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Dr. HOSEIN NADERPOUR
Associate Professor,
Faculty of Civil Engineering, Semnan University,
Semnan, PO Box 35195-363, Iran.
E-mail: naderpour@semnan.ac.ir

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Contact info:
Journal of Soft Computing in Civil Engineering,
Tel (Fax): +98-9127563681
Website: http://www.jsoftcivil.com/
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Description

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Aims and Scope

- Artificial Neural Networks (ANN)
- Fuzzy Logic (FL) and Fuzzy Systems
- Structural Optimization
- Pattern Recognition
- Heuristic Algorithms
- Machine Learning (ML)
- Evolutionary Computation (EC) - based on the origin of the species
- Support Vector Machine
- Genetic Algorithm
- Swarm Intelligence
- Ant Colony Optimizations
- Charged System Search
- Artificial Bee Colony
- Particle Swarm Algorithm
- Cuckoo Search
- Big Bang-Big Crunch
- Imperialist Competitive Algorithm
- Bat Algorithm
- Wolf Search
- Harmony Search
- Stochastic Diffusion Search
- Fish Swarm/School
- Genetic Programming
- Hybrid Algorithms

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Advanced ANN Prediction of Moisture Damage in CNT Modified Asphalt Binder

Md. Arifuzzaman
1
1. Assistant Professor, Department of Civil Engineering, University of Bahrain, Bahrain

* Corresponding author: arafiquzzaman@uob.edu.bh

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ABSTRACT
Moisture penetration causes many direct and indirect distresses in flexible asphalt pavement. Due to damage in asphalt concrete and binder by moisture are the prime concern of failure for flexible pavement worldwide. The causes and prediction are investigated in this study. The asphalt binder was modified with carbon nanotubes (CNT) with very small percentages. The modified binder was simulated with moisture damage with AASHTO T-283 methods. In this study, polymer and carbon nano-tubes (CNT) have been added to liquid asphalt binder to examine whether the resulting modified binder has improved moisture damage resistance. Using laboratory tested data, an artificial intelligence modeling technique has been utilized to determine the moisture damage behavior of the modified binder. Multi-Layer Perceptron (MLP) provides the best prediction for wet and dry samples AFM readings with $R^2$ values respectively 0.6407 and 0.8371.

1. Introduction
Asphalt binder has been used in roadway pavements since the early 1900’s. The USA has nearly 3.2 million kilometers of pavement made of asphalt binder. Since the pavement is not impervious hence the water from various sources enters the pavement and consequently damage it. Nonetheless, the moisture damage occurs globally with the presence of water. In literature, asphalt pavement distresses are related to the moisture intrusion in asphalt roads. Four attributes, namely: the adhesive bond between the binder, cohesive resistance of binder, the frictional resistance between the aggregate particles and the aggregate interlock are related to pavement strength (Divito and Morris 1982).
Damage due to moisture in pavement causes loss of integrity of a Hot Mix Asphalt (HMA) mix through the weakening of the adhesion bond between the asphalt binder and aggregate via the act of water. This occurrence is well known as the stripping which eventually leads to the breaking of the aggregate-asphalt adhesion bond and finally direct towards the failure of flexible pavement. Moreover, asphalt binder may experience changes in strength, stiffness, and viscosity which refer to the cohesion in asphalt as a result of moisture related sensitivity of asphalt pavements (Epps Martin 2003).

Although the research scientist and practicing engineers are thriving to prolong the life of the nation pavement but till now due to lack of proper understanding of moisture interaction with asphalts, pavements are prone to early failure from the infiltration of moisture. Several distresses may occur individually and simultaneously inside pavement due to this moisture entrance. The water reduces the internal bonding strength which leads to fatigue cracking/rutting in pavements (Sebaaly 2007). Since damage starts from nano to micro level, current research aims to conduct binder testing at nano level using Atomic Force Microscopy (AFM). The AFM produced laboratory output data were finally modeled with three advanced artificial neural intelligence tools.

2. Background of Research

Moisture damage in asphalt pavements is one of the main and primary distresses which is associated with the fracturing of the pavement surface, permanent deformation and excessive cracking (Kutay et al. 2007). Some literature related to pavement distresses, and ANN related works are investigated and described below:

Gandhi et al. (2009) constructed ANN models to predict tensile strength ratio (TSR) and the indirect tensile strength (ITS) of various asphalt pavement mixtures considering 5 no. of input variables such as aggregate source, asphalt binder source, anti-stripping agent (ASA), conditioning duration, and asphalt binder content. It is worth mentioning here that, ANN is a widely used computational tool that can identify the complex unknown relationship among the inputs and desired output to the system. The activity of an ANN was introduced following the activities of a biological brain. ANN-based pavement thickness determination in order to back-calculate the layer moduli was accomplished by Tarefder et al. (2015). Xiao et al. (2009) also incorporated ANN for prediction of the stiffness behavior of asphalt concrete in order to reuse reclaimed asphalt pavement materials.

Although, artificial neural network (emphasized on data science and data mining) is not new in civil engineering application (Flood and Kartam 1994). Mohammadhassani et al. applied ANFIS, ANN model to concrete deep beam experiment and analysis (Mohammadhassani et al. 2013). But for moisture damage in asphalt binder and concrete in pavement construction, modelling with artificial network and data science is a relatively new area. Not too many attempts can be found to model and investigate artificial data for modeling the moisture damage and associated effect in the asphalt pavement area.
Arifuzzaman and Hassan (2014) used SVR to predict the moisture damage in asphalt binder without adding CNT. Adham and Arifuzzaman (2014) used CNT to resist moisture damage. They did not accomplish modelling work with ANN. Amirkhanian et al. (2011) evaluated the rheological and engineering properties of different asphalt binder modified with various percentages of carbon nano particles (0.2%, 0.5%, 1.0%, and 1.5% by weight of the binder). They included in the experimental design of their study the utilization of three binder sources containing one type of nano particle (PG 64-22). Hassan (2015) used CNT and ANN to model moisture damage without application of Functional AFM tips (COOH, CH3, NH3 and OH groups) which are needed to predict the asphalt binder adhesion and cohesion forces. To the knowledge, this research is the first time attempt to model the moisture damage behavior with CNT modified asphalt binder with functionalized AFM probes.

3. Aim of the study

To make a good relationship for moisture damage study in carbon nanotubes (CNT) mixed asphalt binder, the research oriented specific objectives are proposed as:

1. Application of artificial neural network (i.e. SVM, ANFIS and MLP) on CNT modified asphalt binder
2. Model the large data set from moisture damage of asphalt binder using ANN, ANFIS and SVM.
3. To compare the performance of all models and to suggest the best one.

4.1. Test matrix

In this experiment, very used small percentages of carbon nano tubes (CNT) were used in SB and SBS modified base asphalt binder. Both dry and wet samples were tested under AFM with functionalized tips (-CH3, NH3, -COOH, -OH and –Si3N4) to get 269 data point for force distance measurement. Three methods SVM, ANFIS and ANN were used several hundred times to model these 269 data points to achieve the perfect results. The description for CNT, SB and SBS additives are given below:

4.2. Materials and additives

Base Binder: The base binder was collected from an oil-asphalt refinery commercial factory. Then SB, SBS and CNT were added to it according to the following discussions.

Description of polymer: Styrene-Butadiene (SB) polymer

This is a latex type polymer used to improve the elastic recovery as well as cohesive and adhesive properties of the pavement structures. In this experiment total 2 percentages (4% and 5%) by weight of SB polymer was mixed with the base binder (Arifuzzaman 2010).

Styrene-Butadiene-Styrene (SBS) polymer: Becker et al. (2001) described SBS to be the most preferable and used polymer to modify the base binder. In this experiment, total 2 percentages (4% and 5%) by weight of SBS polymer was mixed with the base binder.
Carbon Nano Tubes (CNT): Carbon nanotubes are structural as rolled-up graphite sheets having one end as capped. These type of tiny tubes may have single walls or multiple walls. The single-wall carbon nanotubes (SWNT), unlike carbon/graphite black, possess highly desirable mechanical, electrical and thermal properties (Ball 2001, Arepalli et al. 2001), with many potential applications in the computer, electronics as well as in aerospace industries. It is reported that the addition of a very small amount of carbon nanotube CNT (around 1%) by weight may increase both the compressive and the flexural strength as well as mechanical properties of civil engineering materials (Mann 2006). Our research found very few attempts to use CNT with asphalt binder for improvement (Al-Adham and Arifuzzaman 2014; Tarefder and Arifuzzaman 2016). In this study, Single Wall (0.5%, 1.0% and 1.5%) CNT were used to resist moisture damage in asphalt binder.

4.3. Sample preparation

The moisture damage in field was simulated in laboratory sample of the asphalt binder (AASHTO T-283 method). In this method the asphalt samples were conditioned under freezing and thawing environment for several days. Thus the wet samples were ready for AFM testing. Dry samples were usual samples without any interference of water.

5. Modelling Moisture Damage Data with Artificial Intelligence (AI) Approaches

The input values for ANN were Condition (dry and wet), percentages of SB and SBS polymer mixed with the base binder, percentages of CNT, AFM tips type (COOH, CH3, NH3, OH and Si3N4). The output result value was AFM experimental output as adhesion/cohesion force in terms of nano-newton in asphalt binder.

Statistical analysis of the data set are shown in Table 1.

The statistical analysis of the AFM laboratory generated data is shown in Table 1. The standard deviation value tells the necessity of artificial intelligence modeling of the highly deviated values from the standard one. The Kurtosis values of the data indicate that all the AFM produced data are less outlier prone than that of the normal distribution of the data.

<table>
<thead>
<tr>
<th></th>
<th>Dry</th>
<th>Wet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>382.51</td>
<td>405.01</td>
</tr>
<tr>
<td>Minimum</td>
<td>41.95</td>
<td>106.45</td>
</tr>
<tr>
<td>Mean</td>
<td>168.4945</td>
<td>225.7373</td>
</tr>
<tr>
<td>St Dev</td>
<td>88.48392</td>
<td>80.15665</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.360758</td>
<td>-0.996740</td>
</tr>
<tr>
<td>skewness</td>
<td>1.13887</td>
<td>0.50977</td>
</tr>
</tbody>
</table>
To model the 269-data set from AFM run test a total of three advanced ANN was used in this research. The ANN modelling work was accomplished in this study be splitting data set into two subsets: training set (80%) and validation set (20%). In order to train the NN system for tracing the complex and the nonlinear relationships between output and input values the training data set was utilized. The stopping criterion (trials and error) helps prevent the overfitting in ANN. The forecasting ability of the network was tested with 20% ANN dataset. One of the key concern in the NN architecture selection are the hidden layers as well as the number of nodes in each one of them. It may depend on complex relationship which need to be addressed further (Lefteri and Robert 1997). It also requires several trial-error as well as good selective judgment for appropriate ANN architecture which is the best suited for the concerned data set.

The brief description of the three systems are described below:

5.1. Adaptive Network Fuzzy Inference System (ANFIS)

This special ANN was proposed by Jang (1993). It serves as basic function to construct Fuzzy Interference System (FIS) and if-then formulated rules. More precisely, the ANFIS combines both neural network and fuzzy system from the best attributes and characteristics point of view. It can be successfully applicable to many real-life problems which are complicated for modelling work such as highly nonlinear function, for identifying nonlinear components in control type of systems, foresee-disorder time series etc. ANFIS description can be found more in details in Jang (1993).

5.2. Support Vector Machines (SVM)

SVM was proposed by Cores and Vapnik (1995). This simulation tool is best suitable outcome based geometric hyper-plane function for special separating data points. In this technique, the input data are mapped in highly dimensional characteristics space. The main and critical shortcomings of SVM are the duration for runtime and accuracy issues.

5.3. MLP based Artificial Neural Network (ANN)

This process can be described as the human brain performing computational programming which simulates the data learning and predicting tasks. One of the most popular used in this study is Multi-Layer Perceptron (MLP) which has vast applicability in pattern recognition and identification, speech recognition, control systems, petroleum engineering etc. (Agatonovic-Kustrin and Beresford 2000). Hence the MLP based process can be used for novel and efficient system for computational efficiency.

The overall flow diagram for the above mentioned methods is shown in Figure 1.
6. Analyses of Experimental Data

The data Table 2 and Table 3 show the analysis summary of the dry and wet samples with the above three mentioned method with respect to the six measured performances as:
The Correlation Coefficient (CC), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Relative Error (MRE) and Standard Deviation (SD) were calculated to investigate the accuracy of our utilized models. To find how much strong co-relation exists between the trend and the observed data, CC value is used. The value of CC “1” represents very much ideal co-relation exists while “0” means no co-relation can be predicted for the tested results. MAE is the measurement of the size of error while RMSE utilizes squaring mechanism to enlarge bigger error as well as suppressing smaller error. MAPE co-relates the magnitude of error to the magnitude of the observed real data.

### Table 2. Dry Samples Results

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>ANFIS</th>
<th>MLP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train (80%)</td>
<td>Test (20%)</td>
<td>Train (80%)</td>
</tr>
<tr>
<td>RMSE</td>
<td>16.2117</td>
<td>42.9149</td>
<td>38.4550</td>
</tr>
<tr>
<td>CC</td>
<td>0.9810</td>
<td>0.7567</td>
<td>0.8476</td>
</tr>
<tr>
<td>NRMSE</td>
<td>0.2227</td>
<td>0.6672</td>
<td>0.5282</td>
</tr>
<tr>
<td>MAPE (/100)</td>
<td>0.0727</td>
<td>0.3128</td>
<td>0.1869</td>
</tr>
<tr>
<td>MAE</td>
<td>10.3951</td>
<td>30.0103</td>
<td>26.6549</td>
</tr>
<tr>
<td>SD Error</td>
<td>0.2714</td>
<td>6.3164</td>
<td>1.8757</td>
</tr>
<tr>
<td>Time (Sec)</td>
<td>0.780005</td>
<td>0.0156</td>
<td>0.6240</td>
</tr>
</tbody>
</table>

### Table 3. Wet Samples Results

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>ANFIS</th>
<th>MLP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train (80%)</td>
<td>Test (20%)</td>
<td>Train (80%)</td>
</tr>
<tr>
<td>RMSE</td>
<td>36.6028</td>
<td>48.7577</td>
<td>30.5458</td>
</tr>
<tr>
<td>CC</td>
<td>0.9078</td>
<td>0.7723</td>
<td>0.9368</td>
</tr>
<tr>
<td>NRMSE</td>
<td>0.4175</td>
<td>0.6254</td>
<td>0.3484</td>
</tr>
<tr>
<td>MAPE (/100)</td>
<td>0.1119</td>
<td>0.1748</td>
<td>0.1288</td>
</tr>
<tr>
<td>MAE</td>
<td>22.7841</td>
<td>37.5612</td>
<td>24.0691</td>
</tr>
<tr>
<td>SD Error</td>
<td>0.8901</td>
<td>2.2477</td>
<td>0.7049</td>
</tr>
<tr>
<td>AOC</td>
<td>22.1674</td>
<td>35.4661</td>
<td>23.5699</td>
</tr>
<tr>
<td>Time (Sec)</td>
<td>0.8736056</td>
<td>0.0000</td>
<td>0.6240</td>
</tr>
</tbody>
</table>
For all cases, the performance of models was better for training datasets (80% samples) as compared to test datasets (20%) which are understandable. However, the variation between model performance for train and test datasets is more in case of dry samples as compared to wet samples. This could be because dry samples’ data contains more variations/noise. Moreover, the performance measures of all models for error terms (RMSE, MAE, etc.) were higher for wet samples’ test dataset while the relative error terms (MAPE) were lower for them. This could be because the magnitude of the dependent variable for wet samples was higher so the error term magnitude was higher corresponding to that. However, the performance of wet samples’ models was better, which resulted in better relative error terms.

This experimental test analysis run is made with different values of dry and wet samples with SVM, MLP and ANFIS-FCM method. For dry samples, plot of predicted versus measured is developed in these three methods. Generated R² values and equations are shown through linear trend line in the corresponding graph plots for each method in Figures 2 and 3.

Fig. 2. MLP result on Predicted vs Measured Data (Wet Samples)

Fig. 3. MLP result on Predicted vs Measured Data (Dry Samples)
The best two selected graphs out of sixteen are shown below based on the $R^2$ values. Plotting of wet material analysis through SVM, MLP & ANFIS has been created. For wet materials, generated $R^2$ values and equations are also shown through linear trend line in Figure 2 and 3.

The training and prediction time was calculated in terms of seconds in this study. The prediction time was very low for all the models, because it has comparatively small dataset and does not include any optimization algorithm as the model is already developed. Among the three methods for overall computation, MLP took the highest amount of time for training of both the dry and wet samples which was done for 80% of the total dataset. Hence, use of MLP on a large dataset cannot be recommended based upon these observations.

7. Discussion and Conclusion

The investigations provide a detail description of the test methods taking place for dry and wet samples. The measurement techniques & procedures are developed by a generation of linear trend line through the plotted points and comparing the $R^2$ value to find the efficient technique or procedures for the test of dry and wet samples.

Artificial neural network and related modeling (ANFIS, MLP and SVM) tools are used for the first time on AFM produced moisture damage data of CNT modified asphalt binder.

The conclusions drawn from the experimental and modelling work are listed below:

1. Neural network can address the complex relationship between adhesion and test variables incorporated in AFM testing. The developed NN model shows good prediction ability.

2. All models employed in this study, gave CC value more than 70% for all cases which is evident of their applicability for the prediction problem of this study. Moreover, the standard deviation of error was also relatively small for all models for training as well as prediction datasets which shows robustness of these models.

3. The study shows that MLP test for dry and wet sample produces convincing error terms with RMSE improvement of 2–8 units (approximately 3 – 5%) over SVM and ANFIS method.

4. So, it can be concluded with the promising fact that MLP procedure for dry ($R^2 = 0.8371$) and wet ($R^2 = 0.6407$) sample is more effective to predict real life moisture damage data.

5. Despite the above reasoning, it was also observed that MLP took longer training time than SVM and ANFIS. This could be due to optimization algorithm of MLP models; hence their applicability for large datasets should be further investigated.

8. Recommendation

The economic aspect, health consequences and availability of CNT utilization in road and highways are recommended for further investigation.
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References


Comparison Study of Soft Computing Approaches for Estimation of the Non-Ductile RC Joint Shear Strength

M. Mirrashid1*
1. Faculty of Civil Engineering, Semnan University, Semnan, Iran

Corresponding author: m.mirrashid@semnan.ac.ir

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ABSTRACT

Today, retrofitting of the old structures is important. For this purpose, determination of capacities for these buildings, which mostly are non-ductile, is a very useful tool. In this context, non-ductile RC joint in concrete structures, as one of the most important elements in these buildings are considered and the shear capacity, especially for retrofitting goals can be very beneficial. In this paper, three famous soft computing methods including artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and also group method of data handling (GMDH) were used to estimating the shear capacity for this type of RC joints. A set of experimental data which were a failure in joint are collected and first, the effective parameters were identified. Based on these parameters, predictive models are presented in detail and compare with each other. The results showed that the considered soft computing techniques are very good capabilities to determine the shear capacity.

1. Introduction

In the reinforcement concrete structures, shear failure of the element is very destructive and it is highly regarded in the design of these type of elements. Shear failure of RC columns mainly due to weakness in transverse reinforcement is a common failure in the past and in the non-ductile RC joints which have a low percent of the transverse reinforcement, there is a high risk of shear failure. There are a lot of RC structures that because of lack of knowledge of the vulnerability were built non-ductile, especially in their joints. Many studies have been done to strengthen and improve the performance of these elements and several methods such as using FRP material
were also proposed. The studies showed that shear failure of RC joint elements is very dangerous and very special attention is required. Some researchers investigated the shear strength of RC joint with different concrete types. For example, McLean and Pierce [1] investigated the shear of RCC (roller compacted concrete) joints based on an experimental study. They have presented the safety factors which can be used in analyses. Another case is a study which was done by Shiohara [2] to the analysis of the high strength reinforcement concrete joint in shear failure. The analysis of RC joint is a very useful tool to study the behavior of these elements. Ghobarah and Biddah [3] proposed a joint element for modeling of the joint in the nonlinear dynamic analysis with considering shear deformation. Their results show that the modeling of inelastic shear deformation in joints has a significant effect on the seismic response. Bakir and Boduroglu [4] presented a design equation for determining the shear strength of monotonically loaded exterior RC joints. They used several parametric studies to investigate the influence of variables on the behavior of RC joints based on the experimental database. Their results showed that their equation can be able to predict the joint shear strength exterior RC joints. An analytical model for shear strength of high strength RC joints is done by Sayed [5]. He was presented a general model for these type of joints.

One of the studies about the shear capacity of the RC joints is done by Jaehong and LaFave [6]. They used a collection of an extensive database of reinforced concrete (RC) beam–column connection test specimens which were subjected to cyclic lateral loading. They have determined the influence parameters for joint shear stress and finally, the design checks recommended were examined. They also presented probabilistic joint shear strength models for design [7].

The joint shear strength of exterior concrete beam-column joints reinforced internally with Glass Fibre Reinforced Polymer (GFRP) reinforcements was investigated by Saravanan and Kumaran [8]. They tested eighteen specimens and used finite element analysis to simulate the behavior of the beam-column joints. A design equation for assessing the joint shear strength of the GFRP reinforced beam-column specimens was also proposed. Sharma et al. [9] presented a model for simulating the shear behavior of exterior reinforced concrete joints subjected to seismic loads. Their model does not need any special element or subroutine and uses limiting principal tensile stress in the joint. Shear behavior of ultra-high performance concrete was studied by Lee et al. [10]. The results of their tests have been compared with several design formulae for assessing the
joint shear strength. The available models to prediction the shear strength of beam-column joints were reviewed by Pradeesh et al. [11]. The concept, parameters considered, significant observations and their limitations of the models for predicting the joint shear behavior were summarized in their study. Elshafiey et al. [12] investigated the performance of exterior RC joints subjected to a combination of shear and torsion based on the results of an experimental study. They also presented a three-dimensional truss model and showed that their model had an agreement with the experimental results. The shear strength and behavior of beam-column joints in unbonded precast prestressed concrete (PCaPC) frames based on the test results were investigated by Jin et al. [13]. The joint shear input was compared with the nominal shear strength of RC joint panels which was calculated based on common standards in their study.

This paper is an attempt to determine the shear capacity of RC non-ductile joints based on artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and also group method of data handling (GMDH). A collection of experimental which were published in the literature were used and predictive models were proposed to estimation the shear capacity.

2. Soft Computing

Soft computing (SC) tried to build intelligent which provides the ability to derive the answer from the problems with high dimensions and complex. They used to develop systems in similar of the human mind and have been advantageous in many engineering applications. In a general classification, SC techniques can be classified into three groups including artificial neural networks, fuzzy systems and neuro-fuzzy system (which is the combination of the first two groups).

In this section, three most famous soft computing methods including ANN, ANFIS and also GMDH were reviewed. These approaches are the considered methods which were used to the aim of this paper.

2.1. ANN

Artificial neural networks (ANN) are systems which were widely used for function approximation based on a collection of existing samples. They can be able to train the solutions from these data. They are applied in areas where the presentation of an answer is difficult by traditional methods. They have been used to solve engineering problems by three general layers
namely input layer, hidden layer or layers and also output layer. There are several neurons as computational units. These neurons are connected in layers, and signals travel from the first (input) to the last (output) layer. ANN used a set of data to estimate the weights and bias for the input and output signals of each neuron. It is clear that a big and reliable dataset has more ability to estimate the parameters.

2.2. ANFIS
Adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system implemented in the framework of adaptive networks which was introduced by Jang [14]. It was applied both of the fuzzy rules and input–output data pairs. ANFIS is one of the powerful soft computing approaches which was presented a Sugeno-type fuzzy system in a five-layer network (the input layer not counted by Jang). They are the ability of ANN and fuzzy systems together. For create an ANFIS model, three methods are commonly used: grid partition (GP), subtractive clustering (SC) and also fuzzy c-means (FCM) clustering. GP algorithm divides the data space into rectangular sub-spaces. SC algorithm divides the considered data into groups called clusters to discover the solution patterns. FCM which was used in this paper is an unsupervised algorithm. FCM consider the dataset into fuzzy clusters and also allows one data to belong to two or more clusters. This can be very useful to have a flexible and strongest ANFIS.

2.3. GMDH
Group Method of Data Handling (GMDH) network which introduced by Ivakhnenko [15] is a multi-layered perceptron-type network structure for mathematical modeling of systems. It is able to get the solution algorithm using data samples. Each node in GNDH has two input signals and use a second-order polynomial based on these two inputs. A collection of the dataset is applied to determine the coefficient values of polynomials based on least squares approach. They also can self-neglect ineffective inputs. Because of the mathematical manner of GMDH, these type of networks is widely used in engineering problems.

3. Experimental Data
For calculation of the considered soft computing methods, a collection of 149 data which were published in literature was used [16-50]. These data are related to non-ductile RC joints which were a failure in shear and their shear capacity has been reported to them. Table 1 and Fig.1
provides the details of the considered dataset. In this table, \( h_B, BI, \rho_b, f_{yB}, f'_{c}, JP \) and also \( v_{j,\text{exp}} \) are beam height, beam index, beam longitudinal reinforcement, yield stress of beam longitudinal reinforcement, a ratio of the number of sub-assemblages, The effective width of the joint panel and also shear strength of the joint respectively.

<table>
<thead>
<tr>
<th>Table 1. Information of dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>( h_B ) (mm)</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>Average</td>
</tr>
<tr>
<td>Maximum</td>
</tr>
<tr>
<td>Minimum</td>
</tr>
<tr>
<td>Median</td>
</tr>
<tr>
<td>Mode</td>
</tr>
<tr>
<td>St.Dev</td>
</tr>
<tr>
<td>Range</td>
</tr>
</tbody>
</table>

\( JP \) (In plane geometry) = 1 for interior, 0.75 for exterior.

![Fig. 1. Distribution of the considered dataset](image)

To normalization, a relationship which created the data within the value of 0.1 to 0.9 is used by Eq.1:

\[
x_{\text{normal}} = 0.8 \left( \frac{x_{\text{real}} - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \right) + 0.1
\]  

(1)

To training the models, 126 data, which has randomly chosen from the dataset, was used. The remained 22 data means used for the testing phase of the proposed models.
4. Selected Models for Shear Capacity Prediction

The initial modeling of the considered SC methods showed that the most powerful inputs were $f'_c$, $BI$ and $JP$. Therefore, these parameters were selected and used as inputs. This section, the structures and the parameters of the proposed models for considering estimation were presented in details. The results were discussed in section 5.

4.1. ANN-Model

The proposed ANN structure was shown in Fig. 2. The shear strength was considered by $v^n$ in the figure. $BI^n$, $JP^n$ and $f'_c^n$ are also the normal values of input 1, 2 and 3 respectively. They considered as $x1$, $x2$ and $x3$ in this paper. It was clear from the figure that the hidden layer has eight neurons. These nodes transfer its values to the final layer by Tangent-Sigmoid function. For the output layer, Purelin function was used. The details of the layers were presented in Tables 2 and 3. In these tables, $b_1$ and $b_2$ are the bias of the hidden and output layer respectively.

![Fig. 2. The proposed ANN structure](image)

<table>
<thead>
<tr>
<th>Neuron</th>
<th>Neuron 2</th>
<th>Neuron 3</th>
<th>Neuron 4</th>
<th>Neuron 5</th>
<th>Neuron 6</th>
<th>Neuron 7</th>
<th>Neuron 8</th>
<th>$b_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.3565</td>
<td>-0.3483</td>
<td>0.9888</td>
<td>-0.3566</td>
<td>0.3564</td>
<td>-0.3584</td>
<td>-1.4283</td>
<td>1.0587</td>
<td>-0.6522</td>
</tr>
</tbody>
</table>

Table 2. Layer weights and bias for the final layer
Table 3. Input weights and bias for the hidden layer

<table>
<thead>
<tr>
<th>Neuron</th>
<th>Input weights</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Input 1</td>
<td>Input 4</td>
<td>Input 5</td>
<td>b1</td>
</tr>
<tr>
<td>Neuron 1</td>
<td>-0.1299</td>
<td>0.0532</td>
<td>-0.2158</td>
<td>0.1388</td>
</tr>
<tr>
<td>Neuron 2</td>
<td>-0.1282</td>
<td>0.0577</td>
<td>-0.2109</td>
<td>0.1358</td>
</tr>
<tr>
<td>Neuron 3</td>
<td>-1.3420</td>
<td>0.2517</td>
<td>0.5692</td>
<td>0.2158</td>
</tr>
<tr>
<td>Neuron 4</td>
<td>-0.1299</td>
<td>0.0532</td>
<td>-0.2158</td>
<td>0.1388</td>
</tr>
<tr>
<td>Neuron 5</td>
<td>0.1299</td>
<td>-0.0533</td>
<td>0.2157</td>
<td>-0.1388</td>
</tr>
<tr>
<td>Neuron 6</td>
<td>-0.1302</td>
<td>0.0515</td>
<td>-0.2172</td>
<td>0.1395</td>
</tr>
<tr>
<td>Neuron 7</td>
<td>-0.9260</td>
<td>0.0178</td>
<td>-1.0580</td>
<td>-1.1287</td>
</tr>
<tr>
<td>Neuron 8</td>
<td>0.6463</td>
<td>0.3571</td>
<td>-1.0240</td>
<td>0.6312</td>
</tr>
</tbody>
</table>

4.2. ANFIS-Model

The selected ANFIS model, used FCM algorithm and had Gaussian membership function (eq.2) for input parameters as follows:

\[
\mu (x; \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}}
\]

(2)

Where \(c\) is the mean and \(\sigma\) is the variance of \(x\). The proposed ANFIS structure presented in Fig.3.

![Fig. 3. The proposed ANFIS structure](image)

The Gaussian parameters of the membership functions presented in Table 4 for all input parameters. Fig.4-6 showed membership functions of the selected ANFIS.
Table 4. Gaussian membership function’s parameters

<table>
<thead>
<tr>
<th>Membership function</th>
<th>Parameter</th>
<th>Inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>X1</td>
</tr>
<tr>
<td>C1</td>
<td>c</td>
<td>0.2883</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0461</td>
</tr>
<tr>
<td>C2</td>
<td>c</td>
<td>0.5382</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0878</td>
</tr>
<tr>
<td>C3</td>
<td>c</td>
<td>0.4737</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0619</td>
</tr>
<tr>
<td>C4</td>
<td>c</td>
<td>0.1954</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0514</td>
</tr>
<tr>
<td>C5</td>
<td>c</td>
<td>0.3641</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0566</td>
</tr>
<tr>
<td>C6</td>
<td>c</td>
<td>0.3116</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0327</td>
</tr>
<tr>
<td>C7</td>
<td>c</td>
<td>0.2048</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0567</td>
</tr>
<tr>
<td>C8</td>
<td>c</td>
<td>0.4959</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0745</td>
</tr>
<tr>
<td>C9</td>
<td>c</td>
<td>0.2528</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.0479</td>
</tr>
</tbody>
</table>

Fig. 4. Membership functions for input 1
In ANFIS-FCM structure, there are several clusters (CL) for the target. Each of clusters includes a linear function which is showed in eq.3.

\[
CL_j = a_1 x_1 + a_2 x_2 + a_3 x_3 + C \quad j=1,\ldots,10
\]  

(3)

The parameters \(a_1, \ldots, a_6\) are coefficients of input \(x_1, \ldots, x_3\). The parameter \(C\) is deal with a constant value. The amounts of these parameters presented in Table 5.

For the selected ANFIS, the rule base and also rule’s weights showed in Table 6 and 7 respectively.
Table 5. Parameters of the output’s clusters

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Inputs coefficients ($a_i$)</th>
<th>Constant (C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$a_1$</td>
<td>$a_2$</td>
</tr>
<tr>
<td>CL1</td>
<td>-3.8580</td>
<td>0.2218</td>
</tr>
<tr>
<td>CL2</td>
<td>-0.5828</td>
<td>0.0854</td>
</tr>
<tr>
<td>CL3</td>
<td>0.5490</td>
<td>-5.8310</td>
</tr>
<tr>
<td>CL4</td>
<td>0.9090</td>
<td>-0.0661</td>
</tr>
<tr>
<td>CL5</td>
<td>-0.4401</td>
<td>0.0207</td>
</tr>
<tr>
<td>CL6</td>
<td>-1.4010</td>
<td>0.0793</td>
</tr>
<tr>
<td>CL7</td>
<td>4.3990</td>
<td>-0.1364</td>
</tr>
<tr>
<td>CL8</td>
<td>1.4100</td>
<td>-0.2046</td>
</tr>
<tr>
<td>CL9</td>
<td>0.4603</td>
<td>-4.6700</td>
</tr>
<tr>
<td>CL10</td>
<td>1.5740</td>
<td>0.0695</td>
</tr>
</tbody>
</table>

Table 6. ANFIS rules

<table>
<thead>
<tr>
<th>Number</th>
<th>Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule 1</td>
<td>If XI is $C_{1X_1}$ and X2 is $C_{1X_2}$ and X3 is $C_{1X_3}$ then $v_{j,n}$ is CL1.</td>
</tr>
<tr>
<td>Rule 2</td>
<td>If XI is $C_{2X_1}$ and X2 is $C_{1X_2}$ and X3 is $C_{1X_3}$ then $v_{j,n}$ is CL2.</td>
</tr>
<tr>
<td>Rule 3</td>
<td>If XI is $C_{3X_1}$ and X2 is $C_{2X_2}$ and X3 is $C_{2X_3}$ then $v_{j,n}$ is CL3.</td>
</tr>
<tr>
<td>Rule 4</td>
<td>If XI is $C_{4X_1}$ and X2 is $C_{1X_2}$ and X3 is $C_{3X_3}$ then $v_{j,n}$ is CL4.</td>
</tr>
<tr>
<td>Rule 5</td>
<td>If XI is $C_{1X_1}$ and X2 is $C_{1X_2}$ and X3 is $C_{4X_3}$ then $v_{j,n}$ is CL5.</td>
</tr>
<tr>
<td>Rule 6</td>
<td>If XI is $C_{5X_1}$ and X2 is $C_{1X_2}$ and X3 is $C_{5X_3}$ then $v_{j,n}$ is CL6.</td>
</tr>
<tr>
<td>Rule 7</td>
<td>If XI is $C_{6X_1}$ and X2 is $C_{1X_2}$ and X3 is $C_{6X_3}$ then $v_{j,n}$ is CL7.</td>
</tr>
<tr>
<td>Rule 8</td>
<td>If XI is $C_{7X_1}$ and X2 is $C_{1X_2}$ and X3 is $C_{7X_3}$ then $v_{j,n}$ is CL8.</td>
</tr>
<tr>
<td>Rule 9</td>
<td>If XI is $C_{8X_1}$ and X2 is $C_{2X_2}$ and X3 is $C_{8X_3}$ then $v_{j,n}$ is CL9.</td>
</tr>
<tr>
<td>Rule 10</td>
<td>If XI is $C_{9X_1}$ and X2 is $C_{2X_2}$ and X3 is $C_{9X_3}$ then $v_{j,n}$ is CL10.</td>
</tr>
</tbody>
</table>

The normal value of the joint shear strength based on the considered ANFIS-FCM model can be determined by eq. 4.

\[
v^n = \frac{\sum_{j=1}^{10} w_{Rule,j} CL_j}{\sum_{j=1}^{10} w_{Rule,j}} \tag{4}\]
Table 7. Rule’s weight

<table>
<thead>
<tr>
<th>Number</th>
<th>Weight’s relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W_{Rule1}$</td>
<td>$(C1x1) \times (C1x2) \times (C3x3)$</td>
</tr>
<tr>
<td>$W_{Rule2}$</td>
<td>$(C2x1) \times (C1x2) \times (C3x3)$</td>
</tr>
<tr>
<td>$W_{Rule3}$</td>
<td>$(C3x1) \times (C2x2) \times (C2x3)$</td>
</tr>
<tr>
<td>$W_{Rule4}$</td>
<td>$(C4x1) \times (C1x2) \times (C3x3)$</td>
</tr>
<tr>
<td>$W_{Rule5}$</td>
<td>$(C1x1) \times (C1x2) \times (C4x3)$</td>
</tr>
<tr>
<td>$W_{Rule6}$</td>
<td>$(C5x1) \times (C1x2) \times (C5x3)$</td>
</tr>
<tr>
<td>$W_{Rule7}$</td>
<td>$(C6x1) \times (C1x2) \times (C6x3)$</td>
</tr>
<tr>
<td>$W_{Rule8}$</td>
<td>$(C7x1) \times (C1x2) \times (C7x3)$</td>
</tr>
<tr>
<td>$W_{Rule9}$</td>
<td>$(C8x1) \times (C2x2) \times (C8x3)$</td>
</tr>
<tr>
<td>$W_{Rule10}$</td>
<td>$(C9x1) \times (C2x2) \times (C9x3)$</td>
</tr>
</tbody>
</table>

4.3. GMDH-Model

The GMDH structure which was used in this paper presented in Fig. 7. The predictive model has two polynomials in the middle layer with equations 5 and 6.

![Fig. 7. Membership functions for input 3](image)

\[
Y_1 = -0.3981 + 1.9293 X_1 + 1.9412 X_3 - 1.1377 X_1^2 - 0.8803 X_3^2 - 0.9544 X_1 X_3 
\]

\[\text{(5)}\]

\[
Y_2 = 0.0021 + 0.1768 X_2 + 1.6035 X_3 + 1.1766 X_2^2 - 0.7743 X_3^2 - 0.1645 X_2 X_3 
\]

\[\text{(6)}\]

Based on the previous polynomials (eq.5 and 6), the final output of the model was calculated by eq.7.
\[ v^n = -0.2115 + 1.4396 Y_1 - 0.0419 Y_2 - 0.3626 Y_1^2 + 1.0406 Y_2^2 \\
- 0.6305 Y_1 Y_2 \]  \hspace{1cm} (7)

5. Results and Comparison

The output values of the proposed models are normal value and need to be converted to its real value and for this purpose, eq.8 was used:

\[ v_j = \left( \frac{|v^n - 0.1| (10.45 - 1.19)}{0.8} \right) + 1.19 \]  \hspace{1cm} (8)

In the equation, \( v_j \) is the joint shear strength of the non-ductile RC joints which determine by the proposed models. Based on the real values, the distribution of the results of these models presented in Fig8-10. It was clear from the figures that the considered soft computing approaches had suitable predictions.

Fig. 8. Distributed results for all 126 train data
A summary of the final results was also presented in Table 8. It was concluded that although all of the considered methods had suitable results, for all 149 data, ANFIS had less error and higher correlation factor than other models.
**Table 7. Summary results**

<table>
<thead>
<tr>
<th>Model</th>
<th>Train data (126 data)</th>
<th>Test data (22 data)</th>
<th>All data (149 data)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$ MAE RMSE</td>
<td>$R^2$ MAE RMSE</td>
<td>$R^2$ MAE RMSE</td>
</tr>
<tr>
<td>ANN</td>
<td>0.905 0.565 0.807</td>
<td>0.928 0.765 0.924</td>
<td>0.910 0.658 0.807</td>
</tr>
<tr>
<td>ANFIS</td>
<td>0.939 0.526 0.646</td>
<td>0.904 0.793 0.938</td>
<td>0.932 0.567 0.699</td>
</tr>
<tr>
<td>GMDH</td>
<td>0.875 0.727 0.911</td>
<td>0.929 0.633 0.821</td>
<td>0.886 0.713 0.897</td>
</tr>
</tbody>
</table>

In this table: $R^2$ is correlation coefficient, MAE is mean absolute error and RMSE is the root mean squared error.

### 6. Conclusions

Determination of the shear strength of non-ductile of RC joint using three soft computing methods including ANN, ANFIS, and GMDH was considered in this paper. For train and test the models, a collection of experimental was used and the structures of the predictive models presented in details. It was mention that based on try and error approach for all of the considered methods, three inputs including $BI, f'_c$ and $JP$ had more effective on the shear strength and therefore was used for modeling. The results showed that the proposed models have high performance for determining the shear strength. Additionally, the predicted values by ANFIS was more accurate than other two models. The importance results and the predictive models which were presented in this paper can be very useful for purposes such as retrofitting.

### References


No-deposition Sediment Transport in Sewers Using Gene Expression Programming

I. Ebtehaj1 and H. Bonakdari2*
1. Ph.D. Candidate, Department of Civil Engineering, Razi University, Kermanshah, Iran
2. Professor, Department of Civil Engineering, Razi University, Kermanshah, Iran

Corresponding author: bonakdari@yahoo.com

ARTICLE INFO

ABSTRACT

The deposition of flow suspended particles has always been a problematic case in the process of flow transmission through sewers. Deposition of suspended materials decreases transmitting capacity. Therefore, it is necessary to have a method capable of precisely evaluating the flow velocity in order to prevent deposition. In this paper, using Gene-Expression Programming, a model is presented which properly predicts sediment transport in sewer. In order to present Gene-Expression Programming model, firstly parameters which are effective on velocity are surveyed and considering each and every of them, six different models are presented. Among the presented models the best is being selected. The results show that using verification criteria, the presented model presents the results as Root Mean Squared Error, RMSE=0.12 and Mean Average Percentage Error, MAPE=2.56 for train and RMSE=0.14 and MAPE=2.82 for verification. Also, the model presented in this study was compared with the other existing sediment transport equations which were obtained using nonlinear regression analysis.

1. Introduction

Transmitting flow through sewage channel is often accompanied by solid materials. Sediment deposition takes place because of solid materials wide range entry into the sewer as well as the intermittent and variable nature of flow regimes within the sewer. Therefore, the management of sediment transport in sewers is considered as one of the most important items in sewer designing and operation. During wet weather flow, the flow rate is enough to suspend the solid sediments.
Solid materials deposition in sewers takes place especially in low flow rate cases such as the beginning of the layout period, low consumption hours or warm seasons of the year. Permanent deposition on the pipe bed causes cross sectional variation and bed roughness and therefore velocity and shear stress distribution change and sewer hydraulic resistance consequently influences sediment transport capacity and finally causes operation maintenance cost increments. In order to convey minimum entry flow into the sewer, the slope ought to be as much to be able to prevent sediment deposition or for a fixed channel slope, the minimum transmitting flow rate shall be as much to be able to transport solid materials. In addition to design the velocity that is somehow capable of transmitting no-deposition solid materials, pipe diameter shall be selected in a way that transmitting maximum flow rate becomes possible.

Therefore, methods are needed to manage deposit transmission in a way that the transmitting flow would be capable of cleansing deposited sediments. Also, hand design process needs to be economical and optimized (Butler and Clark, 1995). The traditional method of designing sewage channels to prevent sediment deposition in the flow uses minimum velocity or minimum shear stress. In this method, sewer designing was done by presenting a fixed velocity or minimum shear stress at a determined flow depth or specified period of time. For example, ASCE (1970) proposes the constant velocity for full and semi-full flow equal to 0.6 m/s for sanitary sewer and 0.9 m/s for storm sewer. British Standard (1987) proposes 0.75 m/s for full flow and storm sewer and 1 m/s for combined sewer. European Standard (1997) considers the constant velocity for pipes with diameters less than 300 mm equal to 0.7 m/s. While this criterion has not presented any suggestion for larger diameter pipes, flow conditions are not denoted in this standard. Also, for constant shear stress criterion, ASCE (1970) has proposed shear stress within the range of 1.3 to 12.6 N/m² and Lysne (1969) has proposed shear stress between 2 to 4 N/m². Therefore, we can conclude that velocity or minimum shear stress values are not equal in different conditions and countries. This is related to implemented experiments, size of sediments in different region and other parameters. So, in order to determine self-cleansing velocity, one has to achieve factors effective on sediment transport such as sediment concentration and size, flow hydraulic depth or radius, pipe roughness and diameter, so that the designer can achieve minimum required velocity according to regional conditions.
To survey sediment transmission in no-deposition case within sewers, sediment transport has been presented in two general ways: using dimensional analysis and semi-experimental relations. In order to present sediment transport relations with the use of dimensional analysis, dimensionless parameters are determined after implementing various experiments and studying the effect of effective parameters on sediment transport, and finally sediment transport relations are presented. In order to present semi-experimental relations with the use of effective forces exerted on a particle in equilibrium state, relations are presented. Using dimensional analysis, presented relations are given in three different states. The first approach, evaluates densimetric Froude Number \( (Fr) \) with the use of volumetric sediment concentration \( (C_V) \), relative flow depth \( (d/R) \) and overall sediment friction factor \( (\lambda_s) \) (Pedroli 1963; Graf and Acaroglu 1968; Novak and Nalluri 1975; Nalluri 1985). The second approach calculates \( Fr \) similar to the first case, but the difference is that in this approach in addition to the presented parameter in the first case, dimensionless particle number \( (D_{gr}) \) is also used, (Mayerle 1988; Mayerle et al. 1991; Ab Ghani 1993; Azamathulla et al. 2012). The third approach of the presented relations which uses dimensional analysis evaluates \( Fr \) by using volumetric sediment concentration \( (C_V) \) and flow proportional depth \( (d/R \text{ or } d/y) \) (Mayerle et al. 1991; Ota and Nalluri 1999; Yongvisessomjai et al. 2010). Semi-experimental relations are also presented in different ways and will be briefly presented. May (1982) obtained his model of bed load transport based on effective loads which are exerted on particles transmitted at limit of deposition. Using dimensional analysis the author simplified the theoretical model in order to present his model and fit it with experimental data. May et al. (1996) modified the relation of May (1982) by using seven different sets of data. This relation is considered as the best sediment transport relation at limit of deposition, which is achieved semi-experimentally (Ackers et al. 1996). Correcting the relation by Ackers and White (1973) and in order to consider flow cross section form in pipes, Ackers (1991) presented his relation. May (1993) presented his relation in a semi-experimental way to transport at the limit of deposition based on effective shear stress on the sediments surface. To develop a new practical methodology for sewer, a comprehensive research project conducted in the UK based on available experimental knowledge. The results of this project were offered by Butler et al. (2003). The harvest of this study is presented as a self-cleansing sewer design methodology based on a new definition of self-cleansing. The authors considered an efficient self-cleansing sewer which has sediment transport capacity by considering a minimum amount of deposited bed
to balance between consolidated expenses of construction, operation, and maintenance. Banasiak (2008) investigated the behavior of non-cohesive and partly cohesive deposited sediment in a partially full sewer pipe and its effect on the hydraulic performance of sewer. They found the presence of cohesive-like beds is more desirable than granular ones in terms of the bed roughness. Because the attendance of fine sediments as deposited sediment results in partly cohesive deposited solids so that decrease or in such cases prevent bed forms development. Ota and Perrusquia (2013) conducted several experimental tests in two sewer pipes at the limit of deposition condition to the measurement of sediment particle and sphere velocity. As regards, sediment transport depends on sediment repose angle, the authors developed a new semi-theoretical equation based on a reclaimed non-dimensional bed shear stress. Safari et al. (2017) carried out a series of experiment tests on trapezoidal channel cross-section. Using these samples and collected a wide range of experimental data of U-shape, rectangular and circular channel cross sections from the literature, the authors developed a self-cleansing model based on definition of a shape factor to consider the effect of channel cross section.

In recent years, using soft computing (SC) in different sciences has led to desirable results (Mondal et al. 2012; Gad and Khalaf 2013; Gorani et al. 2014; Al-Abadi 2014; Khoshbi et al. 2016; Ahmadianfar et al. 2016; Azimi et al. 2017). To overcome the uncertainty and complexity accompanied with bed load sediment transport estimation in sewers, Azamathulla et al. (2012) presented multi-ninlinear regression-based model and adaptive neuro-fuzzy inference systems (ANFIS). They found that the offered ANFIS model could employed as a strong alternative tool in sediment transport prediction at clean pipe. Ebtehaj and Bonakdari (2013) evaluated the performance of artificial neural network (ANN) in estimation of sediment transport using self-cleansing concept. They found the superior results of ANN in compared with existing regression-based methods. Ebtehaj and Bonakdari (2014) employed two different algorithms; back-propagation (BP) and hybrid of back-propagation and least-square (BP-LS); to train ANFIS in predicting of sediment transport in sewers. Moreover, to the generation of fuzzy inference system (FIS), sub-clustering (SC) and grid partitioning (GP) were utilized. Based on these methods, they introduced four different methods in ANFIS training. The results illustrated that a combination of GP and Hybrid results in the most precise sediment transport prediction.
All computational methods have different advantages and disadvantages depending on the type of problems, the decision on whether or not to use it done. In ANN, the learning and computations are easy but the major drawbacks of this approach are as arriving at the local minimum, less generalizing performance, over-fitting problem and slow convergence speed. Moreover, attaining the optimal structure of a constructed ANN is not simple (Rezaei et al. 2017). The main shortcoming of fuzzy logic (FL) is in finding the shape of each variable and suitable membership functions are untangled by trial and error (Singh et al. 2012, 2013). To overcome the disadvantage of ANN and fuzzy logic, ANFIS has been introduced which are knowing as a most popular strong SC tool. ANFIS is an adaptive fuzzy system which allows to utilization of ANN topology with FL simultaneously. It not only contains the features of both approaches, but also removes some shortcomings of their lonely-utilized case. Indeed, ANFIS consists of ANN advantages such as understanding mathematical details is not obligate and acquaintance with the job data is enough, employed different algorithm within learning course and solving nonlinear complex problems with strong capacity (Isanta Navarro 2013). Moreover, the advantages of ANFIS in comparison with ANN are attained highly nonlinear mapping, better learning capacity, and involves fewer tuneable parameters. However, the most constraints in ANFIS are more complex than FIS, not existe for all types of FIS (Rezaei et al. 2017) and there is no law for tunning the membership functions.

In addition to these drawbacks, the main problem in both of ANN and ANFIS is the existence of a black-box and don’t provide a certain equation to apply in practical applications. Therefore, it needs to a technique to overcome to this shortcoming. One of the newest presented models in soft computing topic is Gene Expression Programming (GEP). The main shortcomings of this method are premature convergence due to derivation of this method from genetic programming and genetic algorithm, preservation of best individual based on roulette-wheel selection method with elitism so that results in losing other better individuals (Gan et al. 2007) and CPU time consuming. Azamathulla and Ab. Ghani (2010) predicted pipeline scour depth with the use of GEP and concluded that in comparison with existing models, the presented model provides better results. Khan et al. (2012) used GEP in order to predict bridge pier scour. The authors compared their presented model with artificial neural network and regression relations and concluded that the presented model leads to more satisfactory results when compared to existing models. Chang et al. (2012) compared three different methods available in soft computing, adaptive neuro-fuzzy
inference system, feed forward neural network and GEP, to survey bed load in the rivers. Azamathulla and Ahmad (2012) used GEP model to predict transverse mixing coefficient in open channels flow. Using laboratorial results mostly, the authors presented a relation in order to estimate transverse mixing coefficient which presented the results with more precession compared with the existing relations. With the use of Gene-Expression Programming (GEP) in this study, sediment transport in sewerage channels has been studied. The presented model is applicable for no-deposition case.

To increase the accuracy of the presented model in this study – in comparison with the existing models (Ab Ghani and Azamathulla, 2011) which only used the four basic mathematical operations multiplication, subtraction, division and addition – various functions which can be seen in Table 1 were used. Firstly, considering the effective parameter on sediment transport, six different models have been presented. Comparing the presented models with data sets which were not used in presenting models, the best model has been selected. To assess the accuracy of the models presented through GEP algorithm versus the existing equations, the experimental results of Ota and Nalluri (1999) which had no role in the training of the GEP were used.

2. Non-deposition sediment transport equations

May et al. (1996), with the use of seven different data sets (Mack 1982; May et al. 1989; Mayerle et al. 1991; May 1993; Nalluri and Ab Ghani 1993; Ab Ghani 1993; Nalluri et al. 1994) studied the existing sediment transport relations. Laboratorial data was used to evaluate these relations. Results of studying the relations showed that each relation presents good results only for data sets which have been used for relation presenting, thus in order to present a relation for sediment transport studying at the limit of deposition, they presented following relation :

\[ C_v = 3.03 \times 10^{-2} \left( \frac{D^j}{A} \right) \left( \frac{d}{D} \right)^{1.5} \left( \frac{V^2}{g(s-1)D} \right)^{0.6} \left( 1 - \frac{V}{V_r} \right)^{0.47} \]  \hspace{1cm} (1)

\[ V_r = 0.125 \left[ g(s-1)d \right]^{0.31} \left( \frac{V}{d} \right)^{0.97} \]  \hspace{1cm} (2)

where \( C_v \) is volumetric sediment concentration, \( D \) pipe diameter, \( A \) Cross-sectional area of the flow, \( d \) median diameter of particle size, \( g \) gravitational acceleration, \( s \) specific gravity of
sediment \( (=\rho_s/\rho) \), \( V \) flow velocity, \( V_i \) the required velocity for incipient motion of sediment (Eq. 2) and \( y \) flow depth.

In order to sediment transport at limit of deposition Ackers et al. (1996) considered the above relation as the best existing relation for designing usage and Vongvisessomjai et al. (2010) too used Eq. 1 for verification of his relation. Considering volumetric sediment consideration \( (C_V) \) and relative flow depth \( (d/R) \), Ebtehaj et al. (2014) presented the \( Fr \) in the form of following relations:

\[
Fr = \frac{V}{\sqrt{g(s-1)d}} = 4.49C_V^{0.25}\left(\frac{d}{R}\right)^{-0.54}
\]  

(3)

Ab. Ghani and Azamathulla (2011) used GEP to predict bed load transport in sewers. The authors presented their equation by considering the parameters of volumetric sediment concentration \( (C_V) \), relative depth of flow \( (d/R) \), dimensionless particle number \( (D_{gr}) \) and Overall sediment friction factor \( (\lambda_s=1.13D_{gr}^{0.01}C_V^{0.02}\lambda^9.98, \lambda^9 \text{ clear water friction factor}) \) as follows:

\[
\frac{V}{\sqrt{gd(s-1)}} = 1.425 + \left(\frac{-0.41}{(R/d)}\right) + \left(\frac{C_V - 1}{5.91}\right) + \left(\frac{0.014}{\lambda_s} + \lambda_c - 8.43\lambda_s^{1.5}D_{gr}\frac{R}{d}\right)
\]  

(4)

3. Data Collection

In this research a combination of the lab test results by Vongvisessomjai et al. (2010) and Ota and Nalluri (1999) was used. The model is proposed using experimental results presented by Vongvisessomjai et al. (2010) and the results of lab experiments are used to verify the feasibility of the model proposed by Ota and Nalluri (1999). Vongvisessomjai et al. (2010) conducted their tests on pipes in two sizes of 100 and 150 mm in diameter and 16 m in length. They employed two sections to measure the flow: one at a distance of 4.5 m upstream, and the other at the distance of 5.5 m downstream. These two points were 6 m apart. In each section the velocities were measured at flow surface, middle depth and near bottom and their mean average was taken as the average velocity. For the air/water phase of the flow, the Manning coefficient of roughness \( (n) \) was equal to 0.0125. Vongvisessomjai et al. (2010) tests were conducted in a non-deposited bed state. More details are given in Vongvisessomjai et al. (2010). To validate the accuracy of
results presented in this article, Ota and Nalluri (1999) data were used for limit of deposition. For the purpose of their tests at limit of deposition, Ota and Nalluri (1999) used six different dimensions of \( d \) (ranging from 0.71 mm to 5.61 mm). They conducted 24 tests in total. Moreover, to test the impact of granulation on sediment transport, they conducted 20 further experiments using five different ranges of sediments with an average diameter of \( d = 2 \) mm. More details are given in Ota and Nalluri (1999). Table 1 shows the range of the data used in their tests.

<p>| Table 1. Range of data in Ota and Nalluri (1999) and Vongvisessomjai et al. (2010) studies |
|---------------------------------|-------------------------------|----------------|-----------------|-----------------|----------------|</p>
<table>
<thead>
<tr>
<th>( y/D )</th>
<th>( V ) (m/s)</th>
<th>( R ) (m)</th>
<th>( C_v ) (ppm)</th>
<th>( d ) (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ota and Nalluri (1999)</td>
<td>0.39-0.84</td>
<td>0.515-0.736</td>
<td>0.005-0.076</td>
<td>16-59</td>
</tr>
<tr>
<td>Vongvisessomjai et al. (2010)</td>
<td>0.2-0.4</td>
<td>0.24-0.63</td>
<td>0.012-0.032</td>
<td>4 to 90</td>
</tr>
</tbody>
</table>

4. Overview of Gene Expression Programming

Gene expression programming (GEP) is an expansion of genetic programming (GP) (Koza 1992). GEP belongs to the family of evolutionary algorithms and is closely related to genetic algorithms and genetic programming. From genetic algorithms it inherited the linear chromosomes of fixed length; and from genetic programming it inherited the expressive parse trees of varied sizes and shapes (Ferreira 2001). The GEP procedure is such that initially required functions for model creation and terminal set are being selected. In the next step, in order to evaluate the aimed parameter (in this study \( Fr \)) and comparing it with the real value, existing data sets are being recalled. Afterwards, in order to randomly present the initial population, chromosomes are being produced. In the next step, for population mass production with the use of existing chromosomes, the program is run and the fitness of target function is surveyed. If we arrive at pause conditions, program is stopped, otherwise with the use of new chromosomes - which have been corrected via genetic operators - as well as new population; again target function is being evaluated. This action continues until program pause conditions are present.

Fitness of an individual program \( (i) \) for fitness model \( (j) \) has been presented by Ferreira (2006) in the following form:

\[
If \ E(ij) \leq p, \ then \ f_{ij} = 1, \ else \ f_{ij} = 0
\]
where \( p \) precision and \( E(ij) \) the error of program \( i \) for fitness case \((j)\). For absolute error, it is being stated as in following form:

\[
E(ij) = |p_{ij} - T_j|
\]  

(6)

Also the fitness value \((f_i)\) for an individual program is stated in the following form:

\[
f_i = \sum (R - |p_{ij} - T_j|)
\]  

(7)

where \( R \) is selection range, \( p_{ij} \) the predicted value by individual program \((i)\) for fitness case \((j)\) and \( T_j \) the target value for fitness case \((j)\). After fitness function determination, the terminal set \((T)\) and function set \((F)\) have to be determined in order to selecting chromosomes.

5. Methodology

In order to survey sediment transport in pipes, effective parameters on flow and sediment particles movement have to be recognized. According to laboratorial studies by researchers (Ab Ghani 1993; May et al. 1996; Vongvisessomjai et al. 2010), the most important surveyed and utilized parameters to present their relations, include parameters like flow velocity \((V)\), dimensionless particles number \((D_{gr})\), volumetric sediment concentration \((C_V)\), median diameter of particles size \((d)\), pipe diameter \((D)\), flow depth \((y)\), hydraulic radius \((R)\), cross sectional area of the flow \((A)\), overall sediment friction factor \((\lambda_s)\) and special gravity of sediment \((s)\). Thus dimensionless parameters could be considered in the form of movement, transport, sediment, transport mode, and flow resistance. Movement parameters are respectively stated as densimetric Froude number \((Fr)\) or \((\psi)\) which uses shear stress instead of velocity. Transport parameter contains volumetric sediment concentration \((C_V)\) or the presented transport parameter \((\phi)\), dimensionless particle number \((D_{gr})\), proportional average size of particles \((d/D)\) and specific gravity of sediment \((s)\). Transport form parameter includes the ratio of hydraulic radius to the median diameter of particles size \((R/d)\), the ratio of squared pipe diameter to the flow cross sectional area \((D^2/A)\), relative flow depth \((y/d)\) - instead of which usually \(R/d\) is being used - and the flow resistance parameter that considers flow overall frictional coefficient \((\lambda_s)\). Based on these explanations, in order to study the effect of each and every parameter in different
dimensionless groups, dimensionless parameters can be presented in order to predict \( Fr \) in the form of Table 2.

<table>
<thead>
<tr>
<th>Parameter type</th>
<th>Dimensionless groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Movement</td>
<td>( Fr = \frac{V}{\sqrt{gd(s-1)}} ), ( l = \frac{\tau_u}{\rho g(s-1)d} )</td>
</tr>
<tr>
<td>Transport</td>
<td>( C_v \cdot \phi = \frac{C_v VR}{\sqrt{g(s-1)d^3}} )</td>
</tr>
<tr>
<td>Sediment</td>
<td>( D_{\nu}, d/D, s )</td>
</tr>
<tr>
<td>Transport mode</td>
<td>( d/R, D^2/A, d/y, y/D )</td>
</tr>
<tr>
<td>Flow resistance</td>
<td>( \lambda_s (k_s - k_y)/D )</td>
</tr>
</tbody>
</table>

It is necessary to use different statistical indexes to verify the feasibility of the proposed model. The statistical indexes used in this study include dimensionless coefficient criteria called R-Squared \( (R^2) \), the relative criteria of Mean Average Percentage Error \( (MAPE) \) and absolute criteria of Root Mean Squared Error \( (RMSE) \). The R-Squared \( (R^2) \) index is the ratio of the combined dispersion of the estimated model and the observed value to the dispersion of the estimated and observed models. The MAPE expresses the estimated value in relation to the observed value. \( MAPE \) is a non-negative index which has no higher limit. The \( RMSE \) is a criterion of mean error that has no upper limit and has the lowest possible value of zero, representing the best estimation by the model.

\[
R^2 = \left[ \frac{\sum_{i=1}^{n}(Fr_{\text{exp}} - Fr_{\text{calc}})(Fr_{\text{calc}} - Fr_{\text{exp}})}{\sum_{i=1}^{n}(Fr_{\text{exp}} - Fr_{\text{calc}})^2} \right]^2 
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n}(Fr_{\text{exp}} - Fr_{\text{calc}})^2}
\]
\[ \text{MAPE} = \left( \frac{100}{n} \right) \sum_{i=1}^{n} \left| \frac{F_{\text{exp},i} - F_{\text{GEP},i}}{F_{\text{exp},i}} \right] \] (10)

The above-mentioned indexes present the estimated amounts as the average of the forecasted error and do not present any sort of information on the forecasted error distribution of the suggested models. It is obvious that a high correlation coefficient (80-90%) is not always considered as an indication of the high accuracy of a model; on the contrary, this index may lead to showing high accuracy for mediocre models (Legates and McCabe 1999). In addition RMSE index indicates the model’s ability to predict a value away from the mean (Hsu et al. 1995). Therefore, the presented model must be evaluated using other indexes such as average absolute relative error (\( AARE \)) and threshold statistics (Jain et al. 2001; Jain and Ormsbee 2002; Rajurkar et al. 2004; Maghreb and Givehchi 2007). \( TS_x \) index indicates forecasted error distribution by each model for \( x\% \) of the anticipations. This parameter is determined for various amounts of average absolute relative error. The amount of the \( TS \) index for \( x\% \) of the predictions is determined as explained below:

\[ TS_x = \frac{Y_x}{n} \times 100 \] (10)

\[ AARE = \left( \frac{1}{n} \right) \sum_{i=1}^{n} \left( \frac{F_{\text{exp},i} - F_{\text{GEP},i}}{F_{\text{exp},i}} \right) \] (11)

where \( Y_x \) is the number of the forecasted amounts of all the data for each amount of \( AARE \) is less than \( x\% \).

6. Derivation densimetric Froude number based on GEP

This section concentrates on GEP method to calculate densimetric Froude number (\( Fr \)). The training set must be selected from amongst all the existing data for the purposes of presenting a model. To that end, the data presented by Vongvisessomjai et al. (2010) was selected as training set and the data presented by Ota and Nalluri (1999) was selected as testing set. The training environment of the system has been defined after selecting the training set. After classifying the data, various parameters must be defined to make a model. To create the generation the initial...
population of the individuals, multi-genic chromosomes, are used which include four genes. We must now determine the number of the initial population. Considering Ferreira’s (2001) suggestion stating that using the size population within the range of 30–100 can lead to good results, the size of the used population include 50 chromosomes in this study which was selected through trial and error. After selecting the population size, the individuals are evaluated and their fitness function is calculated using $MSE$ as follows:

$$f_i = \frac{1000}{1+E_i} \text{ for } E_i = P_i - O_i$$  \hspace{1cm} (12)

where $Q_{ij}$ is the amount observed for fitness case, and $P_{ij}$ is the amount predicted through using $i$ individual chromosome for fitness case $j$. The best state is when the equation $E_{ij} = 0$ is obtained. This means that the amounts predicted using $i$ individual chromosome for fitness case $j$ is equal to the amount observed for fitness case $j$ ($P_{ij} = E_{ij}$). The set of terminals and the set of function must be determined for each gene in the chromosome after selecting fitness function. The function sets used in this study include \{×, -, ÷, ×, Gau2\} while the set of terminals are as follows:

$$T = \left\{ F, C, D, d, D', R, A, D, \lambda \right\}$$  \hspace{1cm} (13)

Afterwards the number of genes and their head and tail length must be determined for each gene in the chromosome. By using trial and error and the succeeding rate, four genes were selected in the present study in each chromosome. The head length was selected to be 5 ($h=5$) and while the maximum number of arguments per function is equal to 2 ($n_{max}=2$) the length of the tail turns out to be equal to 6 ($t=5 \times (2-1) +1$). The genetic operator rate must now be determined. Genetic operators such as mutation, inversion, transportation (IS, RIS, gene transportation), recombination and crossover (one point, two points and gene recombination) were used. The rates of the mentioned parameters are presented in Table 3. We must finally determine the linking function. Considering the fact that using four different sub-expressions in this study has led to having 4 genes, the genes must be bound in order for us to reach the final result. Therefore, \{+\} operator has been used as the linking function among the genes in this study. Simulating the
model begins after determining the essential parameters. $Gau2\{x, y\}$ function presented in Table 2 returns $\exp\left(- (x + y)^2\right)$ amount.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>50</td>
</tr>
<tr>
<td>Number of generations</td>
<td>250000</td>
</tr>
<tr>
<td>Number of chromosomes</td>
<td>50</td>
</tr>
<tr>
<td>Number of genes</td>
<td>4</td>
</tr>
<tr>
<td>Function set</td>
<td>$\times, -, \div, \times, Gau2$</td>
</tr>
<tr>
<td>Linking function</td>
<td>Addition</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.03</td>
</tr>
<tr>
<td>Inversion rate</td>
<td>0.15</td>
</tr>
<tr>
<td>IS transposition rate</td>
<td>0.1</td>
</tr>
<tr>
<td>RIS transposition rate</td>
<td>0.1</td>
</tr>
<tr>
<td>Gene transposition rate</td>
<td>0.15</td>
</tr>
<tr>
<td>One-point recombination rate</td>
<td>0.3</td>
</tr>
<tr>
<td>Two-point recombination rate</td>
<td>0.3</td>
</tr>
<tr>
<td>Gene recombination rate</td>
<td>0.15</td>
</tr>
</tbody>
</table>

7. Result and Discussion

To study sediment transport, different parameters in no-deposition stage and to present a model which could estimate the best results in comparison with actual values, dimensionless parameters in Table 2 have been used. As considered in this table, dimensionless parameters effective on sediment transport in no-deposition mode are categorized in five groups. In order to present a model, the effect of four groups of transport, deposition, and transport form and flow resistance on movement group was surveyed. Thus, six different models are listed in Table 4. In the presented models, volumetric sediment concentration ($C_{V}$) which is related to transport dimensionless group and overall sediment frictional coefficient ($\lambda_o$) which is related to flow
resistance dimensionless group have been considered constant. For sediment group $D_{gr}$ and $d/D$ parameters and for transport form group $d/R \cdot D^2/A$ and $y/D$ have been considered.

### Table 4. Dependent parameters in predicting $Fr$ considering the effect of dimensionless group parameters

<table>
<thead>
<tr>
<th>Model</th>
<th>Dependent parameter</th>
<th>Independent parameters</th>
<th>Train</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$Fr$</td>
<td>$C_V, D_{gr}, d/R, \lambda_s$</td>
<td>0.98</td>
<td>0.16</td>
</tr>
<tr>
<td>2</td>
<td>$Fr$</td>
<td>$C_V, D_{gr}, D^2/A, \lambda_s$</td>
<td>0.89</td>
<td>0.73</td>
</tr>
<tr>
<td>3</td>
<td>$Fr$</td>
<td>$C_V, D_{gr}, y/D, \lambda_s$</td>
<td>0.89</td>
<td>0.53</td>
</tr>
<tr>
<td>4</td>
<td>$Fr$</td>
<td>$C_V, d/D, d/R, \lambda_s$</td>
<td><strong>0.99</strong></td>
<td><strong>2.56</strong></td>
</tr>
<tr>
<td>5</td>
<td>$Fr$</td>
<td>$C_V, d/D, D^2/A, \lambda_s$</td>
<td>0.92</td>
<td>0.65</td>
</tr>
<tr>
<td>6</td>
<td>$Fr$</td>
<td>$C_V, d/D, y/D, \lambda_s$</td>
<td>0.97</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Table 3 shows sextet presented models with the use of Table 1. In order to present models, laboratorial results by Vongvisessomjai et al. (2010) have been utilized. After presenting different models to evaluate the estimated results, via each model, the $Fr$ has been surveyed with the use of Ota and Nalluri (1999) laboratorial results. According to verification criteria presented in Table 3, model 4 which uses volumetric sediment concentration ($C_V$), relative flow depth ($d/R$), proportional average size of particles ($d/D$) and overall frictional factor ($\lambda_s$) to estimate $Fr$ delivers the best result. The $MAPE$ index in $Fr$ evaluation with the use of this model is about 2.56% for test and 2.82% for train and $RMSE$ is 0.12 for train and 0.14 for test. It is considered that the effect of data sets alternations on the precision of this model is about less than 1%. Other presented models in this table, compared to the mode with train data, show better results than test data, and this is an indication that using these models (models 1, 2, 3, 5 and 6) would not be trustworthy. Therefore, it could be said that, to present a model which could well estimate $Fr$ in sewer at limit of deposition state, effective parameters are able to be considered like model 4 in Table 3. This means that using $C_V$ as transport parameter, $d/R$ as transport form parameter, $d/D$ as sediment parameter and $\lambda_s$ as flow resistance parameter in $Fr$ evaluation, leads to good results. The presented equation through using the parameters of model 4 and expression tree presented in Figure 1 can be presented as follows. The amounts of the parameters presented in this figure have been shown in Table 5.
\[ Fr = \left[ \frac{d}{D} - \left( 89.66 - \frac{d}{R} \right) - \frac{\lambda_c}{C_v + \frac{d}{R}} \right] + \left[ \frac{\lambda_c}{4.23 + \frac{d}{R} - \frac{d}{D}} \right] + \left[ 33.1 \times C_v \times \left( \frac{d}{D} + 15.45 \right) \right] \]

\[ = \left[ \frac{d}{D} + 67 \times C_v \right] \times \left[ \exp \left( - \left( C_v - \lambda_c + \frac{d}{D} \right) \right) \times \left( \frac{d}{D} + 92.4 \right) + \left( \frac{d}{D} + \frac{-5.9}{9.54} \right) \right] \]

We can rewrite the above-mentioned formula as follows:

\[ Fr = \left[ 2 \times \left( \frac{d}{D} + \frac{d}{R} \right) - 89.66 + \frac{\lambda_c}{C_v + \frac{d}{R}} \right] + \left[ \frac{\lambda_c}{4.23 + \frac{d}{R} - \frac{d}{D}} \right] + \left[ 33.1 \times C_v \times \left( \frac{d}{D} + 15.45 \right) \right] \]

\[ = \left[ \frac{d}{D} + 67 \times C_v \right] \times \left[ \exp \left( - \left( C_v - \lambda_c + \frac{d}{D} \right) \right) \times \left( \frac{d}{D} + 92.4 \right) + \left( \frac{d}{D} + \frac{-0.62}{9.54} \right) \right] \]
Fig. 1. Expression Tree (ET) for GEP formulation
Table 5. Values of the parameters used in ET (Figure 1)

|   |   |   |   | C<sub>d</sub> |   | d<sub>1</sub> |   | d<sub>2</sub> |   | d<sub>3</sub> |   | G1C5 | G2C2 | G2C0 | G2C5 | G3C8 | G3C6 | G4C7 | G4C0 | G4C6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|   |   |   |   |   |   |   |   |   |   |   |   | 89.66 | 33.10 | 4.23 | 15.45 | 132.42 | 67.08 | 92.40 | -5.90 | 9.54 |

Figure 2 shows the Fr results predicted by model 4 (Eq. 15) in both training and testing stage. Due to the fact that the accuracy of GEP model presented in Table 4 in this research (Eq. 15) has been studied quantitatively for both test (MAPE = 2.82 & RMSE = 0.14) and train (MAPE = 2.56 & RMSE = 0.12) states, in this figure, we will attend to studying the prediction results of the GEP model. The figure indicates that the forecasted Fr which were obtained through using GEP presented fairly good results in both train and test states while almost all estimated amounts have a relative error of less than 10%. The data used for the purpose of test and train of equation 15 have different ranges of Fr in such manner that the Fr used in training the model was within the range of 4 to 9 while the Fr range used in testing the model is 3 to 6. Therefore, it could be stated that while studying the model accuracy in test state all the Fr are not within the range which was used in training the model, thus, considering the qualitative results (Table 4) and quantitative results (Figure 2), it proves the accuracy of the presented results obtained by this equation.

Figure 3 compares the prediction results of Fr through using the GEP model presented in this study (Eq. 15) and the existing regression equation with the actual values. The figure shows that the results of the presented predictions using GEP are almost accurate in a way that all forecasted
points have an error less than ten percent and taking into consideration Figure 4 which shows the accumulative distribution of the error, we can see that the maximum relative error in estimating $Fr$ through using GEP is almost equal to 6%. Also, this figure indicates that approximately 90% of the anticipated amounts have a relative error less than 5%. Now in case we intend to study the results of the presented model through statistical indexes, referring to Table 6 shows us that the amounts of the presented statistical indexes for this model with an $R^2=0.99$, $MAPE=2.82$ and $RMSE=0.14$ is minimum in amount in comparison to other equations presented in this table. The equation presented by Ab. Ghani and Azamathulla (2011) is less accurate ($R^2=0.74$, $MAPE=13.18$ and $RMSE=0.49$) considering Table 6 and Figure 4. The figure indicates that in the majority of the points the results are presented with an error more than 10 percent. Figure 4 shows that only 25% of the amounts estimated by this model have a relative error less than 10%. Also, it indicates that some of the $Fr$ forecasted by this equation have a relative error more than 30 percent which indicates the uncertainty of the equation presented by Ab Ghani and Azamathulla (2011). Therefore, using this equation for the purpose of estimating $Fr$ cannot be that much confident. Ebtehaj et al. (2014) equation is fairly accurate because it estimates the majority of $Fr$ with a less-than-10-percent relative error, but it is less accurate in comparison with the equation presented in this study. This is in a way that considering Figure 4, which indicates the distribution of the estimation error by different models, we can see that approximately 70 percent of the estimation results of this model have an error less than 5% while for the model presented in this study the predicted amounts have an error of less than 5% for almost 90% of the $Fr$. At times, May et al. (1996) equation which has been obtained through semi-experimental method and has been known as one of the best sediment transport equations in limit of deposition (Vongvisessomjai et al. 2010) presents the estimated amounts with a more-than-15% relative error according to Figure 5 while the equation presented in this study has a maximum relative error of 6%. Also, considering Figure 6, the amounts of statistical indexes presented by this equation ($R^2=0.93$, $MAPE=5.74$ and $RMSE=0.24$) indicates lesser estimation accuracy of this equation in comparison with that of the presented equation.
Fig. 3. Comparison of proposed equation and existing equations

![Comparison of proposed equation and existing equations](image1)

Fig. 4. Error distribution of for GEP and existing equations

![Error distribution of for GEP and existing equations](image2)

Table 6. Validation of proposed equation and existing equations with statistical indexes

<table>
<thead>
<tr>
<th>Equation</th>
<th>$R^2$</th>
<th>MAPE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Equation (Eq. 15)</td>
<td>0.99</td>
<td>2.82</td>
<td>0.14</td>
</tr>
<tr>
<td>Ab. Ghani and Azamathulla (Eq. 4)</td>
<td>0.74</td>
<td>13.18</td>
<td>0.49</td>
</tr>
<tr>
<td>Ebtehaj et al. (Eq. 3)</td>
<td>0.97</td>
<td>3.70</td>
<td>0.18</td>
</tr>
<tr>
<td>May et al. (Eq. 1)</td>
<td>0.93</td>
<td>5.74</td>
<td>0.24</td>
</tr>
</tbody>
</table>
Accordingly, in this study, the effects of GEP model output on the variations of dimensionless particle number \( D_{gr} \) were investigated. The discrepancy ratio \( (DR) \) (ratio of predicted to actual values) was employed to measure the sensitivity of the GEP model to \( D_{gr} \) parameter. A \( DR \) value of 1 shows a perfect agreement, while values smaller (or greater) than 1 indicate under (or over) prediction of discharge coefficient in side weir. The result of the GEP model for variations of the discrepancy ratio \( (DR) \) values is plotted versus the dimensionless particle number \( (D_{gr}) \) in Figure 5. The maximum, mean and minimum \( DR \) values for GEP model were obtained 1.06, 1.005 and 0.93, respectively. As Figure 5 shows it, for almost all the \( Fr \) estimated, the \( DR \) is close to 1. When GEP predicts the model using the over design way, the dimensionless particle number will be equal to 1.7 \( (DR= 1.06) \) and when it uses the under-design way to predict \( Fr \), dimensionless particle number is equal to 2.15 \( (DR= 0.93) \).

![Fig. 5. DR values versus Dgr for GEP model](image)

Based on explanations given on Figures 3 and 5, and Table 6, the equation presented in this study is more accurate than the existing regression equations. While it is more accurate in studying the estimation accuracy through using statistical indexes, it is also more accurate in studying the estimation error distribution in Figure 4 and can be utilized as a substituting method in \( Fr \) estimation for sediment transport in no-deposition mode.
8. Conclusion

Transmitting flow from sewerage systems often contains suspended materials. Therefore, transporting suspended materials and preventing their sedimentation are important matters in flow transport through sewerage networks. Different methods have been presented for sediment transport in sewages, but due to the lack of recognition of effective factors on sediment transport these methods show different results in different conditions. Hence, in recent years, soft computations have been utilized in order to estimate densimetric Froude number ($Fr$) in these systems. In this paper, with the use of presented model by Gene-expression programming (GEP), $Fr$ has been estimated. In order to present the effective factor on $Fr$ estimation, six different models were presented. In these models, the effect of movement, transport, sediment, transport mode and flow resistance parameters have been considered. After $Fr$ estimation, the precision of all sextet models has been studied. The results indicated that among the three parameters provided by “Transport mode” group, the best and the worst accuracy were achieved by using $d/R$ and $D^2/A$ (respectively) as improper use of the parameters of this group, up to two-fold increase relative error. In addition to, Also, with the constant parameters in the groups “transport”, “flow resistance” and “transport mode”, the parameter $d/D$ in all input combinations, leading to better results than when used $D_{gr}$ as “sediment” parameter. Therefore, it was revealed that the model which considers volumetric sediment concentration ($C_V$), relative flow depth ($d/R$), proportional average size of particles ($d/D$), overall friction factor ($\lambda_s$) for $Fr$ estimation, shows the best results. The presented model estimates $Fr$ with an average error value about 2.82%. The comparison of existing methods illustrated the high level of accuracy of Ebtehaj et al. (Eq. 3) method in comparison with others. It should not be inappropriate use of GEP functions such as Eq. (4) results in weak performance of model. The presented model with existing values was also studied and the results showed that in proportion with existing relations the model well estimates the $Fr$. Incidentally making use of the proposed GEP-based technique in form of the most superlative formulations has a dominant role to experience in the attaining astonishing and remarkable successes for real-world application. Another plus aspect of this study is the use of extracted mathematical expressions as realistically valuable technique for practical engineering as an alternative for existing methods.

Notation:

$A$ \hspace{1cm} Cross-sectional area of the flow

$C_V$ \hspace{1cm} Volumetric sediment concentration
Pipe diameter

Median diameter of particle size

Dimensionless particle number

Error of program $i$ for fitness case $j$ (Eq. 5)

Densimetric Froude number

Precision (Eq. 5)

Value predicted by individual program $i$ for fitness case $j$ (Eq. 6)

Hydraulic radius, Selection Range (Eq. 6)

Specific gravity of sediment ($=\rho_s/\rho$)

Velocity of flow

Incipient flow velocity which follows from equation (2)

Flow depth

Clear Water friction factor

Overall sediment friction factor

Flow parameter

Transport parameter

References


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Using of Backpropagation Neural Network in Estimating of Compressive Strength of Waste Concrete

A. Heidari1*, M. Hashempour2 and D. Tavakoli3

1. Associate Professor, Department of Civil Engineering, Shahrekord University, Shahrekord, Iran
2. M.Sc. Student, Department of Civil Engineering, Shahrekord University, Shahrekord, Iran
3. Ph.D., Department of Civil Engineering, Shahid Rajaee Teacher Training University, Tehran, Iran

Corresponding author: heidari@eng.sku.ac.ir

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ABSTRACT

Waste concrete is one of the most usable and economic kind of concrete which is used in many civil projects all around the world, and its importance is undeniable. Also, the explanation of constructional process and destruction of them cause the extensive growth of irreversible waste to the industry cycle, which can be as one of the main damaging factors to the economy. In this investigation, with using of constructional waste included concrete waste, brick, ceramic and tile and stone new aggregate was made, also it was used with different weight ratios of cement in mix design. The results of laboratory studies showed that, the using of ratio of sand to cement 1 and waste aggregate with 20% weight ratio (W20), replacing of normal aggregate, increased the 28 days compressive strength to the maximum stage 45.23 MPa. In the next stage, in order to develop the experimental results backpropagation neural network was used. This network with about 91% regression, 0.24 error, and 1.41 seconds, is a proper method in estimating of results.

1. Introduction

Concrete is one of the most usable building materials, its world consumption is more than one tone for one person, which makes it as one of the most usable materials on the earth after water. Also, more than million tons of waste is produced in the world every year. Many of these waste is non-recyclable and accumulate in a variety of tools. Therefore, it is very important to restore this waste to the industry cycle. One of the main parts of this waste is due to tiles and ceramics. Waste of tiles and ceramics are created in transition, during or after burning due to human
mistakes or error of construction and even inferior raw materials. Most of this waste is because of demolishing of buildings [1]. The waste increases due to the extensive growth of production and consumption of these valuable materials. Various studies have been undertaken to recycle the waste in concrete in 2000. The investigation of chemical properties of waste tiles based on standards and then making samples with pozzolan and tests of compressive and bending strength, were done. The results showed that it is possible to use waste tiles in concrete, also, they have pozzolanic properties [2]. In 2013, Heidari et al. studied the effects of ceramic aggregates in concrete. For this purpose, the ceramic was replaced as coarse-grained of 0 to 40% as well as sand as 0 to 100%. The results showed that the use of ceramic has no significant negative effect on concrete properties. The optimum sample in the case of ceramic replacement with sand was about 25 to 50 Percent. The best sample, using of ceramic as coarse grained, was between 10 to 20%. In this case, not only the increase in compressive strength is observed, but also the specific weight is reduced without any significant negative effect on water absorption [1]. In order to improve the mechanical properties and reduce the water absorption, Nano particles of silica were used. Final results showed that, using of Nano particles can highly improve the waste concrete parameters because of filling of capillary voids in cement paste [3]. In the bricks industry, due to the high quantity of bricks in the building industry, researchers have proposed different combinations for the manufacture of concrete containing this type of waste with various tests and studies. In 1983, one of the first experimental studies in this field was carried out, and finally it showed a compressive strength of a downward trend and a reduction of 10-35% for coarse grained of replacing brick with natural aggregate. However, compared to conventional concrete with this reduced compressive strength, the tensile strength increases by 11% [4]. In another study in 2014, in the first phase, Tavakoli and Heidari investigated the effect of replacing sand with clay brick in different proportions and observed that there is not a big problem in using of brick as sand in optimum percent and in mechanical properties like compressive strength. However, due to the high water absorption, a longer examination is required [5]. In 1993, Merlet and Pimienta investigated the use of waste concrete in reproduction of constructional concrete. They used the waste concrete in different ratios as fine grained in new concrete for the first time [6]. Later, shrinkage of drying of this concrete was evaluated. The results showed that there is a high shrinkage in comparison of conventional concrete [7], which can be controlled by adding fly ash [8]. Several studies have also been carried out on the use of different neural networks in estimating laboratory values. In 2017, Kalman et al. used neural network to estimate the properties of concrete with waste brick aggregate. The results showed that the neural network can estimate these properties and show very close results to experimental ones [9]. In another study, neural network, ANFIS, and multi-layer regression (MLR) were used to estimate 28 days compressive strength of concrete with waste aggregate. Finally, due to input data to network, although all of the modeling ways acted well, but MLR network showed the most exact answers for estimating the values [10]. In the same field, the neural network and ANFIS were used simultaneously to study the compressive strength of concrete blocks. 102 samples were used to construct the network and parameters such as the ratio of height to thickness of the concrete charter and compressive strength as the input of the model were used. Finally, it was determined that these models can estimate the required values with high precision [11]. Using of neural networks with a mixture of optimization algorithms such as genetic, PSO and etc. which is used
to improve the workability, not only exist in all of the fields, but also has a wide usage in concrete production. In a study, in order to simulation of concrete slump, genetic algorithm was used to optimize the bias and weights. In this study backpropagation neural network was processed and developed [12].

In this investigation two phases were considered. In the first phase, experimental studies about using waste materials such as brick, ceramic tile and concrete as fine aggregate. The results showed that this method is not only practical, but also economical. In this method, in order to have the best answer for mix design, the ratio of sand to cement should be 1, also a design with 20% of waste had the best results. In the second phases, numerical methods such as practice of data in Excel and backpropagation neural network were used to develop the prediction of values. The results of this phase showed that neural network with high accuracy of measurement can be used to predict the values.

2. Materials

2.1. Aggregate preparation

In this study, in order to use the constructional waste as aggregate in concrete, it should be crushed enough, also its condition in concrete should be examined. In this kind of concrete, gravel was not used and the used aggregate is in size of sand. At first, constructional waste like, concrete, brick, stone also tile and ceramic waste should be crushed completely with the help of impact crusher and then particles of gravel are separated from sand by the sieve 4. Ordinary sand and waste sand are shown in figure 1.

Before doing the experiments, it is essential to make sure about pozzolanic property or lack of it in waste sand, because this property can influence the whole aspects of experimental results. So, the experiment of XRF was done on the samples of these two kind of sand.
Table 1. XRF analysis of sands

<table>
<thead>
<tr>
<th>Element</th>
<th>Sand constituents in percent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ordinary sand</td>
</tr>
<tr>
<td>Al₂O₃</td>
<td>0.59</td>
</tr>
<tr>
<td>SiO₂</td>
<td>0.32</td>
</tr>
<tr>
<td>CaO</td>
<td>54.21</td>
</tr>
<tr>
<td>Fe₂O₃</td>
<td>0.06</td>
</tr>
<tr>
<td>K₂O</td>
<td>0.26</td>
</tr>
<tr>
<td>MgO</td>
<td>1.04</td>
</tr>
<tr>
<td>MnO</td>
<td>0.01</td>
</tr>
<tr>
<td>Na₂O</td>
<td>2.15</td>
</tr>
<tr>
<td>P₂O₅</td>
<td>0.08</td>
</tr>
<tr>
<td>S₂O₃</td>
<td>0.57</td>
</tr>
<tr>
<td>TiO</td>
<td>0.01</td>
</tr>
<tr>
<td>LOI</td>
<td>40.58</td>
</tr>
</tbody>
</table>

Investigating these results showed that there is no pozzolanic property in waste sand and it is similar to stone. Also, grading of these two kinds of sand was done based on figure 3. The results of the study of these two graphs based on the Iran standard of grading showed that both of these two kinds of sand are in standard area and they can be used in concrete.

Fig. 2. Grading of sands
2.2. Cement

The cement which was used, is 1-525 type of Shahrekord cement factory. Analysis of this material is shown in table 2.

<table>
<thead>
<tr>
<th>Chemical properties</th>
<th>%</th>
<th>Physical properties</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SiO₂</td>
<td>20.30</td>
<td>Blain ($cm^2/ gr$)</td>
<td>≥3200</td>
</tr>
<tr>
<td>Al₂O₃</td>
<td>5.65</td>
<td>Setting initial time (minute)</td>
<td>90</td>
</tr>
<tr>
<td>Fe₂O₃</td>
<td>3.30</td>
<td>Setting final time (minute)</td>
<td>170</td>
</tr>
<tr>
<td>CaO</td>
<td>65.70</td>
<td>Autoclave expansion</td>
<td>≤3.0</td>
</tr>
<tr>
<td>MgO</td>
<td>≤1.60</td>
<td>2 days compressive strength</td>
<td>≥24.0</td>
</tr>
<tr>
<td>SO₃</td>
<td>≤2.80</td>
<td>3 days compressive strength</td>
<td>≥35.0</td>
</tr>
<tr>
<td>CL</td>
<td>≤0.03</td>
<td>7 days compressive strength</td>
<td>≥47.0</td>
</tr>
<tr>
<td>F.CaO</td>
<td>≤1.80</td>
<td>28 days compressive strength</td>
<td>≥61.0</td>
</tr>
<tr>
<td>L.R</td>
<td>≤0.65</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L.O.I</td>
<td>≤1.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Alkali</td>
<td>≤0.70</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.3. Water

Potable water was used in this study. In this water, PH is 7.8, Chloride 40 mg/l and Sulphate 29 mg/l. So potable water has standard parameters and it is proper for mix design.

2.4. Superplasticizer

The superplasticizer which was used in this study, is high water reducer based on polycarboxylate copolymer that has a wide range in ultra-high performance concrete. This brown superplasticizer with 1.08 density, less 0.01 CL ion, and 6 to 8 PH is manufactured to be used in UHPC, SCC, impermeable, and concrete with high workability. This superplasticizer with high distribution property of cement particles is an admixture to produce UHPC concrete with minor ratio of water to cement. Moreover, it doesn't have any CL ion, so it is usable in producing the reinforced concrete. Also, with less using of this material, a homogenous mix can be made.

3. Mix design

In this investigation two phases with ratios of sand to cement, 1 and 1.5 are considered and each phase has 11 mix designs, which ordinary and waste sand were used as percent of total aggregate from 0 to 100 percent in each design. Also, in both phases, the ratio of water to cement was 0.5. Table of mix design for this concrete is shown as follows. Meanwhile, W is used in order to name each design, and the number of after it shows the percent of waste sand.
Table 3. Mix design

<table>
<thead>
<tr>
<th>Sample</th>
<th>Type of sand</th>
<th>Superplasticizer (weight ratio of cement)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Waste sand (%)</td>
<td>Ordinary sand (%)</td>
</tr>
<tr>
<td>W100</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>W90</td>
<td>90</td>
<td>10</td>
</tr>
<tr>
<td>W80</td>
<td>80</td>
<td>20</td>
</tr>
<tr>
<td>W70</td>
<td>70</td>
<td>30</td>
</tr>
<tr>
<td>W60</td>
<td>60</td>
<td>40</td>
</tr>
<tr>
<td>W50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>W40</td>
<td>40</td>
<td>60</td>
</tr>
<tr>
<td>W30</td>
<td>30</td>
<td>70</td>
</tr>
<tr>
<td>W20</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
<td>W10</td>
<td>10</td>
<td>90</td>
</tr>
<tr>
<td>W0</td>
<td>0</td>
<td>100</td>
</tr>
</tbody>
</table>

After preparing the aggregate, total weight of 5 Kgs cement and aggregate based on the mix design, was poured into the mixer, then the water contained of superplasticizer was added. This concrete was mixed for 3 minutes which was adjusted based on ACI304-37 standard. Finally, this made concrete was poured into the 5 centimeters cube molds.

4. Experimental results

After curing the concrete samples in water, compressive strength tests were done, and the results were analyzed. Figure 3 shows concrete samples with different percent of waste.

**Fig. 3.** A: Reference sample. B: W50 sample. C: W100 sample
4.1. Compressive strength

The most important experimental test is compressive strength test. This test is based on ASTM C-109 standard. In this investigation, 1, 7, and 28 days samples were broken by 2000KN under load hydraulic jack and then the results were determined. Figure 4 shows the results of phase 1 and 2.

![Graph showing compressive strength results](image)

**Fig. 4.** Results of compressive strength in phase 1 and 2

As it was shown, samples which were cured for 28 days had higher compressive strength in comparison with other samples. Also, 28 compressive strength and 7 days compressive strength were close because of using the cement type 1-525 which can cause strength in short term. Moreover, with increasing the ordinary sand, strength will increase, too. This fact is because of replacing high strength ordinary sand with low strength waste sand. So, mechanical properties of microstructure of concrete will improve. Nevertheless, in the first phase, the sample with 20% waste sand had the highest strength. Also, in the second phase, the sample with 30% of waste had the highest strength.

5. Neural network

Neural networks are derived from human biological intelligence. Each human neurons cell consists of three main parts called axon, dendrite and soma, which dendrites are the agent of reception information from other cells and axons are the agent of information transmission from other cells. The soma or cell body is also the place where the data is entered into the cell. The
neural network also has the same mechanism in which the neuron receives signals that are affected by the weights and biases, as well as the neuron cell as the processor and the information get processed. The processed information is transferred to the neuronal cell again and this cycle is repeating. On the other hand, the neural network can be similar to the model multivariate linear regression is also known. Input neurons similar to independent variables and output neurons like the dependent variable acts and the weights have the same function width of the source or constant sentence in the regression. In general, the role of neurons in the neural network is information processing. This is the case in artificial networks that is the same as the activation function [13].

Since the estimation and prediction of values using neural networks is fast and relatively new, it is therefore necessary to avoid conclusive results from other values that were not possible due to the limitation of laboratory conditions. Assured. First, we estimate the values for fitting the results using Excel software. It is shown in linear fitting data of figure 5.

Excel fittings with low regression cannot estimate the values and they are unreliable. So, in this stage, backpropagation neural network with artificial intelligence basic and optimization algorithms were used. In order to prepare the network, at first layered status and input and output data were determined. For a basic network, five kinds of input, two hidden layers, and three kinds of output based on compressive strength were used. Figure 6 shows this graph.
Before importing the data and training the network, in order to decrease the errors, formula 1 was used to normalized the data [14].

\[
X_i = 0 \cdot 8 \left( \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \right) + 0 \cdot 1
\]  

(1)

Where \( X_i \) is normalized data, \( X \) input or output parameter, \( X_{\text{min}} \) minimum input or output parameter, \( X_{\text{max}} \) is the maximum input or output parameter. In order to, create the network, 70% of data for training, 15% for evaluating and 15% for testing were used. The final answer is in figure 7.

As it is shown, network regression is higher and more acceptable than excel. Network errors are shown in figure 8. In this figure, neural network with high regression and less errors could create the best answer in estimating the values.
Maximum time consumption in this study, was 1.46 seconds, which was recorded for core i7 CPU and 16 gigabyte ram. This value is different for other systems. Totally, this item is proper because of selecting two hidden layers and considering Levenberg Marquardt training function which is one of the fastest functions of toolbox of MATLAB.

6. Conclusion

This study has two experimental and numerical parts which the results are as follows:

1. Adding construction waste as aggregate in concrete is an acceptable and not only compressive strength has not diminished, but has also been remarkable for some designs. For example, the maximum compressive strength for phase 1 is sand-to-cement ratio 1 and the waste is 20% up to 45.23 MPa.
2. The results of compressive strength in 7 and 28 days samples, were so close, which was because of using of cement type 1-525 and its short term strength.
3. In order to develop and estimate the experimental data, two layers back propagation neural network was used.
4. The results of fitting data of neural network were more accurate and closer to real values in comparison with fitting data of Excel.
5. Finally, it was concluded that back propagation neural network is accurate and accelerator in estimating and fitting processing the experimental data.

REFERENCES


A Method for Constructing Non-Isosceles Triangular Fuzzy Numbers Using Frequency Histogram and Statistical Parameters

A. Amini\textsuperscript{1*} and N. Nikraz\textsuperscript{2}

1. Ph.D. Student, Faculty of Science and Engineering, Curtin University, Kent St, Bentley WA 6102, Australia
2. Senior lecturer, Faculty of Science and Engineering, Curtin University, Kent St, Bentley WA 6102, Australia

Corresponding author: amin.amini@postgrad.curtin.edu.au

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ABSTRACT

The philosophy of fuzzy logic was formed by introducing the membership degree of a linguistic value or variable instead of divalent membership of 0 or 1. Membership degree is obtained by mapping the variable on the graphical shape of fuzzy numbers. Because of simplicity and convenience, triangular membership numbers (TFN) are widely used in different kinds of fuzzy analysis problems. This paper suggests a simple method using statistical data and frequency chart for constructing non-isosceles TFN, when we are using direct rating for evaluating a variable in a predefined scale. In this method the relevancy between assessment uncertainties and statistical parameters such as mean value and standard deviation is established in a way that presents an exclusive form of triangle number for each set of data. The proposed method with regard to the graphical shape of the frequency chart distributes the standard deviation around the mean value and forms the TFN with the membership degree of 1 for mean value. In the last section of the paper modification of the proposed method is presented through a practical case study.

1. Introduction

One of the most important steps in solving the problems and analyzing the systems by using fuzzy logic is defining the fuzzy membership functions of the data set. Fuzzy control systems, fuzzy inference engines, fuzzy multi-criteria decision making models and ranking system based on fuzzy logic use fuzzy membership functions as input. So a more accurate defined membership function results in a more accurate outputs and higher efficiency of fuzzy analysis systems. This paper proposed a novel and simple method for constructing the triangular membership function
using frequency chart of a certain set of statistical data when the average point of data is considered the most possible value. This set can be the collected information from a survey using linguistic judgments or qualitative assessments expressed in a numerical defined scale to find an answer to the question: “How \( F \) is \( a \)” where \( F \) is a fuzzy concept and \( a \) is a parameter which is being assessed. In different sections of this paper, after a short review of basic fuzzy logic concepts and membership function construction methods, we introduced the proposed method through some numerical examples.

2. Fuzzy and classic logic

In the classical logic, a simple proposition ‘\( P \)’ is a linguistic, or declarative statement contained within a universe of elements, \( X \), that can be identified as being a collection of elements in \( X \) that are strictly true or strictly false [1]. In classical logic, a binary truth value is assigned to the veracity of an element in the proposition ‘\( P \)’, which is a value of 1 (truth) or 0 (false). For example, consider the ‘\( P \)’ statement as: “water with the temperature over 60 centigrade degree is hot”, based on classical logic, water to 59.9 degrees is not considered hot water at all. So there is a crisp boundary between true and false in classical logic, which causes making decisions about processes that contain nonrandom uncertainty, such as the uncertainty in natural language, be less than perfect. Treating truth as a linguistic variable leads to a fuzzy linguistic logic, or simply fuzzy logic [2]. The original fuzzy logic founded by Lotfi Zadeh as a key to decision-making when faced with linguistic and non-random uncertainty. Fuzzy logic is a precise logic of imprecision and approximate reasoning [3]. It may be viewed as an attempt at formalization/mechanization of two remarkable human capabilities; First, the capability to converse, reason and make rational decisions in an environment of imprecision, uncertainty, incompleteness of information, conflicting information, partiality of truth and partiality of possibility - in short, in an environment of imperfect information- and second, the capability to perform a wide variety of physical and mental tasks without any measurements and any computation [4].

In Fuzzy logic, a statement can be either true or false and also can be neither true nor false. Fuzzy logic is non-monotonic logic. It is a superset of conventional logic that has been extended to handle the concept of partial truth, the truth values between ‘completely true’ and ‘completely false’. It is a type of logic that recognizes more than simple true and false values. With fuzzy logic, propositions can be represented with degrees of truthfulness and falsehood. For example, the statement “today is sunny” might be 100% true if there are no clouds, 80% true if there are a few clouds, 50% true if it's hazy and 0% true if it rains all day.

3. Fuzzy set vs crisp set

In contrast to classical set theory, each element, either fully belongs to the set or is completely excluded from the set. In other words, classical set theory represents a special case of the more general fuzzy set theory. In crisp set, membership of element \( X \), \( \mu_A(X) \) of set \( A \) is defined as:

\[
\mu_A(X) = \begin{cases} 
1 & X \in A \\
0 & X \notin A 
\end{cases}
\]  

(1)
For example, figure 1.a, shows a crisp set of height between 5 to 7 feet, thus every height in this range has the same value of truth equals to 1 which means it belongs to this set, and every height out of this range has a value of 0 that means this value doesn’t belong to this set.

Dr. Zadeh developed the concept of ‘fuzzy sets’ to account for numerous concepts used in human reasoning which are vague and imprecise e.g. tall, old [5]. In his paper of 1965 he stated: “The notion of a fuzzy set provides a convenient point of departure for the construction of a conceptual framework which parallels in many respects the framework used in the case of ordinary sets, but is more general than the latter and, potentially, may prove to have a much wider scope of applicability, particularly in the fields of pattern classification and information processing. Essentially, such a framework provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria of class membership rather than the presence of random variables.”

A fuzzy set expresses the degree to which an element belongs to a set. If \( X \) is a collection of objects denoted generically by \( x \), then a fuzzy set \( A \) in \( X \) is defined as a set of ordered pairs:

\[
A = \{(x, \mu_A(x)) \mid x \in X\}, \quad \mu_A(X) \in [0,1]
\]

The characteristic function of a fuzzy set, \( \mu_A (x) \) is allowed to have values between 0 and 1, which denotes the degree of membership of an element in a given set and is called as ‘membership function’ (or MF for short) If the values of the membership function is restricted to either 0 or 1, then \( A \) is reduced to a classical set [6]. In figure 1.b, a fuzzy set of heights between 5 and 7 feet and around 6 has been illustrated. In this example the fuzzy set \( A \) may be described as follows: \( A = \{(5, 0), (5.5, 0.5), (6, 1), (6.5, 0.5), (7, 0)\} \).

Fuzzy sets are often incorrectly assumed to indicate some form of probability. Even though they can take on similar values, it is important to realize that membership grades are not probabilities. The probabilities of a finite universal set must add to 1 while there is no such requirement for membership grades.

In this paper, we use the partial truth concept in a form of fuzzy membership function to show the truth degree of the average point of a set of data collected based on a scaled assessment system.
4. Fuzzy set vs fuzzy number

A fuzzy number is a fuzzy set on the real numbers. It represents information such as ‘about m’. A fuzzy number must have a unique modal value ‘m’, be convex, normal and piecewise continuous [7]. Fuzzy numbers generalize classical real numbers and roughly speaking a fuzzy number is a fuzzy subset of the real line that has some additional properties. They are capable of modelling epistemic uncertainty and its propagation through calculations. The fuzzy number concept is basic for fuzzy analysis and fuzzy differential equations, and a very useful tool in several applications of fuzzy sets and fuzzy logic [8].

A fuzzy set is not a fuzzy number since it is not fuzzy convex and normal. An alternative and more direct definition of convexity is the following [5]: A is convex if and only if for all \(x_1\) and \(x_2\) in \(X\) and all \(\lambda\) in \([0, 1]\):

\[
\mu_A(\lambda x_1 + (1 - \lambda)x_2) \geq \min[\mu_A(x_1), \mu_A(x_2)]
\]

A fuzzy set \(A\) is normal if we can always find a point \(x \in X\) such that \(\mu_A(x) = 1\). The shape (a) represented in figure 2, is a fuzzy set not a fuzzy number and shape (b) in that figure is a convex set, but not a normal one.

![Fig. 2. Normal but not convex fuzzy set (a) and convex but not normal fuzzy set (b).](image)

A fuzzy set is completely characterized by its membership function (MF). A membership function associated with a given fuzzy set, maps an input value to its appropriate membership value. The only condition a membership function must really satisfy to be considered a fuzzy number is that it must vary between 0 and 1. The function itself can be an arbitrary curve whose shape we can define as a function that suits us from the point of view of simplicity, convenience, speed, and efficiency.

4.1. L-R Fuzzy Numbers

There are various types of membership functions, e.g. S-shaped function, Z-shaped function, triangular membership function, trapezoidal membership function, Gaussian distribution function, exponential function, Pi function and vicinity function [8]. A more convenient and concise way to define a MF is to express it as a mathematical formula. Dubois and Prade [9], introduced the concept of L-R approximations of fuzzy numbers and replaced the convolution type operations by interval based ones. All of the mentioned membership functions are presentable in a form of L-R fuzzy numbers. A L-R fuzzy number (or interval) \(u\) has the membership function of the form [10]:
\[ \mu_u(x) = \begin{cases} 
\frac{x-a}{b-a} & \text{if } x \in [a, b] \\
1 & \text{if } x \in [b, c] \\
\frac{d-x}{d-c} & \text{if } x \in [c, d] \\
0 & \text{otherwise} 
\end{cases} \]  

(4)

Where \( f_L, f_R: [0, 1] \rightarrow [0, 1] \) are two continuous, increasing functions, fulfilling \( f_L(0) = f_R(0) = 0, f_L(1) = f_R(1) = 1 \). The compact interval \([a, d]\) is the support and the core is \([b, c]\). The usual notation is \( u = (a, b, c, d), f_L, f_R \) for an interval and \( u = (a, b, c) \) for a number.

L-R fuzzy numbers are considered important in the theory of fuzzy sets and their particular cases as triangular and trapezoidal fuzzy numbers, when the functions \( f_L \) and \( f_R \) are linear, are very useful in applications. These straight line membership functions have the advantage of simplicity.

The trapezoidal membership function has a flat top and really is just a truncated triangle curve. A ‘trapezoidal MF’ is specified by four parameters \( \{a, b, c, d\} \) as follows: \((a \leq b \leq c \leq d) \) [11]. Figure 3, illustrates a trapezoidal MF defined by trapezoid \((x; 1, 3, 6, 9)\).

\[ \text{Trapezoid } (x; a, b, c, d) = \begin{cases} 
0 & x \leq a \\
\frac{(x-a)}{(b-a)} & a \leq x \leq b \\
1 & b \leq x \leq c \\
\frac{(d-x)}{(d-c)} & c \leq x \leq d \\
0 & d \leq x 
\end{cases} \]  

(5)

4.2. Triangular membership function

The simplest MF is the triangular membership function. A triangular MF is specified by three parameters \( \{a, b, c\} \) as follows:
The parameters \{a, b, c\} (with \(a < b < c\)) determine the \(x\) coordinates of the three corners of the underlying triangular MF. Figure 4, illustrates a triangular MF defined by a triangle \((x; 1, 3, 7)\) on a 10 grade scale which can be based on 10 fuzzy linguistic values or 10 pre-defined conditions such as effectiveness grade, importance degree, agreement level, etc.

A fuzzy uncertain quantity has a range of values between the lowest possible limit (below which there are no possible values) and highest possible limit (beyond which there are no possible values). The membership grades represent the degrees of belief in the truth levels of the values in the range of the fuzzy number. The three corners of a TFN present the lowest possible value (a), the most possible value (b), and the highest possible value (c). The values in the range between the lowest and highest possible values have a membership grade between 0 and 1, with the most possible value having a membership grade of 1. The lowest and highest possible values have membership grades of 0 because they represent the lower and upper limits of the fuzzy range outside which no values belong to the fuzzy number. The membership grade for a given value in the range between the lowest possible value and the highest possible value is evaluated using linear interpolation by finding the membership grade on the straight line corresponding to a given value in the fuzzy range.

5. Membership value assignments

By summarizing subjective versus objective on one dimension and individual versus group on the other hand, Biligic and Turksen [12] considered five categories of interpretations for production of membership functions. They discussed these interpretations for the meaning of \(\mu_{T}(x) = 0.7\), represented for the vague expression: “John (x) is tall (T)”, where \(\mu_{T}(x)\) is the membership degree of \(x\) defined on a fuzzy set tall (T), as:

1. Likelihood view: 70% of a given population consider John as a tall person.
2. Random set view: 70% of a given population described ‘tall’ as an interval containing John’s height.
3. Similarity view (typicality view): to the degree 0.3 (a normalized distance), John’s height is away from the prototypical object, which is truly “tall”.
4. Utility view: the utility of confidence that John is tall is 0.7.
5. Measurement view: when compared to others, John is taller than some and this privilege is 0.7.

After introducing eight methods: polling, direct rating (point estimation), reverse rating, interval estimation (set valued statistics), membership function exemplification, clustering methods and neural-fuzzy methods for constructing the membership function in their paper (See [13] for...
details and original references) they discussed measurement theory [14] as a framework which can find the appropriate method for each type of interpretation. Where in direct rating [12] the parameter or variable is being classified according to a fuzzy concept (like importance degree, tallness, darkness,...) and the question is: “How \( F \) is \( a \)?”, in polling technique we find the membership functions values proportional to positive answers to a presented subject. The question in this method is: “Do you consider \( a \) as \( F \)?” where ‘\( a \)’ is the parameter and ‘\( F \)’ is a fuzzy concept. In such kind of indirect way, we can define an interval scale and generate the membership value based on the frequencies that each interval gets when the scale is being questioned by a group of experts. In other words, each interval gets a weight equal to the number of agreement [15].

In [16] Saaty proposed a pairwise comparison matrix for computing the membership values. The entries of this matrix were relative preference defined on a rational scale. Introducing the possibility theory against the probability theory by Zadeh [17] opened a new vision for many authors to study the conversion problem of probability distribution to possibility distribution when membership functions are considered numerically equivalent to possibility distribution. Two famous transformation methods are: bijective transformation by Dubois and Prade [18] and the conservation of the uncertainty method by Klir [19].

In [20] Civanlar and Trussell proposed a membership function generation method for statistically based data. They believed that the membership function has a relationship to some physical property of the set so they considered two properties for membership functions derived from statistics: making some allowance for deviation from the value obtained by the measurement and being naturally quantitative. The produced membership functions using their method are optimal with respect to a set of reasonable criteria and also adjustable to possibility-probability consistency principle.

Valliappan and Pham [21] discussed a membership function construction method using subjective and objective information. The subjective part is experts’ opinions and judgments and the objective part are statistical data and their known probability density function (pdf). In the proposed framework assumptions of the “program-evaluation and review technique” (PERT) was used to derive the normalized subjective measures through the beta distribution. Then, by using the kernel of the fuzzification, the subjective part is transformed into a fuzzy set.

In [22] Chen and Otto suggested a method using measurement theory and constrained interpolation for constructing the membership function in a way that they used a measurement scale construction for a given finite set of determined membership values and determined the remaining membership values using interpolation. Witold Pedrycz [23] has shown that the routinely used triangular membership functions provide an immediate solution to the optimization problems emerging in fuzzy modelling.

Whereas describing all the methods and efforts done in constructing the membership functions is beyond the scope of this paper, most famous methods and techniques have been summarized in Table 1. The major part of this table is based on studies done by Medasani et al. [24], Sancho-
Royo and Verdegay [25] and Sivanandam and Sumathi [26] about different methods and techniques for membership functions generation.

Many of these techniques are not applicable to many practical problems involved prevailing uncertainty or in multi-attribute decision making problems where we need to have convex and normal fuzzy numbers as input weights to form the decision making matrix. However, the technique proposed in this paper is categorized as a subjective/direct rating method and use the frequency histogram of a parameter which has been evaluated by a group of experts on a graded scale; it tries to utilize the objective data in a way to emphasize the principle of uncertainty and imprecise judgment and generate unique triangular fuzzy numbers. In a numerical example the discussed method is compared to other subjective methods of polling and direct rating for a better understanding of the differences.

<table>
<thead>
<tr>
<th>Membership Function Generating Methods</th>
<th>Applied Techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subjective perception based methods</td>
<td>• Interval estimation</td>
</tr>
<tr>
<td></td>
<td>• Continues direct valuation</td>
</tr>
<tr>
<td></td>
<td>• Direct rating</td>
</tr>
<tr>
<td></td>
<td>• Reverse rating</td>
</tr>
<tr>
<td></td>
<td>• Polling</td>
</tr>
<tr>
<td></td>
<td>• Pairwise comparison(Relative preference)</td>
</tr>
<tr>
<td></td>
<td>• Parameterized MF( Based on distance from ideal state or deductive reasoning)</td>
</tr>
<tr>
<td>Heuristic methods</td>
<td>• Piecewise linear functions( linearly increasing, linearly decreasing or a combination of these)</td>
</tr>
<tr>
<td></td>
<td>• Piecewise monotonic functions(S-functions, Sin(x), n-Functions, exponential functions,....)</td>
</tr>
<tr>
<td>Histogram based methods</td>
<td>• Modeling multidimensional histogram using a combination of parameterized functions</td>
</tr>
<tr>
<td>Transformation of probability distributions to possibility distributions</td>
<td>• Bijective transformation method</td>
</tr>
<tr>
<td></td>
<td>• Conservation of uncertainty method</td>
</tr>
<tr>
<td>Fuzzy nearest neighbor method</td>
<td>• K-nearest neighbors(K-NN)</td>
</tr>
<tr>
<td>Neural network based methods</td>
<td>• Feed forward multilayer neural networks</td>
</tr>
<tr>
<td>Clustering based methods</td>
<td>• Fuzzy C-Means(FCM)</td>
</tr>
<tr>
<td></td>
<td>• Robust agglomerative Gaussian mixture decomposition(RAGMD)</td>
</tr>
<tr>
<td></td>
<td>• Self-Organizing feature map(SOFM)</td>
</tr>
<tr>
<td>Genetic Algorithm</td>
<td>• Fitness function evaluation</td>
</tr>
<tr>
<td>Inductive Reasoning</td>
<td>• Entropy minimization(Clustering the parameters corresponding to the output classes)</td>
</tr>
</tbody>
</table>

6. The proposed method for constructing a non-isosceles triangular fuzzy number

In recent decades using fuzzy theory in management and engineering has increased significantly. Fuzzy science is able to construct models which can process qualitative information intelligently almost like a human.

The first step of every fuzzy analysis is fuzzification. Fuzzification [26] is the process of converting a real scalar value into a fuzzy value. This is achieved with the different types of fuzzifiers or membership functions. In a multi-criteria decision making problem, decision matrix
entries and weight vectors are fuzzy rather than crisp numbers. In Fuzzy ranking problems, the items or options introduced in the form of fuzzy numbers are being prioritized using different fuzzy ranking methods. In fuzzy management, knowledge and skills needed to manage the systems can be obtained from experts in natural language and create models and computer programs easily by using fuzzy inference engines. In this case, natural language often uses the attributes and constraints, such as ‘very’, ‘little’, ‘some’ and ‘approximately’ that can be shown by membership functions and give as input to computer programs [27]. As mentioned before, triangular fuzzy numbers are very useful in all kinds of problems using fuzzy theory because of simplicity and ease.

Now we need to answer this question that “What’s new with our proposed method?” Ordinary methods which use statistical data to generate triangular fuzzy numbers usually use the normal distribution of data for this purpose. The normal distribution is a continuous probability distribution that shows the probability that any real observation will fall between any two real limits or real numbers (Fig. 5.a). The ordinary method of converting a normal distribution function to a TFN results in an isosceles triangular fuzzy number. (Fig. 5.b.)

This paper suggests a simple method for constructing non-isosceles triangular fuzzy number (TFN) of an item, parameter, value or concept which has been surveyed statistically via questionnaire, interview or other investigating methods based on utility view for constructing the membership degree using a pre-defined scale for converting the linguistic judgments or cluster distances to quantitative values. In other word the proposed method converts the data of a frequency chart to corresponding TFN. The origin or main idea for generating fuzzy membership function by this method is the deviation of the responses from average value when a fuzzy concept is judged or rated. Applying this method in a practical case study will be discussed later for the verification.

The triangular fuzzy number could not be in a form of a simple isosceles triangle with two equal sides when the data statistical distribution around the mean point is not homogenous. Thus, for constructing the TFN that can represent the judgment deviations, we try to determine the left and right boundaries about the average value of data by proposing the following steps:

Computing the average or mean value of frequency chart data using equation (7) that is presented by point ‘M’ and standard deviation of data ‘σ’ using equation (8).
\[ M = \frac{1}{n} \sum_{i=1}^{n} (x_i) \]  
\[ \sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - M)^2} \]

Forming the histogram of the frequency chart in the form of a continuous graph which introduced by \( f(x) \), where the \( X \)-axis indicates the scale degrees and \( Y \)-axis indicates the frequency data.

Introducing and computing the following parameters with regard to \( f(x) \) for a ‘0 to \( k \)’ graded \( X \)-axis:

\[ L_M = \int_{0}^{M} f(x) \, dx \]  
\[ R_M = \int_{k}^{k} f(x) \, dx \]  
\[ S = \frac{L_M}{R_M} \]  
\[ \sigma_R (M) = \frac{\sigma}{(1+S)} \]  
\[ \sigma_L (M) = \frac{\sigma_S}{(1+S)} \]

Finding the lower limit \((LL)\) and the upper limit \((UL)\): So that the lower limit is obtained by subtracting the \( \sigma_L(M) \) from the mean value and the upper limit is obtained by adding the \( \sigma_R(M) \) to the mean value. In the presentation of a TFN in equation (6), \((LL)\) and \((UL)\) are point ‘a’ and point ‘c’ respectively.

\[ (LL) = M - \sigma_L(M) \]  
\[ (UL) = M + \sigma_R(M) \]

Scaling the data in the form of fuzzy number membership function with a membership degree of 1 for the mean point and the membership degree of zero for the lower limit \((LL)\) and upper limit \((UL)\).

\[ \text{triangular} (x; LL, M, UL) = \begin{cases} 
0 & x \leq LL \\
\frac{(x-LL)}{(M-LL)} & LL \leq x \leq M \\
\frac{(UL-x)}{(UL-LL)} & M \leq x \leq UL \\
0 & UL \leq x 
\end{cases} \]

Referred to the equation (9) and (10), ‘\( L_M \)’ is the area under the frequency graph for the left side of the mean point and ‘\( R_M \)’ is the area under this diagram on the right side of the mean point. \( \sigma_L(M) \) and \( \sigma_R(M) \) are left and right boundaries of the fuzzy number. These values are obtained by distributing the standard deviation value \( (\sigma) \) of data regarding the ratio ‘\( S \)’ using the direct
proportion. In this way the side with bigger area due to more scattered responses, leads to a bigger boundary around the average value, which represents less certainty and more vagueness.

6.1 Numerical example 1:

Through a numerical example, we try to show the described method steps clearer. Table 2 shows the frequency chart of a rated parameter evaluated by 80 experts in a 10 grade scale that can be the importance degree or weight or degree of impact of a parameter so the question is: "How important is parameter i (P_i)?" Values from 0 to 10 can define 10 different fuzzy states or linguistic expressions. Where the score (0) indicates the unimportance of being, (1) too little importance, (2) the relatively low importance, (3) low importance, (4) the low average, (5) the average, (6) the upper average, (7) the relatively high, (8) high importance, (9) very high importance and (10) is the special importance [28].

In the conversion of statistical data into fuzzy numbers, Continuous fuzzy numbers are used. Thus, the distances between these 10 points become meaningful.

<table>
<thead>
<tr>
<th>Rating scale</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency of Responses</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>10</td>
<td>24</td>
<td>16</td>
<td>5</td>
<td>8</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>80</td>
</tr>
</tbody>
</table>

If the rating scale represents the importance degree of the parameter, data of table 2 shows that 5 experts realized that this parameter has the importance degree 2 (the relatively low importance) whereas 2 out of 80 inquired experts considered a 10 importance degree (special importance) for this parameter. The corresponding diagram for the parameter is obtained from the frequency chart. The graph represents the frequency of values for the sample parameter has been illustrated in figure 6. The sum of total frequencies is equal to the number of the inquired experts, which are 80 people.

![Fig. 6. Continuous diagram of frequency for parameter importance degree based on a ten grade scale.](image-url)

The result of the proposed algorithm for obtaining the membership function for the sample parameter has been shown in table 3. The related membership function has been illustrated in figure 7.
Table 3. The results of the proposed algorithm for calculating the lower and upper limits of the sample parameter

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean (M)</th>
<th>Standard deviation (σ)</th>
<th>$S=(L_a/R_a)$</th>
<th>$σ_δ(M)$</th>
<th>$σ_L(M)$</th>
<th>Lower limit (LL)</th>
<th>Upper limit (UL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>4.49</td>
<td>2.04</td>
<td>1.38</td>
<td>0.86</td>
<td>1.188</td>
<td>3.30</td>
<td>5.35</td>
</tr>
</tbody>
</table>

This method reflects the uncertainty of qualitative judgments because it is exclusive for each set of evaluation. For example, two sets of data with the same average value won’t have the same TFN because of different standard deviations and also different distribution of frequency histogram around the mean point. In this method a smaller standard deviation indicated a more certain set of assessment or judgment that results in narrower boundaries of the fuzzy number about the average point. For example, in a case that all the experts consider a parameter with an average degree of importance equals to 5, the standard deviation would be zero (0), so there isn’t any boundary around the single point core and the fuzzy triangle turn into a singleton fuzzy number. A singleton fuzzy number shows that there isn’t any doubt or uncertainty about the importance degree of the parameter (Fig. 8).

6.2 Numerical example 2:
Consider the fuzzy subject ‘F’ is ‘warmth’ and the variable $x$ is $50^\circ$ water. We try to find the membership degree of $50^\circ$ water via asking the opinions of 40 people through some kinds of subjective methods and proposed technique for a better understanding of the differences between them.

6.2.1. Polling method: The responses to this question: “is $50^\circ$ water warm?” with ‘yes’ or ‘no’ have been presented in table 4. If we calculate the positive answers to this question proportional to all
responses, the membership degree for “warmth” of 50° would be 0.875. Repeating this question for a range of temperatures may lead to a membership function for warmth illustrated in figure 9.

Table 4. Polling frequency chart for warmth of 50° water

<table>
<thead>
<tr>
<th>“Is 50° water warm?”</th>
<th>Yes</th>
<th>No</th>
<th>Membership degree of ‘Yes’</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>35</td>
<td>5</td>
<td>(35/40) = 0.875</td>
</tr>
<tr>
<td>Total</td>
<td>40</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

![Fig. 9. MF of warmth for different temperature degrees using polling method.](image)

6.2.2. Direct rating: we can assign a number from 1 to 10 to “How 50° water is warm?” and rate the degree of warmth of 50° water. We reach to a fuzzy function for “How 50° water is warm” by assigning the membership degree of 1 for the maximum frequency and finding the other grades proportional to the largest frequency these results are summarized in table 5.

Table 5. Frequency chart for a sample surveyed parameter

<table>
<thead>
<tr>
<th>“How is 50° water warm?”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating scale</td>
</tr>
<tr>
<td>Frequency</td>
</tr>
<tr>
<td>Membership degree</td>
</tr>
</tbody>
</table>

![Fig. 10. a) Frequency histogram of direct rating of 50° water’ warmth.](image)

![Fig. 10. b) MF of “how 50° water is warm”.](image)

So how should we use direct rating for forming the diagram of a fuzzy concept (warmth in this example) for a range of variables (different temperature degrees) when many experts are being asked to express their opinion? Turksen and Norwich in [29] described a method for constructing
the diagram for a linguistic variable (pleasing and tallness) using direct rating. They defined three diagrams, one based on the mean value of rating and two others by adding and deducting the double value of standard deviation to mean point value in a way that all the membership grades are greater than 0 and smaller than the maximum scale rate. Consider the table 6; the information of this table shows the rating of ‘warmth’ fuzzy concept for water by 40 people using a ten grade scale for temperature degrees between 0° to 100°. If we form the diagrams using the mentioned method we reach to diagrams of figure 11.a, due to direct rating of this range of temperature degrees and figure 11.b for corresponding fuzzy sets diagrams.

**Table 6.** Frequency chart of warmth rating scale for a set of temperature degrees

<table>
<thead>
<tr>
<th>Rating scale</th>
<th>0°</th>
<th>20°</th>
<th>40°</th>
<th>50°</th>
<th>60°</th>
<th>80°</th>
<th>100°</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>40</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>35</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>20</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>2</td>
<td>5</td>
<td>0</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0</td>
<td>11</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>15</td>
<td>16</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Mean 0 2.55 6.93 9.38 8.80 3.63 0.13  
Std. Dev. 0 1.04 0.92 0.70 0.94 0.87 0.33  
Mean-2Stdv. 0 0.48 5.09 7.98 6.92 1.89 0  
Mean+2Stdv. 0 4.62 8.76 10.78 10.68 5.36 0.79

![Fig. 11.a. Warm water rating diagrams using direct rating method.](image1)

![Fig. 11.b. Fuzzy sets of warm water using direct rating method.](image2)
6.2.3. The proposed method approach: By using the frequency chart data of table 6, we can summarize the proposed method parameters as shown in table 7.

Table 7. Proposed method parameters for a set of temperature degrees using the frequency chart of “warm water rating scale”

<table>
<thead>
<tr>
<th>Method Parameters</th>
<th>0°</th>
<th>20°</th>
<th>40°</th>
<th>50°</th>
<th>60°</th>
<th>80°</th>
<th>100°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of rating</td>
<td>0</td>
<td>2.55</td>
<td>6.93</td>
<td>9.38</td>
<td>8.80</td>
<td>3.63</td>
<td>0.13</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0</td>
<td>1.04</td>
<td>0.92</td>
<td>0.70</td>
<td>0.94</td>
<td>0.87</td>
<td>0.33</td>
</tr>
<tr>
<td>AL</td>
<td>0</td>
<td>20.49</td>
<td>18.81</td>
<td>15.98</td>
<td>16.92</td>
<td>15.70</td>
<td>4.14</td>
</tr>
<tr>
<td>AR</td>
<td>0</td>
<td>16.51</td>
<td>19.47</td>
<td>11.52</td>
<td>16.08</td>
<td>19.30</td>
<td>15.86</td>
</tr>
<tr>
<td>S=(AL/AR)</td>
<td>0</td>
<td>1.24</td>
<td>0.97</td>
<td>1.39</td>
<td>1.05</td>
<td>0.81</td>
<td>0.26</td>
</tr>
<tr>
<td>ϖL</td>
<td>0</td>
<td>0.57</td>
<td>0.45</td>
<td>0.41</td>
<td>0.48</td>
<td>0.39</td>
<td>0.07</td>
</tr>
<tr>
<td>ϖR</td>
<td>0</td>
<td>0.46</td>
<td>0.47</td>
<td>0.30</td>
<td>0.46</td>
<td>0.48</td>
<td>0.27</td>
</tr>
<tr>
<td>LL (µ=0)</td>
<td>0</td>
<td>1.98</td>
<td>6.47</td>
<td>8.97</td>
<td>8.32</td>
<td>3.24</td>
<td>0.06</td>
</tr>
<tr>
<td>Mean (µ=1)</td>
<td>0</td>
<td>2.55</td>
<td>6.93</td>
<td>9.38</td>
<td>8.80</td>
<td>3.63</td>
<td>0.13</td>
</tr>
<tr>
<td>UL (µ=0)</td>
<td>0</td>
<td>3.01</td>
<td>7.39</td>
<td>9.67</td>
<td>9.26</td>
<td>4.10</td>
<td>0.39</td>
</tr>
</tbody>
</table>

We calculate the sub areas segregated on the frequency histogram by indicating the mean point of assessment on the rating scale axis (Fig. 12.a) and after determining the upper and lower limits we can form the triangular fuzzy number of each temperature degree that represents: “how that temperature degree is warm” (Fig. 12.b).

When a utility view of a fuzzy concept for different types of variables is considered, using this method is very appropriate, especially when we want to determine the fuzzy multi-attribute decision making matrix (FMADM) weights; where each decision making factor is different and has its own weight and impact factor. For example, imagine we want to form the decision making matrix for evaluating several projects to different risk factors (cost, political and technical) where each risk factor impact or importance degree is needed to enter to the decision making matrix as a triangular fuzzy number which represents how that factor is important.

Figure 13.a illustrates the diagrams of the calculated boundaries (mean, LL and UL) presented in table 7, for ‘warmth’ fuzzy concept for a range of temperature degrees from 0° to 100° and figure 13.b is the scaled corresponding diagrams to [0,1]. In this case, we can determine the membership degree of each temperature degree in three states of most possible values (mean), highest possible values (Upper Limits) and lowest possible values (Lower Limits).
From the perspective of fuzzy logic, the space between the diagrams is the space arisen from vagueness and uncertainty. In the 100 percent certainty state we only have one value for each variable, which is equal to the average value of ratings. In this case, the standard deviation of data will be zero (0) and these three diagrams coincide.

The fuzzy sets illustrated in figure 13.b may not be fuzzy numbers because as we mentioned in later sections the fuzzy set must be convex and normal to be considered a fuzzy number as well. However, using the linear regression and finding the trend line is not part of the introduced method in this paper, it can be used as a solution for forming the triangular fuzzy number out of three sets of data (lower limit, mean and upper limit) produced by this method.

Figure 14.a shows the triangular forms due to linear regression of each three diagrams (LL, Mean, and UL). The equations of ultimate linear regression for all set of data have been shown in figure 14.b these equations result in the ultimate triangular shape of figure 14.c by scaling this shape to [0,1] we reach to a normal TFN.(Fig.14.d.)
We can show the triangular fuzzy number of figure 14.d in equation 17. The most possible value of this TFN with membership degree \( I \) is 54.7°. It means the water with this degree can be considered warm water with maximum certainty.

\[
\text{Triangular } (x; 0, 54.7, 100) = \begin{cases} 
0 & x \leq 0 \\
\frac{(x-54.7)}{54.7} & 0 \leq x \leq 54.7 \\
\frac{54.7}{45.3} & 54.7 \leq x \leq 100 \\
0 & 100 \leq x 
\end{cases}
\]

The main advantages and properties of this method can be listed as followings:

- It is simple, quick and functional.
- It makes the space between rating scale grades meaningful.
- This method produces exclusive TFNs for each set of data even with same mean values, different distributions of frequency chart result in different TFN shapes.
- This method tries to emphasize the uncertainties hidden in subjective perceptions and direct rating method, which is the main idea of fuzzy logic.

7. Verification of the proposed method

The method proposed in this paper was used in a study which has been formed and carried out by the author based on a framework to apply fuzzy concepts and logic in bridge management field [30]. In that research one of the defined problems was evaluating, ranking, and assign fuzzy weights to the parameters which were effective for prioritizing the urban roadway bridges for maintenance operations. In that study 45 parameters were identified under 4 main categories: destruction, bridge damage consequences, cost and facilities and strategic factors. We had to assign 45 triangular fuzzy numbers to these 45 parameters to use them as fuzzy weights in fuzzy decision making matrix and rank them using fuzzy ranking methods. So after identifying the parameters, their degree of importance and effectiveness in bridge maintenance operations were surveyed through a closed questionnaire in a 10 distance elaborated scale by 80 bridge experts of
four main groups of contractor, consultant, researcher and employer. Numbers from 0 to 10 were assigned to 11 linguistic variables that defined the importance degree of parameters in a range from unimportant to special important degree.

The verification was performed from two aspects. First, in ranking the parameters and second, in selecting the most important parameters for further process.

7.1. Ranking the parameters

After collecting the completed questionnaires, their data were analyzed by using classic statistical methods and parameters were ranked by using the Friedman test [31] then the result was compared with the produced TFNs’ fuzzy ranking output. In this study, the Mabuchi [32] algorithm was used for ranking the fuzzy numbers. This method proposes a ranking method by using multiple level of $\alpha$-cut which will have the weights role. Figure 15 shows two diagrams represent this comparison. The blue diagram illustrates the ranking result using Mabuchi method for TFNs constructed by using the proposed method and the red diagram indicates the ranking based on the classic method of the Friedman test. In figure 15, P1 to P45 are parameters’ row numbers in the questionnaire.

![Fig. 15. Parameters ranking diagrams based on fuzzy approach and Friedman test method.](image_url)

7.2. Selection the most effective parameters

In a non-fuzzy study [33], selecting the most important parameters which affect the bridge priority for maintenance operations was based on this fact that the number of parameters shouldn’t be limited as much as to raise the prioritizing error. Also they should not be such extended that encounter analysis process with complexity. So after performing the ranking using the Friedman test rank value, on the corresponding diagram that shows the rank value of priority numbers (Fig. 16), 24 parameters before the point that a big fracture appears in the diagram, were selected as most important parameters.
In the fuzzy approach, for selecting the most effective parameters, those that their minimum fuzzy desirability of 50% with $\alpha = 0.5$ is below the average index of the importance degree are excluded [28]. To avoid the complexity of the drawing, a schematic diagram of the determination of the 50% fuzzy desirability has been illustrated for 4 parameters in figure 17. In this diagram the minimum fuzzy desirability of 50% for P2, P27 and P24 is below the average importance degree (5), so they would be excluded. Thirty two parameters out of 45 parameters (4 more parameters than the non-fuzzy approach) were selected in this way for further process. This case shows the fuzzy uncertainties involvement in determining the parameters prioritization.

Wider range and stronger uncertainties involved in the fuzzy ranking process for selecting the most effective parameters are such cases that cannot be seen in classic statistical methods such as Friedman test.

8. Conclusion

Using the fuzzy logic is a solution to overcome the limitations of decision making in an uncertain environment or analysis, judgment and evaluating values or concepts where there is a lack of transparency or imperfect information. In other words, fuzzy logic covers a wider area of judgments includes the vagueness. In this paper, a simple algorithm for constructing the triangular membership function was presented based on a direct rating method using the frequency chart data of a rated variable on a numerical graded scale. These grades can be a conversion of oral judgment or qualitative assessment of a fuzzy parameter or concept. In the proposed method we used statistical values of average and standard deviation to form the
boundaries of TFN, in a way that represents the uncertainty of parameter assessment, which is evident in distribution of frequency chart. In the described algorithm only a symmetrical distribution of frequency diagram about the average index leads to an isosceles triangle fuzzy number and when there is a 100 percent certainty about the parameter assessment we can see a singleton fuzzy number without any boundaries. Using this method in cases that the evaluated parameters are the importance degree or weight factors of a multi-criteria decision making matrix can reflect the assessment uncertainties in a reasonable way.

In the last section of this article we verified the proposed method with non-fuzzy classic methods in a practical case study by comparing the fuzzy ranking of triangular fuzzy numbers of 45 parameters, constructed using the proposed method, with the Friedman test rank values. This verification justifies the partial differences in output results due to considering the uncertainties of qualitative assessments.

References

GMDH-Network to Estimate the Punching Capacity of FRP-RC Slabs

A. Azimi
1. Dept. of Civil Engineering, University of Birmingham, UK

Corresponding author: alla.azimi@gmail.com

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ABSTRACT

Determination of the punching shear capacity of FRP-reinforced concrete slabs was studied in this paper. A database including 81 pairs of data was collected and used. The method was considered in the paper, was group method of data handling (GMDH) which is one of the most structures which is used by researchers. The section area of column, effective flexural depth of slab, compressive strength of concrete, Young’s modulus of the FRP slab and reinforcement ratio were used as input variables. The target of the model was also determination of the ultimate punching capacity of the FRP-reinforced concrete flat slab (Target). Based on this dataset, ten polynomials specified and its coefficients was presented. All of these ten polynomials used for the considered prediction. The proposed GMDH structure also validate by several experimental data. The results indicated that group method of data handling (GMDH) is very useful for the prediction of the punching shear capacity of slabs.

1. Introduction

Group Method of Data Handling (GMDH) which presented by Ivakhnenko [1] is a powerful method to create a mathematical network based on a multilayered perceptron-type network structure. The use of this method studied by a lot of researchers in many fields of engineering. In Structural engineering, soft computing approaches such as ANN and also fuzzy systems are very popular and used for prediction [2-4] or for FRP material [5]. GMDH as one of the soft computing approach GMDH is a useful method to create equations which can be used in the codes. An essential different between this type of network and other networks is the mathematical approach which can help to understand the way of the solution. GMDH is a neural network structure for function approximation of complex engineering problems. In this paper,
punching shear capacity of FRP-reinforced concrete slabs was estimated by GMDH based on experimental data which were published in literatures.

2. Experimental Data

For train the GMDH structure, the author used 81 pairs of data which were published by researchers [6-8]. The details of the database is presented in Table. 1. The section area of column (Input 1), effective flexural depth of slab (Input 2), compressive strength of concrete (Input 3), Young’s modulus of the FRP slab (Input 4) and reinforcement ratio (Input 5) are considered as input parameters that determine the ultimate punching capacity of the FRP-reinforced concrete flat slab (Target). 69 data used for training phase of the selected GMDH and 12 remained data was used for validating the proposed structure.

<table>
<thead>
<tr>
<th>Type</th>
<th>Input1</th>
<th>Input2</th>
<th>Input3</th>
<th>Input4</th>
<th>Input5</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>625.000</td>
<td>131.000</td>
<td>38.600</td>
<td>48.200</td>
<td>0.810</td>
<td>329.000</td>
</tr>
<tr>
<td>Minimum</td>
<td>50.270</td>
<td>55.000</td>
<td>26.000</td>
<td>28.400</td>
<td>0.180</td>
<td>61.000</td>
</tr>
<tr>
<td>Maximum</td>
<td>2025.000</td>
<td>284.000</td>
<td>75.800</td>
<td>147.600</td>
<td>3.780</td>
<td>1600.000</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>572.349</td>
<td>60.440</td>
<td>10.122</td>
<td>33.125</td>
<td>0.695</td>
<td>355.903</td>
</tr>
</tbody>
</table>

3. GMDH Network for prediction

Based on five inputs and one output, the best structure of GMDH for prediction of the considered goal had three layers and ten polynomials. This structure showed in Fig. 1. Each of this polynomial is a two-order polynomial with two variables which is defined by Eq. 1:

\[ Y_n = c_1 + c_2X_i + c_3X_j + c_4X_i^2 + c_5X_j^2 + c_6X_iX_j \quad n=1,...,10 \]  

where, \( X_i \) and \( X_j \) are the input variable \( i \) and \( j \).

The coefficients of the polynomials for the proposed structure of GMDH presented in Table. 2. These values determined based on normal values between 0.1 to 0.9. It means that for any prediction by the proposed structure, first, the input values should be normalized. For this purpose, the author used the Eq. 2:

\[ x_n = 0.8 \frac{x_{ex} - x_{min}}{x_{max} - x_{min}} + 0.1 \]  

where \( x_n \), \( x_{ex} \), \( x_{min} \) and \( x_{max} \) are normalized, experimental, minimum and maximum values in the database respectively. It was clear that after calculating the normal value for the target, it can be simplicity converted to the real value.
Fig. 1. The proposed GMDH structure

Table 2. Coefficients of the polynomials for GMDH structure

<table>
<thead>
<tr>
<th>Polynomial</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
</tr>
</thead>
<tbody>
<tr>
<td>y1</td>
<td>-0.1331</td>
<td>0.8352</td>
<td>0.4037</td>
<td>-0.1833</td>
<td>-0.2475</td>
<td>0.3439</td>
</tr>
<tr>
<td>y2</td>
<td>0.3212</td>
<td>-0.1891</td>
<td>-0.9119</td>
<td>0.4542</td>
<td>0.5052</td>
<td>1.6049</td>
</tr>
<tr>
<td>y3</td>
<td>-0.2476</td>
<td>1.5969</td>
<td>0.7983</td>
<td>-1.1768</td>
<td>-0.7926</td>
<td>0.2705</td>
</tr>
<tr>
<td>y4</td>
<td>-0.0377</td>
<td>1.7376</td>
<td>-0.2021</td>
<td>-1.1957</td>
<td>0.2515</td>
<td>-0.4072</td>
</tr>
<tr>
<td>y5</td>
<td>0.1203</td>
<td>-0.0822</td>
<td>0.0031</td>
<td>-0.4463</td>
<td>-1.1091</td>
<td>3.5583</td>
</tr>
<tr>
<td>y6</td>
<td>0.0384</td>
<td>0.0215</td>
<td>0.5142</td>
<td>1.1856</td>
<td>-0.0094</td>
<td>-0.4107</td>
</tr>
<tr>
<td>y7</td>
<td>0.0835</td>
<td>0.6307</td>
<td>-0.3364</td>
<td>2.3476</td>
<td>2.7797</td>
<td>-4.2688</td>
</tr>
<tr>
<td>y8</td>
<td>0.0012</td>
<td>0.8388</td>
<td>0.1302</td>
<td>-0.3876</td>
<td>0.4114</td>
<td>0.0400</td>
</tr>
<tr>
<td>y9</td>
<td>0.0153</td>
<td>0.6031</td>
<td>0.2581</td>
<td>1.7816</td>
<td>2.2043</td>
<td>-3.8154</td>
</tr>
<tr>
<td>y10</td>
<td>0.0096</td>
<td>0.3101</td>
<td>0.6180</td>
<td>22.6804</td>
<td>21.9818</td>
<td>-44.6125</td>
</tr>
</tbody>
</table>

4. Results of the GMDH structure

as mentioned in the section 2, the number of training data and test data in this paper were 69 and 12 respectively. The results of the proposed structure of the GMDH presented in Fig. 2-4.
The results of the train and test data showed that GMDH can be used for estimating the considered capacity. Correlation coefficient ($R^2$) for train and test were 0.96 and 0.89 which was showed that GMDH had suitable results. Scatter plots of train and test were presented in Fig. 5-6.
Fig. 4. The results for all data.

Fig. 5. Scatter plot for train data (R2=0.96)
It was clear from the figures 2 and 3 that it was clear that the ANN-GA had suitable results and can be used for the shear capacity prediction.

6. Conclusions

GMDH-neural network used to predict the punching shear capacity of RC-slabs in this paper. The proposed structure had five inputs and three layers. Each of layer had several nodes which was included a two-order polynomial with two variables. The GMDH network trained based on experimental data and also validated. It was concluded that GMDH with a suitable accuracy can be used for considered prediction.

References


Capacity Prediction of RC Beams Strengthened with FRP by Artificial Neural Networks Based on Genetic Algorithm

Gh. Hosseini1*
1. Dept. of Civil Engineering, University of New South Wales, Sydney, Australia
Corresponding author: ghazal.1792@yahoo.com.au

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Artificial neural networks, FRP, Shear strength, Genetic algorithm.

ABSTRACT

In this paper, the ability of the artificial neural network which was trained based on Genetic algorithm, used to prediction the shear capacity of the reinforced concrete beams strengthened with side-bonded fibre reinforced polymer (FRP). A database of experimental data including 95 data which were published in literatures was collected and used to the network. Seven inputs including width of the beam, effective depth, FRP thickness, Young modulus, tensile strength of FRP and also FRP ratio were used to predict the shear capacity of the reinforced concrete beams strengthened with side-bonded fibre reinforced polymer. The best values of the weights and the biases was obtained by the Genetic algorithm. For increasing the ability of the model to predict the considered target, it was suggested that the predicted values considered smaller. The results indicated that the proposed neural network based on genetic algorithm was able to predict the shear capacity of the considered elements.

1. Introduction

Shear strength is one of the most powerful problems in the concrete elements [1]. In the recent years, the use of FRP material with the aim of rehabilitations or strengthening of reinforced concrete elements such as beams is a common tool. There are also many research about the suitable effects of this materials in RC structures. FRP is a fibre material which is based on carbon fibres (CFRP), glass fibres (GFRP) and also aramid fibres (AFRP). They are classified as the brittle material but their sheets can be used for ductility goals.

Soft computing approaches such as Artificial neural networks (ANN) or fuzzy systems are a very powerful tools which are used in the complex engineering problems and widely used in structural
engineering such as for earthquake [2, 3] and some building material such as mortars [4]. ANN is a common approach which was widely used by researchers. The ability of this method for those problems with multi-variables were investigated by many researchers in several studies. They are used for function approximation with high accuracy based on an observed dataset. In this paper, a database includes 96 pairs data which were published in literatures was collected to predict the shear capacity of RC beams strengthen with FRP sheets.

2. Experimental Data

A neural network needs a database for training. For this purpose, the author used the 95 test results which were tested and published by researchers [5-23]. The details of the database is presented in Table. 1. In this table, input1,…,input7 are b (mm), h (mm), d (mm), FRP thickness(mm), Young modulus (GPa), tensile strength of FRP (MPa) and FRP ratio (calculated by Eq.1) respectively. The target is the shear capacity of the considered beams (KN). The Fig.1 showed the FRP parameters in a RC beam.

$$FRP\ ratio = \frac{W_f}{S_f \cdot \sin \beta}$$  

(1)

<table>
<thead>
<tr>
<th>Type</th>
<th>Input1</th>
<th>Input2</th>
<th>Input3</th>
<th>Input4</th>
<th>Input5</th>
<th>Input6</th>
<th>Input7</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>150</td>
<td>250</td>
<td>220</td>
<td>0</td>
<td>230</td>
<td>3290</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Minimum</td>
<td>70</td>
<td>110</td>
<td>100</td>
<td>0</td>
<td>16</td>
<td>89</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Maximum</td>
<td>380</td>
<td>500</td>
<td>420</td>
<td>3</td>
<td>390</td>
<td>4500</td>
<td>1</td>
<td>215</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>58.11</td>
<td>109.71</td>
<td>96.84</td>
<td>0.74</td>
<td>73.83</td>
<td>1197.97</td>
<td>0.27</td>
<td>45.32</td>
</tr>
</tbody>
</table>

Fig. 1. FRP parameters in RC beams [24].
3. Artificial Neural Networks based GA

Artificial neural networks (ANN) is a very popular tool which is used for function approximation. It has a number of variables as neurons in several layers with biases. Each node (or neuron) has an un-known weight value. The biases of the ANN structure also are another un-known values. All of these parameters should be calculated by a learning algorithm. In this paper all of the un-known parameters of the initial ANN extracted and optimized by Genetic algorithm (GA) to find the best value for them. Also, in this paper; the author used feed forward back propagation type of the neural networks in one middle layer. Tangent sigmoid and also Purlin were used as transfer function of the middle layer and the output layer respectively. It was mentioned that the first layer has seven nodes as inputs. For the middle layer, eight nodes was considered. The results of the ANN was presented in the next section.

4. Prediction the shear capacity by ANN-GA

as mentioned in the previous section, in this paper 95 data set collection from experimental studies. seven parameters used as inputs, while the target was shear capacity. 81 pairs of this database used for training the ANN while the remained data (14 pairs) used for testing the model. Figures 2 and 3 shows the results for train and test phases.

![Fig. 2. The results for train data.](image_url)
Fig. 3. The results for train data.

It was clear from the figures 2 and 3 that it was clear that the ANN-GA had suitable results and can be used for the shear capacity prediction.

5. Conclusions

Artificial neural network as a very useful tool was considered to predict the shear capacity of RC beams which were strengthened with FRP material. A network based on Genetic algorithm including one middle layer and eight nodes with Tangent sigmoid transfer function, seven inputs and also Purelin function for the output layer was created and tested by the author. For increasing the ability of the model to predict the considered target, it was suggested that the predicted values considered smaller. However, the results of the proposed network showed that it can be used for the shear capacity of the RC beams strengthened with FRP.

References


AIMS AND SCOPE

The idea behind soft computing is to model the cognitive behavior of human mind. Soft computing is the foundation of conceptual intelligence in machines. Unlike hard computing, soft computing is tolerant of imprecision, uncertainty, partial truth, and approximation. Soft computing aims to surmount NP-complete problems, uses inexact methods to give useful but inexact answers to intractable problems, and also it is well suited for real world problems where ideal models are not available. Today, soft computing algorithms are becoming important classes of efficient tools for developing intelligent systems and providing solutions to complicated civil engineering problems.

The focus of this journal is on applications of soft computing methods in civil engineering. Domains of applications include structural engineering, design, diagnostics, and health monitoring, hydraulic engineering, geotechnical engineering, transportation engineering, environmental engineering, coastal and ocean engineering and construction management. Articles submitted to this journal could also be concerned about the most significant recent developments on the topics of soft computing and its application in civil engineering. The journal also provides a forum where civil engineering researchers can obtain information on relevant new developments in optimization. We encourage the submission of articles that make a genuine soft computing contribution to a challenging civil engineering problem.

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