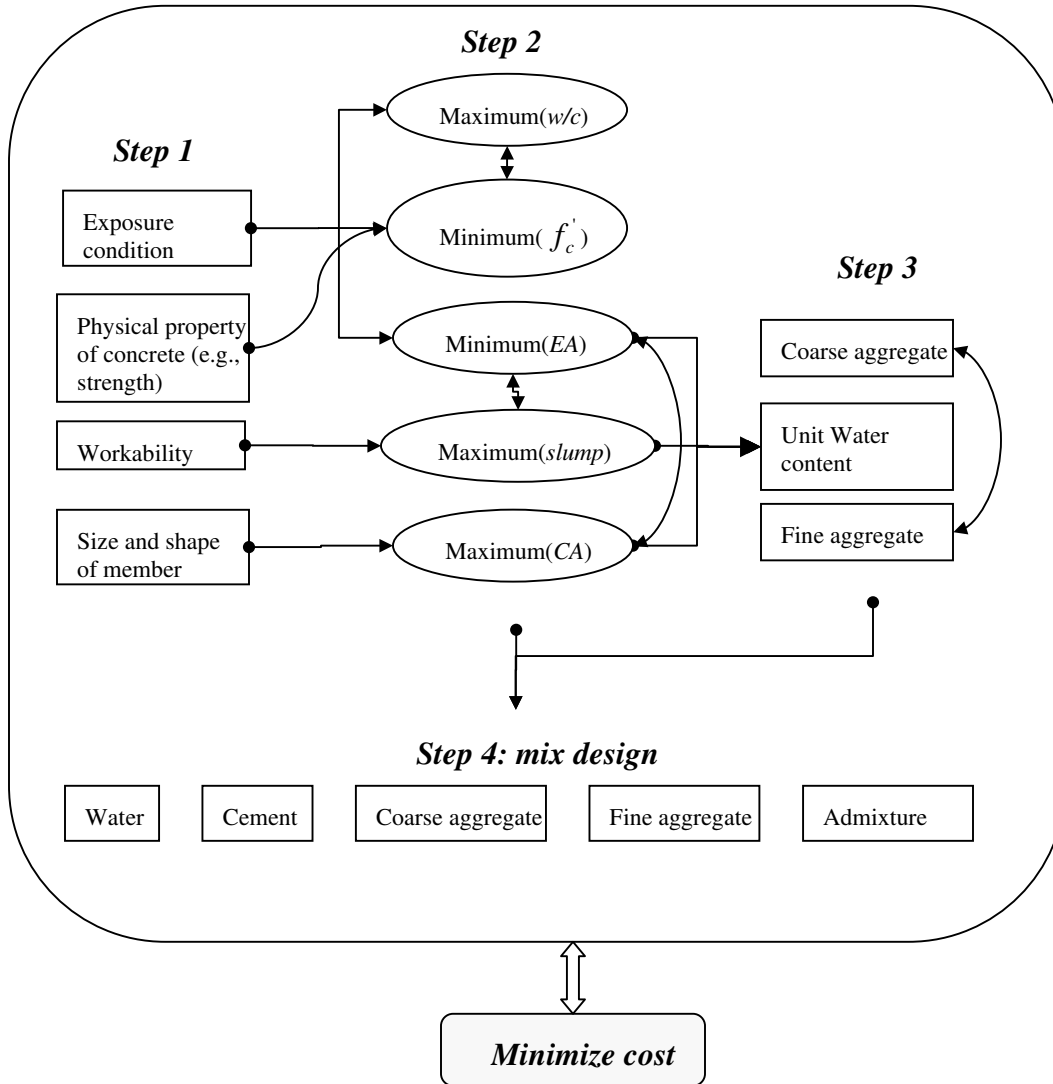
Figure 1. Concrete mix proportioning
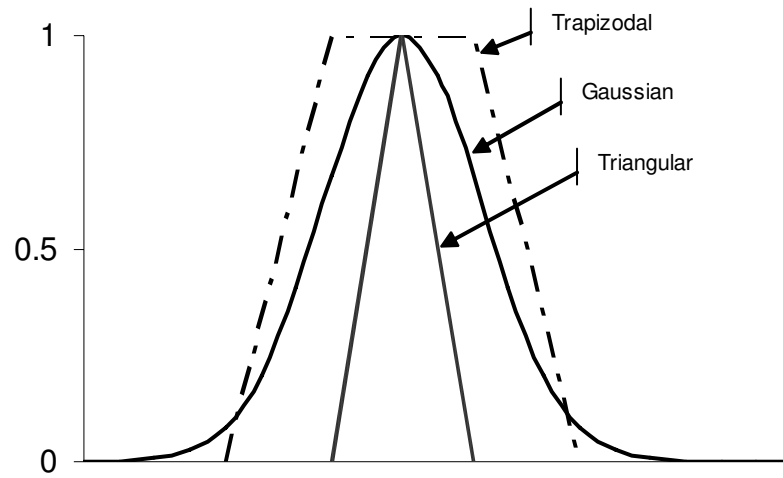
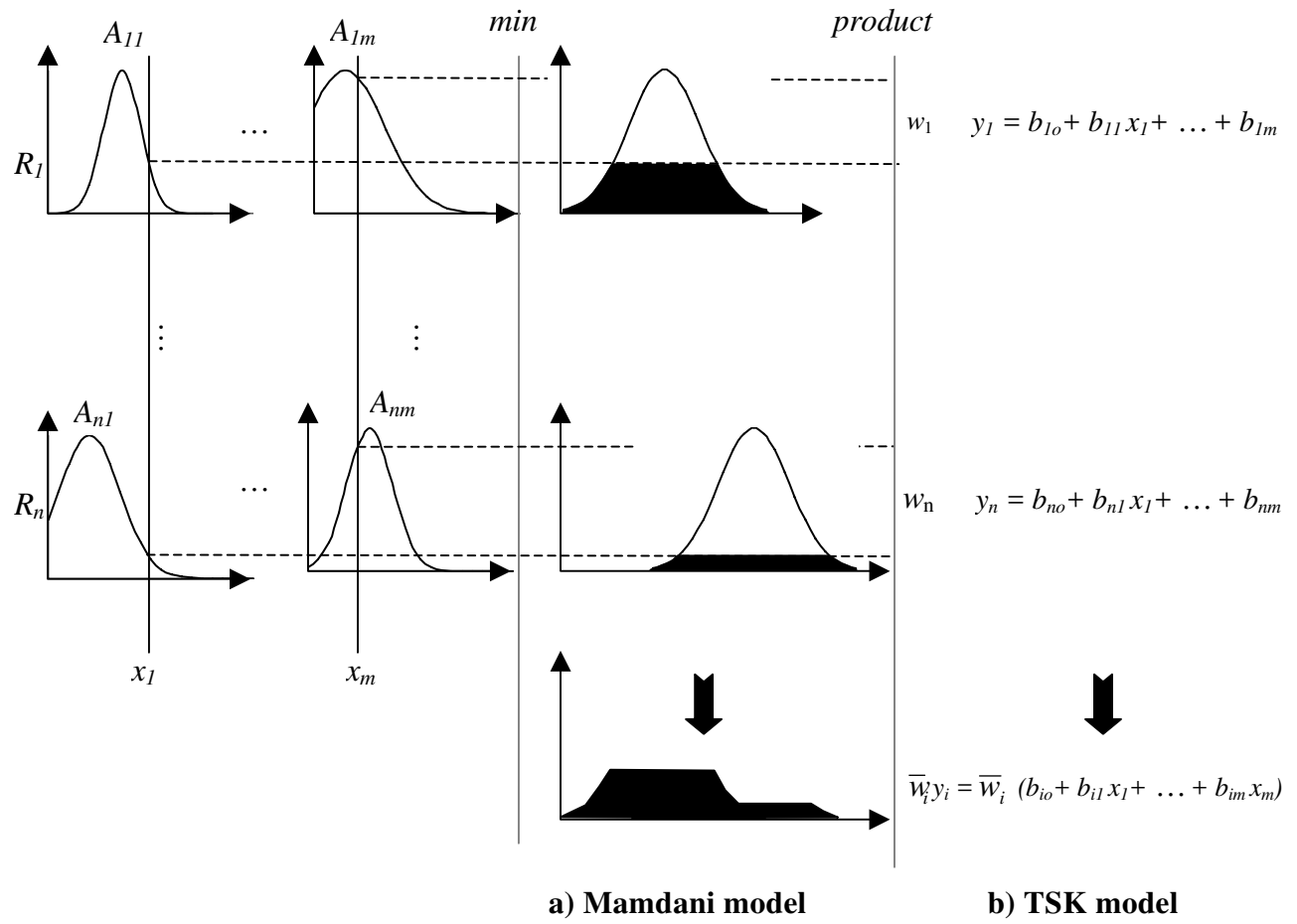**Figure 2.** Typical Fuzzy Membership Functions
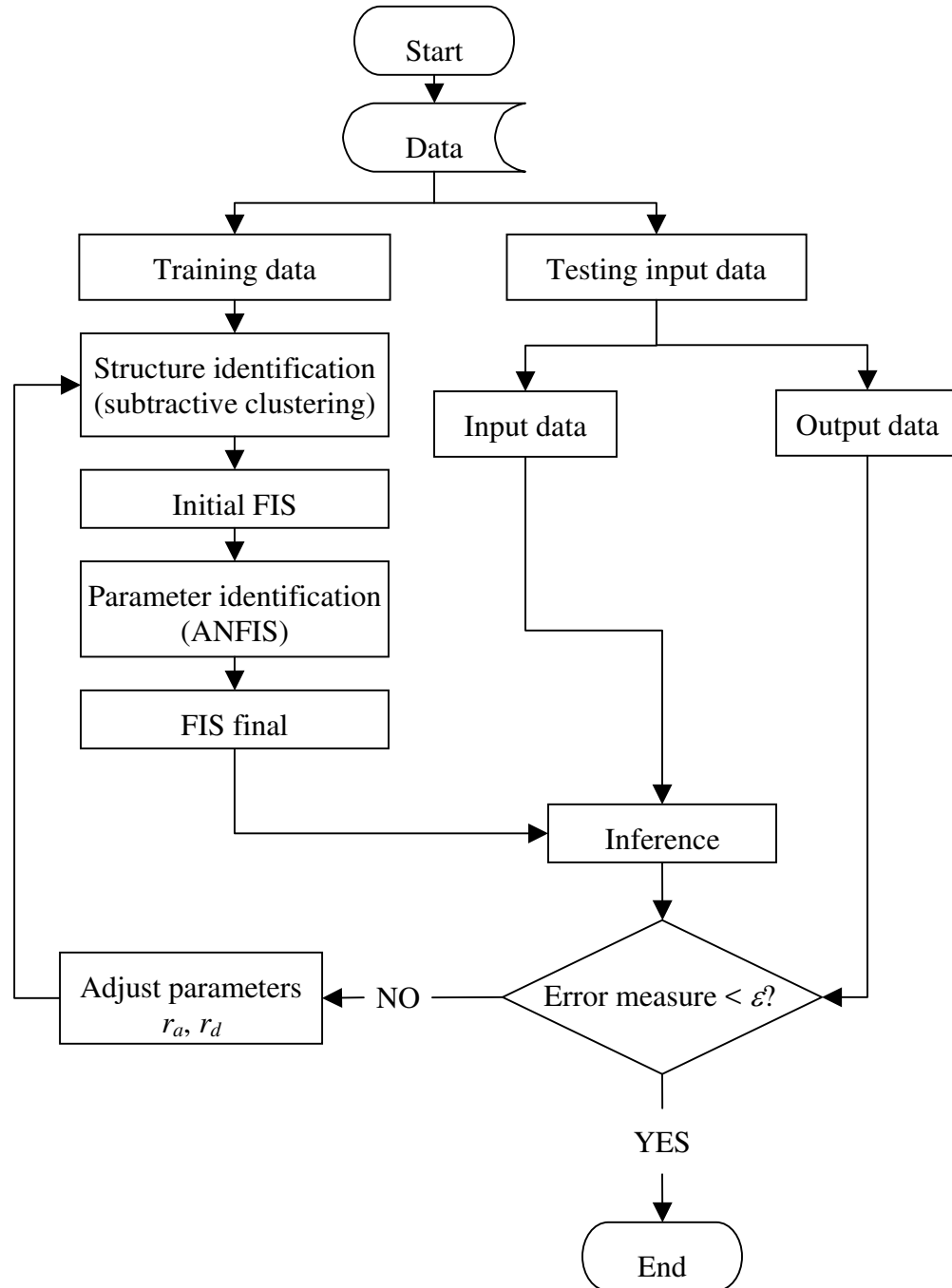
Figure 3. Fuzzy reasoning models

Figure 4. Flowchart of ANFIS model development for concrete strength modeling
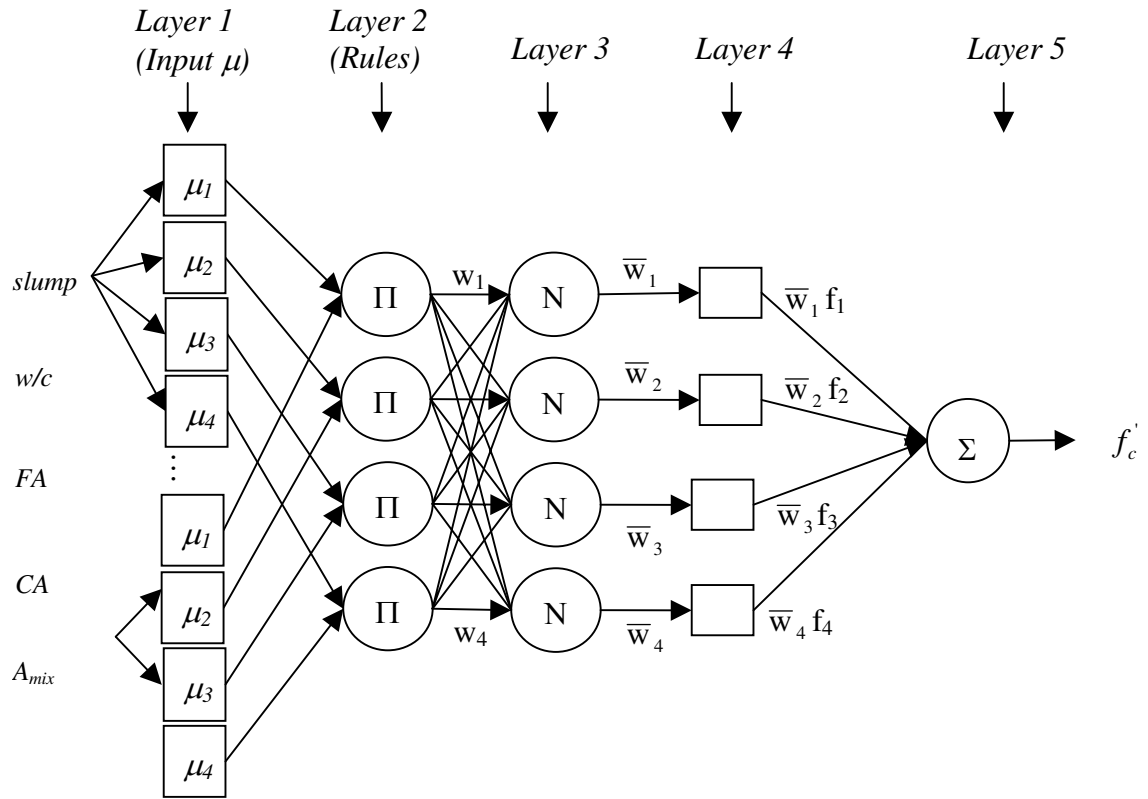
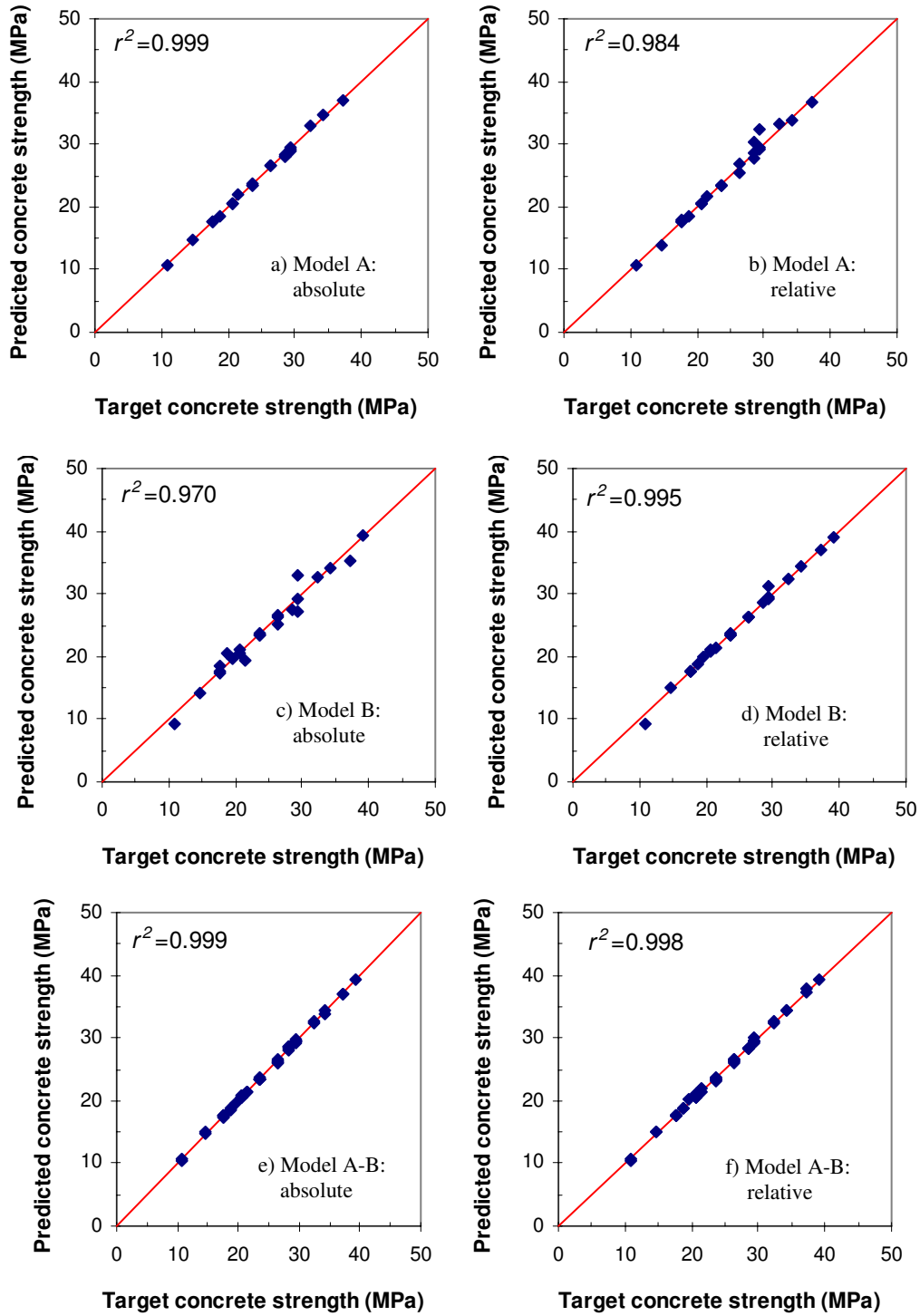**Figure 5.** ANFIS equivalent of TSK model for concrete strength modeling

Figure 6. Comparison of target and predicted concrete strength for
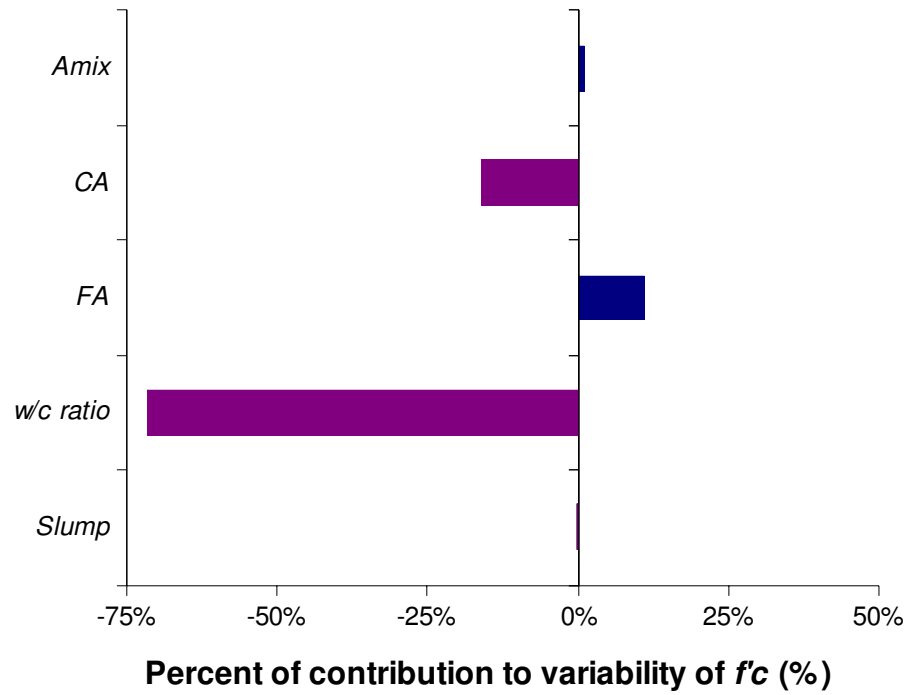
a combined and relative model.

Figure 7. Sensitivity analysis of concrete strength input parameters using a tornado graphs
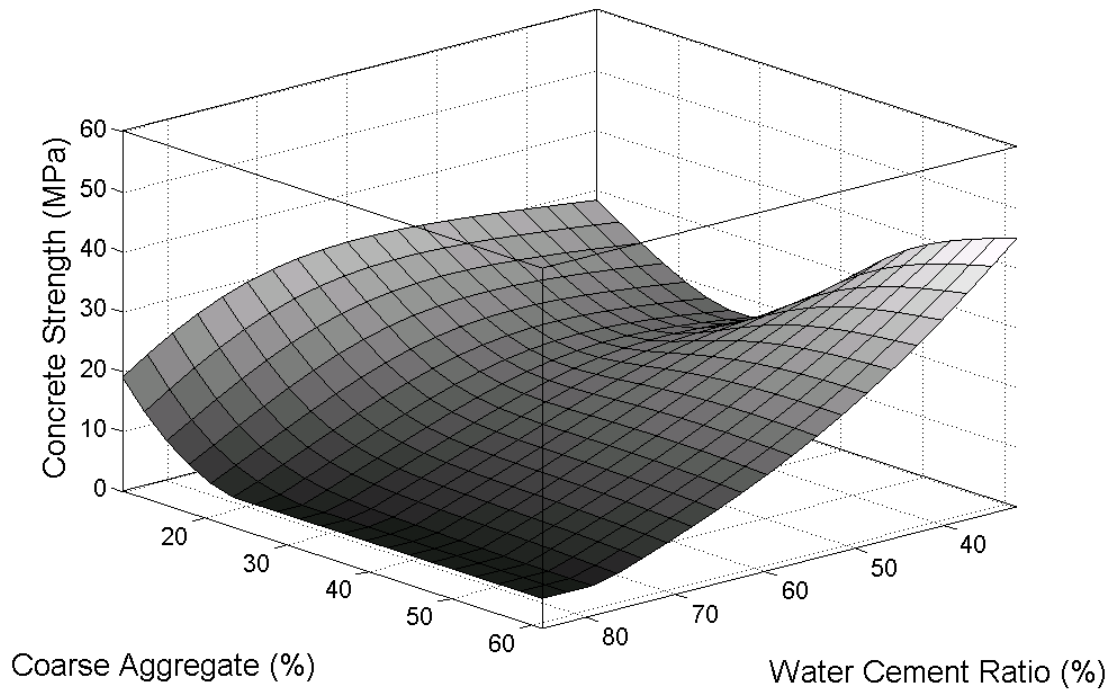
Figure 8a. Impact of variation in water cement ratio and coarse aggregate on the estimated concrete

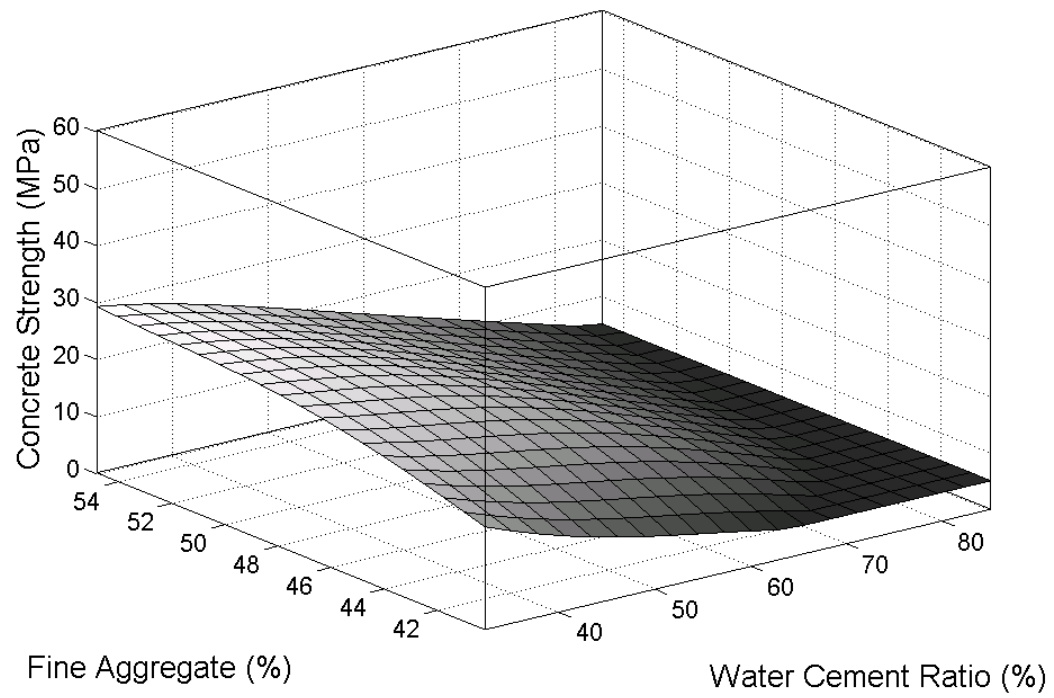strength: *Slump* (10 mm), *Amix* (1.5%) and *FA* (50%)

Figure 8b. Impact of variation fine aggregate and water cement ratio on the estimated concrete

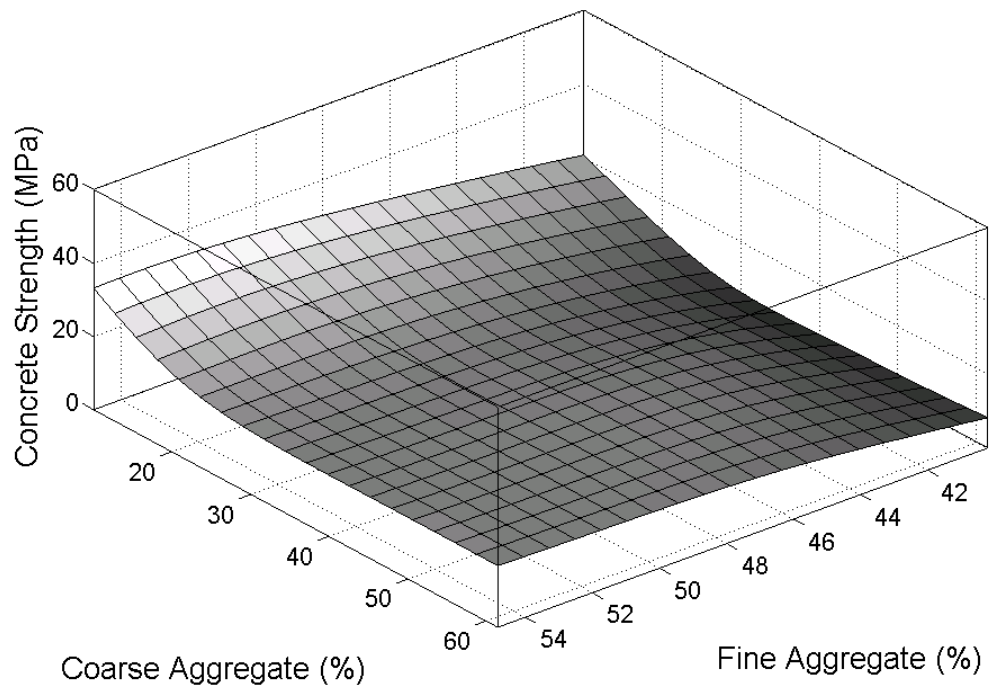strength: Slump (10 mm), Coarse Aggregate (40%) and Admixture (1.5%)

Figure 8c. Impact of variation in coarse aggregate and fine aggregate on the estimated concrete

strength: Slump (10 mm), Water cement ratio (60%) and Admixture (1.5%)