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A Comparative study of concrete strength prediction using fuzzy modeling and neuro-fuzzy modeling techniques.

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ABSTRACT – In this study, a comparative study of concrete strength prediction have been carried out by using three different models called type-1 fuzzy model, type-2 fuzzy model, and neuro-fuzzy model. These three models have been applied for concrete strength prediction of ready mix concrete based on its design mix constituents, namely cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and age. Three different statistical performance measures have been used for evaluating the models. The experimental results show that type-2 fuzzy model give a better performance measures.

1. INTRODUCTION

Concrete is the most important material used in building construction. The modeling of concrete material is a difficult task based on its composite nature [1]. There are various empirical results have been done from experimental studies and are widely implemented in modeling the concrete material. However, these studies do not provide accuracy and predictability where the interactions among the number of variables that are unknown, complex or nonlinear [1]. Fuzzy model is suitable for solving a non-linear problem, especially when the underlying physical relationships are not easy to understand. The framework for a fuzzy model is based on the concepts of fuzzy sets, fuzzy rules-based system, and fuzzy reasoning. The designed fuzzy models are capable of conducting perceptual uncertainties, such as the ambiguity and vagueness involved in a real-world problem [2].

In practice, the expert commonly used standard uniaxial compressive test to determine compressive strength. For example, the coring tests that widely used in the construction field [3]. However, the process is time-consuming and costly. Moreover, there is a practical limit to decide how many samples should be taken for a consideration. Besides that, only small numbers of samples are used, and it will lead to the difficulty in finding the reliable or meaningful statistical conclusions.

In order to overcome the limitation of the existing method, many studies have been done on finding a new approach to predicting concrete compressive strength physically and analytically. In recent years, the used of Artificial Intelligent (AI) as an analytical approach have increasingly been applied to concrete strength prediction [4][5]. Here, the AI techniques such as Artificial Neural Network (ANN) use the basic procedure to predict material behavior by using the training dataset. However, ANN is black box learning approach; the modeling result cannot interpret the relationship between the input and the output data. Besides that, AAN also cannot deal with uncertainties problem. Meanwhile, type-2 fuzzy model is good in handling uncertainties, and we can easily interpret the relationship between the input and output data by producing the rules. In this research, a methodology using type-2 fuzzy model, type-1 fuzzy model, and neuro-fuzzy model is developed to predict the concrete compressive strength. Then a comparative study of concrete prediction has been done based on the statistical performance measures.

2. METHODOLOGY

In this subsection, we discuss the process of constructing the fuzzy model and neuro-fuzzy model for concrete strength prediction. In this study, we implement *Takagi–Sugeno* (TS) fuzzy model for all three variants of fuzzy models.

2.1 Fuzzy Modeling

The *Takagi–Sugeno* (TS) fuzzy model provides a systematic approach for generating fuzzy rules from a given input-output data set. This model is also called the Fuzzy Functional Model, where the rule base is composed by using fuzzy rules, whose consequent parts are a function of the antecedent variables [6]. The consequent rules are represented by either the crisp number or linear functions of the input given. The antecedents' part is represented by a number of fuzzy regions based on the partition of the input space. The format of the TS model provides an effective way to represent the non-linear system by combining a rule-based description with local functional description, for example, in the form of linearization [6][7]. The main process of TSK model can be divided into a two-step procedure of system identification: structure identification and parameter estimation. Here, the structure of the model is identified by using the given input-output data [7].

Consider a function y=f(**x**) being mapped by the TS fuzzy model, in which y is the output variable (dependent variable), and **x** is the input variable (independent variable). The data set is in the form of finite input-output pairs, k=1, 2, …, M, where M is the total number of the input-output data available for parameter estimation. By considering N number of rules for generating the TSK fuzzy model, the representation of the TSK fuzzy model is:

R_i : if x_1 is $A_{i,1}$ and … x_n is $A_{i,k}$ Then $y_i=\mathbf{a}_i^T \mathbf{x} + a_{i0}$

In this study, we implement two types of fuzzy model called fuzzy type-1 and fuzzy type-2.

2.2 *Neuro-Fuzzy Modeling*

The neuro-fuzzy model has the learning capability of neural network. Here, the fuzzy inference structure and parameter can be tuned by using the training algorithm in neural network. In this study, Adaptive Neural Fuzzy Inferences System (ANFIS) based on if-then rules of Takagi-Sugeno Fuzzy Model is used for predicting the concrete strength [8].

3. EXPERIMENTAL RESULT

In this section, we elaborate on a set of experiments, in which we used concrete dataset from machine learning repository. The main objective of these experiments is to show the abilities of the developed method and quantify the performance of the predicted concrete compressive strength. A brief summary of the data sets used in the experiment is presented in Table 1.

Table 1The range of training data

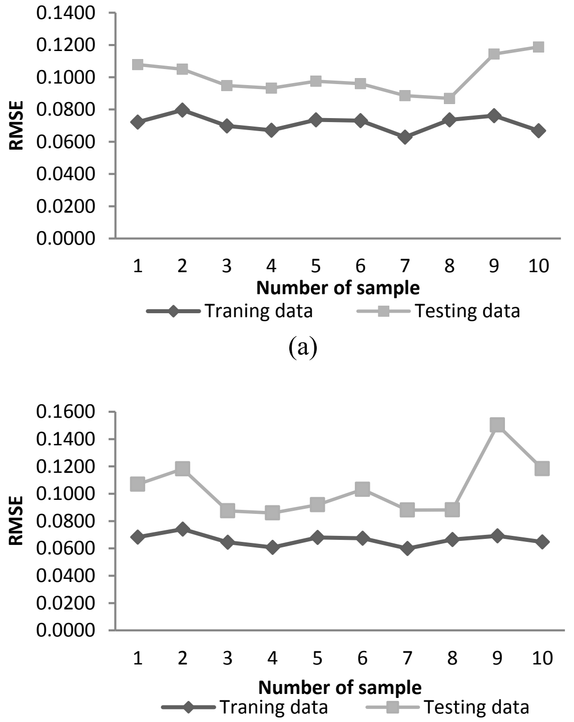
Input / Output variables	Minimum data	Maximum data
Cement	0	900.9
Water	118	238
Sand	208	879
Gravel	389	1285
Superplasticizer	0	3.5
Fly ash	0	275
Silica fume	0	90
Slag	0	500
Compressive strength	6.3	107.7

Three models were developed by using eight input variables and one output variable (compressive strength). The comparisons of results are summarized in Table 2. This table emphasizes the comparison performance of the fuzzy models in terms of three different statistical measures. The results show that Fuzzy type-2 model give the best performance compared to the other two models.

Table 2 Comparison of Prediction Models

Model	Root Means Square Error (RMSE)	
	Traning	Testing
Type-1 Fuzzy	0.0715	0.1003
ANFIS	0.0663	0.1038
Type-2 Fuzzy	0.1327	0.0427

Figure 1 show the performance of fuzzy models for training and testing data. Figure 2 show the RMSE for testing data using all three models. Here, the fuzzy type-2 model outperforms the other two approaches.



(a)

(b)

Figure 1 The performance for training and testing data (a) type-1 fuzzy model and (b) ANFIS

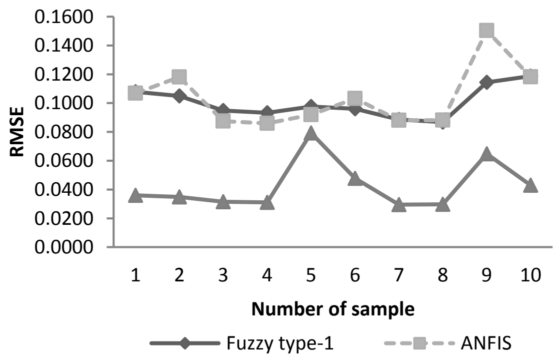


Figure 2 The RMSE for testing data.

4. SUMMARY

The prediction of the best compressive strength of concrete data is not an easy task because it contains highly complex materials. The proposed comparative study of three models helps to improve the prediction that will lead to reducing the waste of physical material and design and time cost.

In this paper, the effect of different fuzzy model on the performance of concrete strength prediction has been studied. The results of fuzzy type-2 model give a better performance compared to fuzzy type-1 and ANFIS models.

5. REFERENCES

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