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Compression ratio of municipal solid waste simulation using artificial neural network and adaptive neurofuzzy system

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ABSTRACT

The compression ratio of Municipal Solid Waste (MSW) is an essential parameter for evaluation of waste settlement. Since it is relatively time-consuming to determine compression ratio from oedometer tests and there exist difficulties associated with working on waste materials, it will be useful to develop models based on waste physical properties. Therefore, present research attempts to develop proper prediction models using ANFIS and ANN models. The compression ratio was modeled as a function of the physical properties of waste including dry unit weight, water content, and biodegradable organic content. A reliable experimental database of oedometer tests, taken from the literature, was employed to train and test the ANN and ANFIS models. The performance of the developed models was investigated according to different statistical criteria (i.e. correlation coefficient, root mean squared error, and mean absolute error) recommended by researchers. The final models have demonstrated the correlation coefficients higher than 90% and low error values; so, they have capability for acceptable prediction of municipal solid waste compression ratio. Furthermore, the values of performance measures obtained for ANN and ANFIS models indicate that the ANFIS model performs better than ANN model.

Key words: Municipal solid waste, Compression ratio, Physical properties, ANFIS model, ANN model, Statistical criteria

RESUMEN

El índice de compresión de residuos sólidos es un parámetro esencial para la evaluación del asentamiento de un basurero municipal. Debido al desgaste de tiempo para determinar el índice de compresión a partir de pruebas edométricas y debido a las dificultades asociadas al trabajo con materiales desechados es necesario desarrollar modelos basados en las propiedades físicas de los desechos solidos. Además, la presente investigación pretende desarrollar modelos de predicción apropiados a partir de los esquemas ANFIS y ANN. El índice de comprensión se modeló como una función de propiedades físicas de desechos que incluyen el peso seco de una unidad, el contenido de agua y el contenido orgánico biodegradable. De la literatura se tomó una base de datos confiable de pruebas edométricas experimentales que fue empleada para preparar y evaluar los modelos ANFIS y ANN. El desempeño de los modelos desarrollados fue investigado de acuerdo con diferentes criterios estadísticos (por ejemplo, el coeficiente de correlación, el error cuadrático medio y el error medio absoluto) recomendados por investigadores. Los modelos finales han demostrado coeficientes de correlación mayores al 90 por ciento y valores bajos de error. Esto significa que estos modelos tienen una capacidad de predicción aceptable para el índice de comprensión del basurero municipal. Además, los valores de las medidas de desempeño obtenidos para los modelos ANFIS y ANN indican que el modelo ANFIS tiene una mayor asertividad que el modelo ANN.

Palabras clave: Basurero municipal; índice de compresion; propiedades físicas; modelo ANFIS; modelo ANN; estándar estadístico.

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Introduction

Settling municipal solid waste (MSW) is a significant issue considered in geotechnical design of a landfill. Waste settlement influences the stability, deformation, and structural performance of landfills (Chen et al., 2010). The settlement of MSW is composed of three mechanisms: primary compression, mechanical creep, and bio-compression (Sowers, 1973; Edgers et al., 1992; Wall and Zeiss, 1995; El-Fadel and Khoury, 2000; and Bareither et al., 2011). Primary compression occurs quickly in response to self-weight and an external load applied to the waste. Secondary compression (i.e. Mechanical creep) is due to long-term slippages, reorientation of particles, and delayed compression of some waste constituents. Bio-compression is related biochemical processes associated with the decomposition of biological solids and gas generation. A commonly used parameter for predicting the primary compression strain in MSW is the compression ratio (C'c):

$$\varepsilon_i = C_c^{'} \frac{\sigma_{v0}^{'} + \Delta\sigma_v^{'}}{\sigma_{v0}^{'}} \tag{1}$$

where ε_i is the primary compression in MSW, $\sigma_{vo}^{'}$ is the existing vertical effective stress and $\Delta\sigma_v^{'}$ is the change in the vertical effective stress. The compression ratio represents the slope of the curve of the strain versus the logarithm of the effective pressure. It is conventionally determined through an oedometer test and is related to the compression index (Cc), which is commonly applied for soils by the equation $C'_c = \frac{C_c}{1+e_0}$, where e_0 = initial void ratio. Considering some difficulties in calculating the initial void ratio of the waste materials, it is usually preferred to use the compression ratio instead of the compression index.

There have been several studies investigating the effect of various parameters on waste compressibility. Chen et al. (2010) and Landva et al. (2000) examined waste samples with different initial densities. Their results demonstrate that an increase in the waste density reduces the C'c. Experimental works conducted by Sowers (1973), Swati and Joseph (2008), and Chen et al. (2009) on waste settlement revealed an increase in organic compounds and compressible materials could bring about an increase in C'c. Karimpour-fard and Machado (2009) and Chen et al. (2009) tried to examine the compressibility of waste samples that were at different ages. The results demonstrated that an increase in the age; thus, further waste decomposition decreased the waste compressibility and compression ratio. Durmusoglu et al. (2006) tested waste materials with a natural moisture content and field capacity moisture. The results indicated that wastes with field capacity moisture had a higher C'c than those with a natural moisture content. Other researchers, such as Vilar and Carvalho (2004) and Reddy et al. (2009b), examined waste samples with a similar composition and a dry unit weight. They reported higher C'c values for wastes with higher water contents. Earlier experimental works introduced such parameter as dry unit weight, water content, and contribution percentage of biodegradable organic materials (paper, food wastes, and yard wastes) as the most significant factors which affect the compressibility of municipal solid waste.

Earlier studies have addressed the effect of some parameters on waste compression ratio. It is to be noted that determining compression ratio through an oedometer test is time-consuming. Another problem with doing this test on waste materials is the scale effect. Owing to the fact that the particles of waste materials are much larger than those of fine-grained soil, it is not possible to precisely determine the waste compressibility by commonly used oedometers such as Casagerande oedometer. In many cases, therefore, any precise investigation of the compressibility behavior of waste entails designing and manufacturing oedometer instruments that suit the size of waste materials. Also, owing to the specific nature of waste materials, it would be hard to work on them. Therefore, it seems necessary to develop models that are based on effective parameters measured through more simple experimental methods. In recent years, soft computing methods such as neural networks and neuro-fuzzy have been used successfully to solve a wide variety of problems in geosciences and geotechnical engineering. These include the estimation of the prediction of compression ratio of soils (Park and Lee, 2011; and Ozer et al., 2008), strength parameter modeling of different soils (Sezer, 2013; Khanlari et al., 2012; and Heshmati et al., 2009), Simulation of waste generation (Noori et al., 2009), estimation of probability of the liquefaction (Hanna et al., 2007; and Venkatesh et al., 2013). In the present study, two soft computing methods, i.e. adaptive neuro fuzzy inference system (ANFIS) and neural network (ANN), have been utilized to propose efficient models for predicting the compression ratio of MSW.

Artificial neural network (ANN)

A neural network consists of parallel layers of simple computational elements called 'artificial neurons'. All of the layers are connected to each other by interconnection weights. Figure 1(b) shows an artificial neuron model. The artificial neurons basically include three parts: weight, bias and transfer function. In each neuron, coming signals from the previous layer, x_i, are multiplied by the related adjustable connection weight, W_{ij}, and then summed in addition to an bias value, θ_j, . Then the combined input, I_j, is passed through a nonlinear transfer function, $f(I_j)$, to yield the output of the neuron (yi) (Jaksa et al., 2008). Output of each neuron creates the input of the neuron in the next layer. This process is summarized in Equations (2) and (3), and illustrated in Fig 1(b):

$$I_j = \sum w_{ji} x_i + \theta_j \tag{2}$$

$$y_i = f(I_j) \tag{3}$$

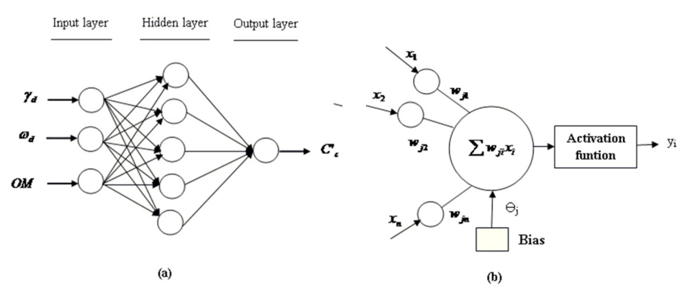

Fig. 1 (a) The feed forward neural network structure used for modeling compression ratio of MSW, (b) The artificial neuron model

One of the most practical artificial neural networks for solving the problems of engineering and geotechnics is Multi-Layer Perceptron (MLP) network (Khanlari et al., 2012). The MLP networks contain an input layer, one or more hidden layers, and one output layer. This network is a feed-forward network, the information of which only flows in one direction, from the input to the output. Figure 1 depicts a three-layered feed-forward network. MLP utilizes a supervised learning technique called 'back propagation' for training the network. Back propagation algorithm is one of the most common supervised learning algorithms for training feed forward multilayer networks. This algorithm involves two main phases, namely forward pass and backward pass. In the forward pass, an input training pattern is shown to the network, and its effect propagates in the network layer by layer until the output of the network is obtained. In the forward pass, the error between the network prediction and the target value is calculated and distributed; then, by means of a technique called gradient descent, it is propagated from the output layer to the input layer in order to reduce the error value. This process is iterated, and the weights are updated until the summed square of the errors comes below an acceptable value. To enhance speed and performance of the back propagation algorithm, Levenberg-Marquardt algorithm can be alternatively used instead of the conventional gradient descent method.

Adaptive neuro-fuzzy inference system (ANFIS)

Neuro-fuzzy systems are the result of the integration of fuzzy logics and artificial neural networks. So they benefit from the advantages of both fuzzy systems and neural networks. In this hybrid method, the fuzzy system provides the relation between input and output variables, while parameters of membership functions of the fuzzy system are optimized by the neural network. One of the well-known neuro-fuzzy models is adaptive neuro-fuzzy inference system (ANFIS) which is capable of modeling any nonlinear function with a desirable accuracy (Jang et al., 1997). ANFIS uses a feed forward network to optimize the parameters of a fuzzy inference system and perform well on a given task. The most common fuzzy inference system with this compatibility located in an adaptive network is Takagi-Sugeno fuzzy system. The first order Sugeno model was adopted in this study as it is also extensively used in many engineering problems. An example of the first order Sugeno fuzzy inference system with two inputs, one output and two membership functions for each of the inputs is illustrated in Figure 2(a). Two typical if-then rules can be stated for such a model (Sugeno and Kang, 1998):

$$f\ x = A_1\ and\ y = B_1\ then\ f_{1(x,y)} = p_1x + q_1y + K_1 \quad (4)$$

$$If\ x = A_2 and\ y = B_2\ \ then\ f_{2(x,y)} = p_2x + q_2y + K_2 \quad (5)$$

where A_1, A_2, B_1, and B2 are the membership functions for inputs x and y, respectively, while k_1, p_1, q_1 and k_2, p_2, q_2 represent the parameters of output functions for the two defined rules. The discussed architecture of the ANFIS is also depicted in Figure 2(b). It can be seen that calculations of the ANFIS model are implemented in five layers. The detail and formulation on ANFIS are addressed by Jang et al. (1997). ANFIS utilizes a back propagation learning algorithm or a hybrid algorithm which is an integration of back propagation and least square techniques in order to generate fuzzy rules and tune member function.

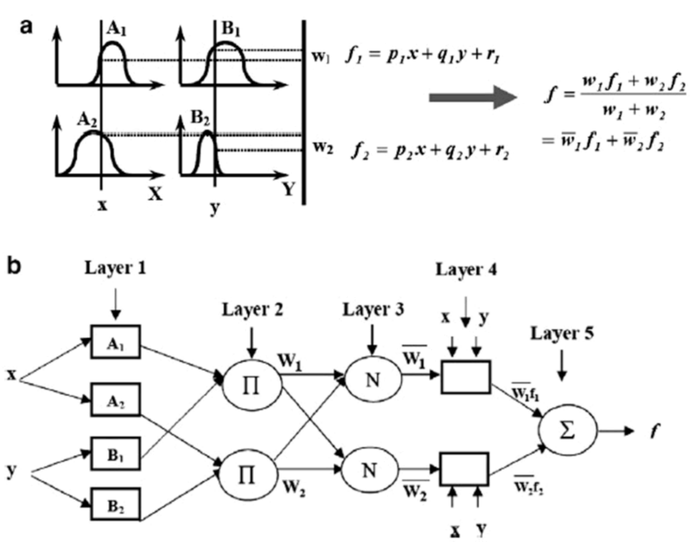

Fig. 2 (a) The first order Sugeno fuzzy model, (b) corresponding ANFIS architecture (Padmini et al., 2008)

Experimental Database

A valid database was used for modeling. It included the results of 64 oedometer tests on MSW as well as information related to the tested waste properties such as dry unit weight (γ_d), dry weight water content (ω_d), and percentage of biodegradable organic materials (OM) obtained in previous studies. A considerable part of these data and references cited by Bareither et al. (2012) were combined with the data provided by Hyun II et al. (2011), Reddy et al. (2011), and Karimpour-fard and Machado (2012). The employed data are indicated in Table 1. The physical properties of wastes (i.e ω_d, γ_d, and OM) were used as the input parameters and the $C'c$ as the target in the ANFIS and the ANN models.

Table 1. The sources of the database

Reference	No. of oedometer Test
Beaven and Powrie (1995)	5
Chen and Lee (1995)	1
Gabr and Valero (1995)	6
Landva et al. (2000)	4
Olivier and Gourc (2003)	1
Vilar and Carvaleho (2004)	4
Olivier and Gourc (2007)	2
Stoltz and Gourc (2007)	1
Chen et al. (2009)	5
Reddy et al. (2009a)	3
Reddy et al. (2009b)	4
Reddy et al. (2009c)	3
Reddy et al. (2011)	5
Chen et al. (2010)	2
Stoltz et al. (2010)	9
Breither et al. (2011)	6
Hyun II et al. (2011)	1
Karimpour- fard and Machado (2012)	2

In order to simulate the compression ratio, the database was randomly divided into two subsets, training and testing subsets. The training subset was used to calibrate the models, and the testing subset was used for validation of the developed models based on the training subset. The selection was such that the maximum, minimum, and mean value as well as the standard deviation of the parameters got to be close to each other in the training and the testing of the sub- sets. Eighty percent of the data (51 cases) were assigned for the training subset and twenty percent (13 cases) for the testing subset. To control network overtraining and over-fitting, the training set was divided into two subsets: training and cross validation. The use of about 10% of the training data as a cross validation set has been suggested by researchers (Kucuk 2008). As a result, in this study, 10% of the training subset was randomly taken and used for cross validation. The statistical properties of the divided subsets are summarized in Table 2.

Table 2. Statistical properties of the training and testing sets

Parameter	Statistics	Training data	Testing data
$_d$(%)ω	Max	151.00	135.00
	Mean	71.02	73.79
	Min	15.60	31.30
	Std Dev	33.72	34.59
γ_d (KN/ m^3)	Max	12.50	9.14
	Mean	5.48	5.85
	Min	2.45	1.86
	Std Dev	1.86	2.18
OM (%)	Max	60.00	60.00
	Mean	32.91	34.12
	Min	0.49	2.00
	Std Dev	19.79	20.03
C'c	Max	0.39	0.34
	Mean	0.24	0.21
	Min	0.09	0.14
	Std Dev	0.06	0.07

Performance measures

Various statistical parameters including correlation coefficient (r), root mean squared error (RMSE), and mean absolute error (MAE) were investigated in order to evaluate the efficiency and accuracy of the proposed models. These parameters are defined as:

$$r = \frac{\sum_{i=1}^{n}(M_i - \overline{M})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(M_i - \overline{M})^2(\sum_{i=1}^{n}(P_i - \overline{P})^2}} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(M_i - P_i)^2}{n}} \quad (7)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|M_i - Pi\right| \quad (8)$$

In equations (6), (7) and (8), n is the number of the data, M_i and P_i display the measured and predicted values, respectively. Also, $\overline{M}$ and $\overline{P}$ are the mean values corresponding to the measured and predicted values, respectively.

Development of ANN model

As the topology of a network directly influences its computational complexity and generalization capability, it is important to devise appropriate network architecture in neural network modeling. This needs determination of the number of hidden layers and the number of neurons in each layer. Theoretical works have revealed that a multilayer feed forward network with one hidden layer is able to approximate any continuous and complex nonlinear function with the desired degree of accuracy (Hornik et al., 1989). Consequently, one hidden layer was used in this study.

The number of neurons in the input and output layers is dependent on the number of model inputs and outputs. The input layer of the ANN model, developed in this study, has tree neurons, including one for each input. The output layer has only one neuron representing the measured value of compression ratio. The ANN performance is influenced by the number of neurons in hidden layers. However, there are no specific guidelines that can be used to select the optimum number of neurons in a hidden layer for a given problem. This parameter is often selected through a trial and error method. To obtain the optimum network architecture, different numbers of hidden-layer neurons, from 3 to 8, were employed to train different networks. Finally, an appropriate ANN network with best performance was selected by considering r and RMSE values of the testing data set and the training data set.

A back-propagation algorithm was used to train the MLP neural network. Specifically, the Levenberg–Marquardt algorithm was used to improve the speed and efficiency of back propagation algorithm. Also, a tan-sigmoid function was used as the activation function in the hidden and output layers. After the training phase, the generalization capability of the trained model was evaluated using the test data set (13 data). The output value of the optimal network, compression ratio, can be calculated by equation (18):

$$C_C^{'} = f_2\left[\left[W_2\right]f_1\left[\left[W_1\right]\begin{bmatrix}\omega_d\\ \gamma_d\\ OM\end{bmatrix} + \left[b_1\right]\right] + \left[b_2\right]\right] \quad (9)$$

where W_1 and W_2 are the weight matrices, and b_1 and b_2 are the biases vectors. The values of these parameters are presented in Table 3.

Development of ANFIS model

In the ANFIS system, each input parameter must be clustered into several class values in order to form fuzzy rules, and each fuzzy rule is made up of two or more membership functions .Various methods have been proposed for the clustering of the input parameter and development of the rules, the most common of which are: "Subtractive Clustering" method (Chie, 1994) and "Grid Partitioning" method (Jang and Sun, 1995). The former was adopted in this study because it required less computational effort and calculation time.

The subtractive clustering algorithm assumes that every data point is a candidate that can become a cluster center. Then, a measure of density for each data point is used to determine the potential of a point to become a cluster center (Chiu, 1994). The data point with the highest potential is selected as the first cluster center, and the data points near the first cluster center are removed, as determined by the influential radius. The algorithm searches for a new data point having the highest number of neighbors as the next cluster center. Then the data points near the new cluster center with fewer neighbors are removed. This is repeated until all the data points are examined and sufficient numbers of cluster centers can be generated. The influential radius is necessary for determining the number of clusters. A smaller radius leads to many smaller clusters in the data space, thereby resulting in more rules, and vice versa.

The value of the optimal radius in a trial and error process was determined by changing the radius from 0.1 to 1 with an increment of 0.05. At last, the radius value was chosen to be 0.9 that resulted in approximately two clusters. Therefore, each input and output was characterized by two membership functions and, hence, two rules were created. The Gaussian-type membership function was assigned to each input variable. After constructing the initial FIS structure, the training stage was done. The hybrid learning algorithm was employed as an optimizing method in the training stage. In this step, the number of iterations of the hybrid algorithm for the correction of model parameters and goal error were considered 100 and 0, respectively. The constructed ANFIS model has 20 parameters (8 linear and 12 nonlinear). The membership function (MF) plots of the dry weight water content, dry unit weight, and biodegradable organic compounds used in the training stage are shown in Fig. 3.

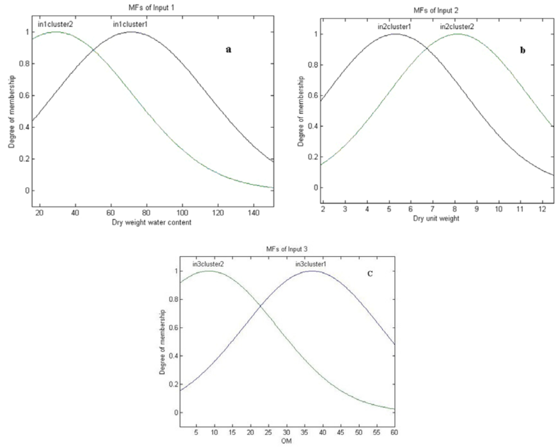

Fig. 3 Membership function plots of the compression ratio, (a) dry weight water content, (b) dry unit weight, and (c) biodegradable organic compound

Results and discussion

ANN model

Fig. 1(a) schematically depicts the ANN architecture used in this study. A study on different networks with different hidden neurons showed that a network comprising five neurons in a hidden layer approaches the lowest prediction errors and maximum correlation coefficient. A comparison of the prediction made by the ANN with the experimental value for each of the training and testing data set is shown in Fig 4. As it can be seen, most of the cases in the training and testing subsets are around the middle, indicating a good agreement between the ANN model prediction and the experimental values.

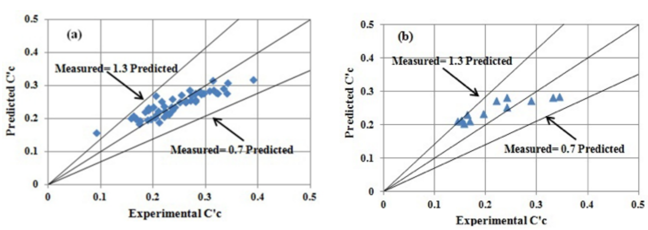

Fig.4. Measured versus predicted compression ratio of MSW using ANN model, (a) Training data set, (b) Testing data test

Table 3 shows the weights of the input-hidden and hidden-output layer connections and biases of the proposed ANN model after the end of the training procedure. The relative importance of the input parameters can be assessed by partitioning the hidden-output connection weights into components connected with each input variable. Table 4 lists the relative importance of the input variables in the ANN model. As seen in this Table, the dry density and the dry weight water content have the most significant effect on the predicted compression ratio with average relative importance values of 41.88 and 43.47%, respectively.

Table 3. Connection weights and biases

Hidden neurons	Connection weights w_d	γ_d	OM	Output	Bias b_1	b_2
1	2.392048	-0.5424	-0.16996	0.85305	-3.40087	
2	-0.99725	1.993881	1.326822	-0.30535	-1.01113	
3	1.068502	1.114304	0.902626	0.482927	0.10878	
4	1.394682	1.820413	0.112775	-0.432	-0.18422	
5	0.44533	2.31615	-0.41531	-0.49832	2.493959	
Output neuron						0.876667

Table 4. The relative importance of the ANN model input variables.

Input parameter	w_d	g_d	OM
Relative importance (%)	43.47	41.88	14.65

According to Smith (1986), if a proposed model provides r> 0.8 and the error values (e.g. MAE and RMSE) are at the minimum, there is a strong correlation between the measured and predicted values. The training and testing results of the ANN model are presented in Table 5. The results show that the ANN model performs well, with r, RMSE, and MAE at the values of 0.93, 0.0187, and 0.0219 in the training stage and 0.928, 0.0378, and 0.0404 in the testing stage, respectively.

ANFIS model

Fig. 5 represents the structure of the proposed ANFIS model in this study. The fuzzy radius of this model is 0.9, and it is formed of two rules.

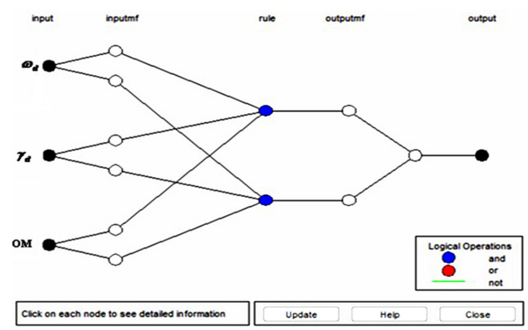

Fig. 5 The schematic of ANFIS architecture based on Sugeno fuzzy model developed in this study

Fig. 6 compares the ANFIS predictions with the experimental values of the compression ratio of MSW for the training and testing data sets. The proposed model shows a very good correlation to the training and testing data. The predictive performance of the ANFIS model is summarized in Table 5. The results demonstrate that the ANFIS model with a high r and low RMSE and MAE values is trained well and able to estimate the target values with an acceptable degree of accuracy.

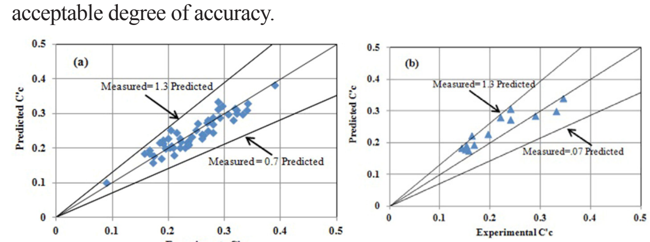

Fig.6 Measured versus predicted compression ratio of MSW using ANFIS model, (a) Training data set, (b) Testing data test

Table 5. Performance of the proposed models

Model	Training			Testing		
	R	MAE	RMSE	R	MAE	RMSE
ANN	0.904	0.0235	0.0602	0.9	0.048	0.0515
AN-FIS	0.923	0.0187	0.0222	0.923	0.0347	0.0396

Prediction results obtained from the ANN and ANFIS models are compared in Table 5. The high correlation coefficient and the lower error in both models demonstrate the capability of those models in acceptably predicting the compression ratio. As suggested by the results, the error rates of the ANFIS model are lower than ANN model; so, ANFIS has performed more precisely. Table 5 also shows that the results obtained for each of the models during testing are generally consistent with those obtained during training. This suggests that the proposed models are able to generalize within the range of data used for training.

It is noteworthy that, although the predictive capability of the proposed models is limited to the range of the data used for their calibration, if a new data set becomes available, these models can be retrained and updated easily without repeating the development procedures from the beginning.

Conclusions

In this research, ANFIS and ANN models were used to predict the compression ratio of municipal solid waste. The models were developed based on a reliable database obtained from the literature. The following emerge as the conclusions of the study:

1 - The proposed models developed through ANN and ANFIS modeling techniques can precisely predict the compression ratio of MSW.

2 - The relative importance study indicates that dry unit weight and dry weight water content have a significant effect on the compression ratio of MSW.

3 - A major advantage of ANN and ANFIS models is that, once a new set of data becomes available, they can be easily updated and improved without repeating the development procedures from the beginning.

References

Bareither, C.A., Benson, C.H. and Tuncer, T.B. (2012). Compression behavior of municipal waste: Immediate Compression, Journal Geotechnical Geoenvironmental Engineering. 138, 1047-1062.

Beaven, R.P. and Powrie, W. (1995). Determination of the hydrogeological and geotechnical properties of refuse using a large scale compression cell, Proceedings of the 5th International Sardinia Landfill Conference, S. Margherita Dipula, Cagliari, Italy, 745-760.

Chen, R.H. and Lee, Y.S. (1995). Settlement analysis of a waste landfill, Proceedings of the 3th International Symposium on Environmental Geotechnology, San Diego, CA, USA, 539-553.

Chen, Y.M., Zhan, T.L.T., Wei, H.Y. and Ke, H. (2009).Aging and compressibility of municipal solid wastes, Waste Management journal. 29, 86-95.

Chen, R.H., Chen, K.S. and Liu, C.N. (2010). Study of the mechanical compression behavior of municipal solid waste by temperature-controlled compression tests, journal of Environmental Earth Sciences. 61, 1677-1690.

Chiu, S.L. (1994). Fuzzy Model Identification Based on Cluster Estimation, Journal of Intelligent Fuzzy Systems. 2, 267-278.

Durmusoglu, E., Sanchez, I. and Corapcioglu, M. (2006). Permeability and compression characteristics of municipal solid waste samples, Environmental Geology. 50, 773-786.

Edgers, L., Noble, J.J. and Williams, E. (1992). A biologic model for long-term settlements in landfills, Proceedings of the Environmental geotechnology, Balkema, Rotterdam, The Netherlands, 177-183.

El-Fadel, M. and Khoury, R .(2000). Modeling settlement in MSW landfills: A critical review, Environmental Science and Technology. 30, 361-327.

Erzin, Y.and Gul, T.O. (2012). The use of neural networks for the prediction of the settlement of one- way footings on cohesionless soils based on standard penetration test, Neural Computing and applications, DOI 10.1007/s00521-012-1302-x.

Gabr, M.A. and Valero, S.N. (1995). Geotechnical properties of municipal solid waste, Geotechnical Testing Journal.18, 241-251.

Hanna, A. M. Derin, U. and Saygili, G. (2007). Neural network model for liquefaction potential in soil deposits using Turkey and Taiwan earthquake data. Soil Dynamics and Earthquake Engineering, 27, 521-540.

Heshmati, A.A.R., Alavi, A.H., Keramati, M. and Gandomi, A.H. (2009). A radial basis function neural network approach for compressive strength prediction of stabilized soil. Geotech Spec Pub ASCE, Changsha Hunan, China, 191, 147–153.

Hornik, K., Stinchcombe, M. and White, H. (1989). Multilayer feed forward networks are universal approximators, Neural Network journal. 2, 359-366.

Hyun II, P., Borinara, P. and Hong, K.D. (2011). Geotechnical considerations for end-use of old municipal solid waste landfills, International Journal Environmental Research. 5, 573-584.

Jaksa, M.B., Maier, H.R. and Shahin, M.A. (2008). Future challenges for artificial neural network modeling in geotechnical engineering, The 12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG), Geo, India, 1710–1719.

Jang, J.S.R., Sun, C.T. and Mizutani, E. (1997). Neuro-fuzzy and soft computing,Prentice-Hall, New Jersey.

Jang, J. S. R. and Sun, C. T. (1995). Neuro-fuzzy modeling and control, Proceedings of the IEEE, 378–406.

Kalkan, E., Akbulut, S.,Tortum, A. and Celik, S. (2009). Prediction of the unconfined compressive strength of compacted granular soils by using inference systems, Environmental Geology. 58, 1429–1440.

Karimpour-Fard, M. and Machado, S.L. (2012). Deformation characteristics of MSW materials, Electronic Journal Geotechnical Engineering. 17(A), 2009-2024.

Khanlari, G.R., Heidari, M., Momeni, A.A. and Abdilor, Y. (2012). Prediction of shear strength parameters of soils using artificial neural networks and multivariate regression methods, Engineering Geology, 131-132, 11-18.

Kucuk, N. (2008). Modeling of gamma-ray energy absorption buildup factors using neural network, Ann. Nucl. Energy. 35, 1787–1790.

Landva, A.O., Valsangkar, A.J. and Pelkey, S.G. (2000). Lateral earth pressure at rest and compressibility of municipal solid waste, Canadian Geotechnical Journal. 37, 1157-1165.

Noori, R., Abdoli, M.A., Farokhnia, A. and Abbasi, M. (2009). Results uncertainty of solid waste generation forecasting by hybrid of wavelet transform-ANFIS and wavelet transform-neural network, Expert Systems with Applications. 36, 9991–9999.

Olivier, F., Gourc, J.P., Lopez, S., Benhamida, S. and Van-Wyck, D. (2003). Mechanical behavior of solid waste in a fully instrumented prototype compression box, Proceedings of the 9th International Waste Management and Landfill Symposium, Cagliari, Italy, 1-12.

Olivier, F. and Gourc, J.P. (2007). Hydro-mechanical behavior of municipal solid waste subject to leachate recirculation in a large-scale compression reactor cell, Waste Management journal . 27, 44-58.

Ozer, M., Isik, N.S. and Orhan, M. (2008). Statistical and neural network assessment of the compression index of clay-bearing soils, Bull Eng Geol Environ. 67, 537–545.

Padmini, D., Ilamparuthi, K. and Sudheer, K.P. (2008). Ultimate bearing capacity prediction of shallow foundations on cohesionless soils using neurofuzzy models, Computers and Geotechnics. 35, 33-46.

Park, H.L. and Lee, S.R. (2011). Evaluation of the compression index of soils using an artificial neural network, Computers and Geotechnics. 38, 472–481.

Reddy, K.R., Hettiarachchi, H., Parakalla, N.S., Gangathulasi. and J., Bogner, J. E. (2009a). Geotechnical properties of fresh municipal solid waste at Orchard Hills Landfill, USA, Waste Management. 29, 952-959.

Reddy, K.R., Gangathulasi, J., Parakalla, N.S., Hettiarachchi, H., Bogner, J.E. and Lagier, T. (2009b). Compressibility and shear strength of municipal solid waste under short-term leachate recirculation operations, Waste Management and Research. 27, 578-587.

Reddy, K.R., Hettiarachchi, H., Gangathulasi, J., Bogner, J. and Lagier,T. (2009c). Geotechnical properties of synthetic municipal solid waste, International Journal of Geotechnical Engineering. 3, 429-438.

Reddy, K.R., Hettiarachchi, H., Gangathulasi, J. and Bogner, J. E. (2011). Geotechnical properties of municipal solid waste at different phases of biodegradation, Waste Management.31, 2275-2286.

Sezer, A. (2013). Simple models for the estimation of shearing resistance angle of uniform sands, Neural computing and applications. 22,111-123.

Smith, G.N. (1986). Probability and Statistics in Civil Engineering: An Introduction. Collins, London.

Sowers, G. (1973). Settlement of waste disposal fills, Proceedings of the 8th International Conference on Soil Mechanics and Foundation Engineering, Balkema, Rotterdam, 207-210.

Sugeno, M. and Kang, G.T. (1988). Structure identification of fuzzy model, Fuzzy Sets Systems. 28, 15–33.

Stoltz, G., and Gourc, J. P. (2007). Influence of compressibility of domestic waste on fluid permeability, Proceedings of the 11th International Waste Management and Landfill Symposium, Cagliari, Italy, CISA, Environmental Sanitary Engineering Centre, Italy, 1-8.

Stoltz, G., Gourc, J.P. and Oxarango, L. (2010). Characterisation of the physico-mechanical parameters of MSW, Waste Management journal. 30, 1439-1449.

Swati, M. and Joseph, K. (2008). Settlement analysis of fresh and partially stabilized municipal solid waste in simulated controlled dumps and bioreactor landfills, Waste Management journal. 28, 1355-1363.

Venkatesh, K., Kumar, V. and Tiwari, R. P. (2013). Appraisal of liquefaction potential using neural network and neuro fuzzy approach, Applied Artificial Intelligence: An International Journal. 27, 700-720.

Vilar, O.M. and Carvalho, M. F. (2004). Mechanical properties of municipal solid waste, Testing and Evaluation journal. 32, 438-449.

Wall, D. and Zeiss, C. (1995). Municipal Landfill Biodegradation and Settlement, Environmental Engineering journal. 121, 214-224.