ESTIMATION OF THE CARBON TO NITROGEN (C:N) RATIO IN COMPOSTABLE SOLID WASTE USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Organic waste constitutes a majority of all municipal solid waste (MSW), a fact which yields some unfavorable results at open dumps, sanitary landfills, and incineration plants. As part of an integrated solid waste management strategy, composting could be applied to mixed collected MSWs or separately collected leaves, food, and yard wastes. The factor most crucial to successful composting is the carbon to nitrogen (C:N) ratio of the waste. This study employs two predictive models to estimate the C:N ratio of compostable MSW, an artificial neural network (ANN) and multiple linear regression (MLR). These models are based on 52 solid waste samples taken from the MSW open dumping area in Gümüşhane Province, Turkey. To estimate the C:N ratio, seven predictive variables were adopted. The proportions of food and yard (F&Y), and ash and scoria (A&S) waste; the moisture content (MC), the fixed carbon (FC) content, the total amount of organic matter (TOM), high calorific value (HCV), and pH. Forty-two of the samples were used for training, and the remaining ten were used to test the models. The average relative error attained by the best ANN was 6.376 %, while that attained by the MLR model was 11.002 %. The effects of TOM content, F&Y percentage, and A&S percentage on the C:N ratio were investigated by running the ANN model for a range of input variables.

KEYWORDS: Artificial neural network, C:N ratio, Composting, Municipal solid waste

1. INTRODUCTION

Municipal solid waste (MSW) is generated and accumulated as the result of human activities. The waste poses grave environmental pollution unless a proper solid waste management system is adopted. One of the most widespread disposal methods for MSW is landfilling, particularly in developing countries. However, this type of technology ought to be upgraded or substituted by other processes due to the limited land area and some environmental problems associated with the landfilling process such as gas emissions and leachate production [1].

Organic wastes spelling some unwanted problems at open dumps, sanitary landfills and incineration plants constitute a major part of MSW. Some of the onsite problems are leachate with polluting potential for groundwater and superficial water sources, generated as a result of degradation and decomposition of organic materials, uncontrolled release of landfill gases, which may cause serious health problems when inhaled, such as hydrogen sulfur (H_2S), carbon dioxide (CO_2) and methane (CH_4). Some of the problems in incineration are additional fuel because of the organic materials' high moisture content and low calorific value and air pollution, the unfavorable result of the activity. In order to produce economical and environment-friendly answers for these problems some studies were commenced. And at the end of these studies, the conclusion of utilizing organic waste as a soil conditioner or fertilizer by composting has been reached. Composting method has been adopted and implemented as a solid waste disposal alternative to open dumping or sanitary landfilling [2].

Composting is one element of an integrated solid waste management strategy that can be applied to mixed MSW or to separately collected leaves, food and yard wastes [3]. It is the biological decomposition of the biodegradable organic fraction of MSW under controlled conditions that provides sufficiently stability for trouble-free storage and handling and safe use in land applications [4, 5].

When composting, C:N ratio is the most critical environmental factor. By and large, an initial C:N ratio of 30:1 is considered ideal. When the C:N ratio is greater than 35:1, the composting process slows down. When the ratio is less than 25:1, there can be odor problems owing to anaerobic conditions, release of ammonia and accelerated decomposition. As the composting process proceeds and carbon is

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lost to the atmosphere, this ratio narrows. Finished compost should have a C:N ratio of 15:1 to 20:1 [6].

Carbon is oxidized to produce energy and metabolized to synthesize cellular constituents. Nitrogen is an important constituent of protoplasm, proteins, and amino acids. An organism can neither grow nor multiply in the absence of nitrogen in a form that is accessible to it. Although microbes continue to be active without having a nitrogen source, the activity rapidly dwindles as cells age and die [3].

Artificial neural networks (ANNs) are able to detect relationships in multi-dimensional data and organize this dispersed information into a nonlinear classification model [7, 8]. Thus, they provide an ideal means to estimate the C:N ratio of MSW.

In fact, ANNs have already been applied in many research papers related to MSW. Dong et al. [1] used a feed-forward neural network to predict the heating values of MSWs. Shu et al. [9] used multilayer perceptron neural networks to predict the energy content of Taiwan MSW. Jalili and Noori [10] predicted the weight of waste generation in Mashhad, and Xiao et al. [11] predicted the gasification characteristics of MSW. Noori et al. [12] compared the ability of neural networks and principal component analysis to predict solid waste generation in Tehran. Jahandideh et al. [13] applied ANNs and multiple linear regression (MLR) to predict the rate of medical waste generation. Akkaya and Demir [14] developed an ANN model based on the Levenberg-Marquardt back-propagation algorithm to predict the heating value of MSW, taking as inputs the proportions of water, carbon, hydrogen, nitrogen, oxygen, sulfur, and ash.

ANNs have also been used successfully in the field of water quality prediction and forecasting. Sengorur et al. [15] examined the potential of ANN in estimating the dissolved oxygen (DO) from nitrite nitrogen, nitrate nitrogen, biochemical oxygen demand, water discharge and temperature employing feed forward type ANN for computing monthly values of DO in the Melen River, Turkey. Li et al. [16] applied neural networks to model the relationship between water quality parameters and the biomass of four dominant genera (*Microcystic* spp., *Anabaena* sp., *Quadricauda* (Turp.) Breb, *Pediastrum* Mey) in the Lake Dianchi, China. He et al. [17] used an ANN to investigate the relationships between land use, fertilizer, and hydrometeorological conditions in 59 river basins of Japan, and then estimated the monthly total nitrogen concentration of the rivers.

This study applies the ANNs technique to estimate C:N ratios in compostable MSW generated by the city of Gümüşhane, Turkey. The seven predictor variables are food and yard (F&Y) percentage, ash and scoria (A&S) percentage, moisture content (MC), fixed carbon (FC) content, the total proportion of organic matter (TOM), high calorific value (HCV), and pH. The data were obtained every week from March 2004 to February 2005, for a data set of 52 weeks [18-22].

2. ARTIFICIAL NEURAL NETWORK APPROACH

ANNs are human attempts to simulate and understand what goes on in nervous system, with the hope of capturing some of the power of these biological systems. ANNs are inspired by biological systems with large number of neurons which collectively perform tasks that even the largest computers have not been able to match.

The function of artificial neurons is similar to that of real neurons; they are able to communicate by sending signals to each other over a large number of biased or weighted connections. Each of these neurons has an associated transfer function which describes how the weighted sum of its input is converted to an output (Fig. 1).

Different types of ANNs have evolved based on the neuron arrangement, their connections and training paradigm used. Among the various type of ANNs, the multilayer perceptron (MLP) trained with back propagation algorithm has been proved to be most useful in engineering applications. Back propagation is a systematic method for training MLP.

The MLP network comprises an input layer, an output layer and a number of hidden layers (Fig. 2). The presence of hidden layers allows the network to present and com-

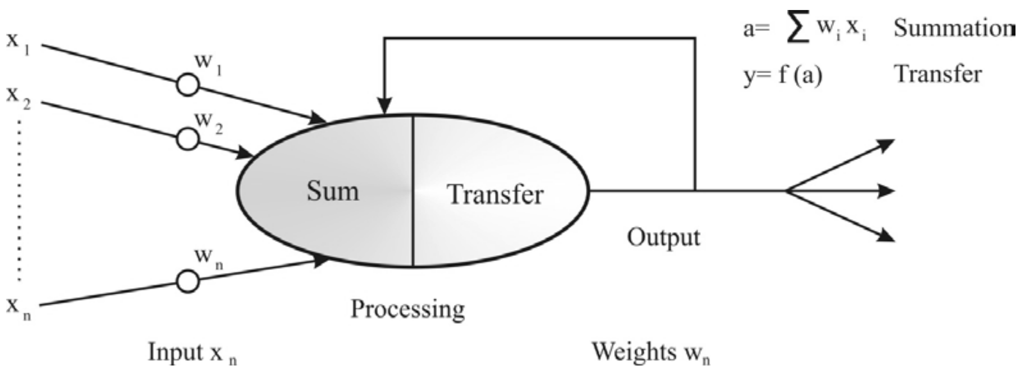

FIGURE 1 - Artificial neuron

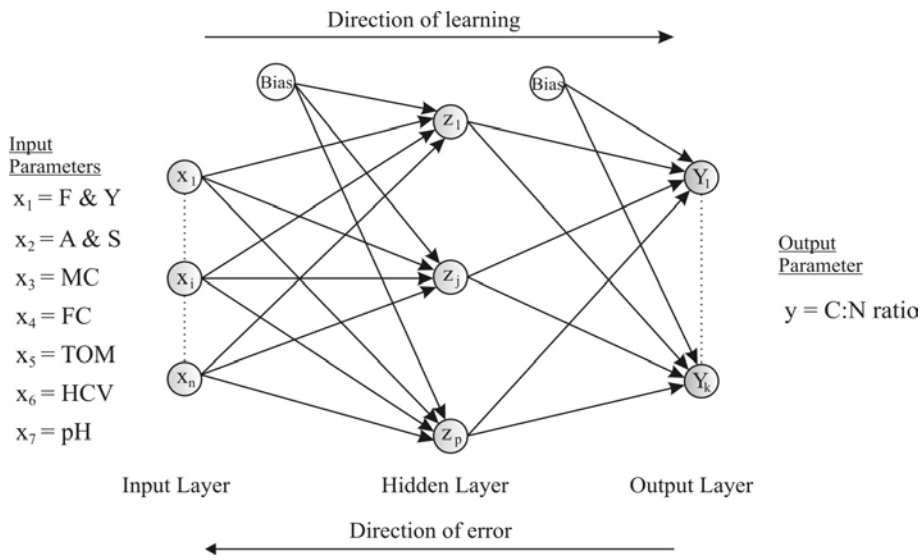

FIGURE 2 - The architecture of back propagation network model

pute more complicated associations between patterns. Basic methodology of ANNs consists of two processes; network training and testing.

The connection weights of the ANN are adjusted through the training process, while training effect is referred to as supervised learning. The training of ANNs usually involves modifying connection weights by means of learning rule. The learning process is done by giving weights and biases computed from a set training data or by adjusting weights according to a certain condition. Then, other testing data are used to check the generalization. The purpose of the bias input of a back propagation network is to stabilize the origin of activation function for providing better learning [23]. The initial weights and biases are commonly assigned randomly. As input data are passed through hidden layers, sigmoidal activation function is by and large used. The data are uniformly selected during the training process. A specific pass is completed when all data sets have been processed. Generally, several passes are required to attain a desired level of estimation accuracy. Training actually means for each input pattern and then compares it with the correct output. The total error based on the squared difference between predicted and actual output is computed for the whole training set. The adjustment of the corrections weights has been carried out using the standard error back propagation algorithm, which minimizes the total error (E) with the gradient decent method [24, 25].

Weight update formula in the back-propagation algorithm is given as follows:

$$w_{j_{(L-1)}h_L}(t+1)=w_{j_{(L-1)}h_L}(t)+\alpha\delta^k_{h_L}x^k_{j_{(L-1)}}+\eta[w_{j_{(L-1)}h_L}(t)-w_{j_{(L-1)}h_L}(t-1)] \quad (1)$$

where α, η, L and x^k are learning rate, momentum parameter, layer number, and output vector, respectively.

The total sum squared error (TSSE) is calculated as follows:

$$\langle E^k\rangle=\left\langle \frac{1}{2}\sum_{i_0=1}^{M}(y^k_{i_0}-x^k_{i_0})^2 \right\rangle \quad (2)$$

where y^k is a desired output vector [26].

The foregoing algorithm used in this study updates the weights after an epoch is presented. Epoch is one cycle through the entire set of training patterns [27].

3. DESCRIPTION OF THE STUDY AREA

Gümüşhane, located in the Eastern Black Sea Region of Turkey, lies between longitudes 38°45' and 40°12', and latitudes 39°45' and 40°50'. The region has a surface area of 6,437 km^2, and is characterized by rugged topography. The average elevation is 1,210 m, and the lowest and highest elevations are 1,105 m and 1,455 m. The temperature and other climatic conditions vary drastically over the course of the year [28, 29]. According to temperature and rainfall data records between 1975 and 2010, the minimum daily temperature varies from -25.7 °C in February to 4.9 °C in August, while the maximum daily temperature varies from 12.4 °C in January to 41.0 °C in July. Gümüşhane receives an average monthly rainfall of 38.6 kg/m^2 [30].

4. MATERIALS AND METHODS

4.1. Sampling and sorting process

The waste samples were taken from a MSW open dumping area in Kurudere valley, on the southwest side of Parmaklik Hill (1,633 m), once a week from March 2004 to February 2005. Four samples were taken simultaneously in every week, for a total of 208 samples over the year. Each sample container used in the process had a capacity of 0.072 m^3. In order to obtain a representative sample, 0.288 m^3 of the MSW was collected. After the MSW was disposed of, the solid waste samples were taken promptly. However, some large volume items such as car tires, and old house belongings were excluded from the samples, as was all medical waste.

The samples were transported to an indoor area, the solid waste laboratory. Here they were spread out on a plastic sheet and manually sorted by a team of two people who received previous instruction. The waste was divided into nine categories: F&Y, P&C, metals, glass, plastics, textiles, A&S, diapers and other. Each component was weighed separately and compared with the total [28].

4.2. Sample processing (drying and grinding)

The compostable waste was manually reduced in size and homogenized as follows. First, a 4-5 kg sample of waste was roughly ground. Then four samples of ground waste, each weighing 125 g, were placed in a drying oven for 24-48 hours at 75 °C. Each sample was dried until its weight stabilized [31]. The resulting dry matter (DM) samples were then placed in desiccators for cooling, ground again to obtain an average particle size less than 0.2 mm, and stored in desiccators until needed.

4.3. Analysis

The MC of a sample was determined from its decrease in weight during drying. The TOM content of the dry matter was determined by igniting it in a furnace at 550 °C [32]. The HCV of the dry matter was determined using an AC-350 calorimeter. The pH of the samples was determined using a mobile pH meter (pH 330i), according to EPA Method 9045D [33]. The total Organic Carbon (TOC) and Total Nitrogen (TN) contents were determined using a UV-VIS spectrophotometer (Dr. Lange Cadas 200) and cuvette tests (TOC cuvette test measuring range 2-65 mg/L TOC and LATON TN cuvette test measuring range 20-100 mg/L TN). The ground samples were extracted according to EPA Method 1310B [34] before the determining TOC and TN. Determination principle of TOC: Total carbon (TC) and total inorganic carbon (TIC) are converted to the CO_2 by, respectively, oxidation and acidification. The CO_2 passes from the digestion cuvette through a membrane and into the indicator cuvette. The change of colour of the indicator is photometrically evaluated. TOC is determined as the difference between the TC and TIC values. Determination principle of TN: Inorganically and organically bonded nitrogen is oxidized to nitrate by digestion with peroxodisulphate. The nitrate ions react with 2.6-dimethylphenol in a solution of sulphuric and phosphoric acid to form a nitrophenol.

5. ANALYSIS OF THE SAMPLE CHARACTERISTICS

5.1. Multiple linear regression

The MLR model for the estimation of C:N (y) is,

$$y=\sum_{i=1}^{7} a_i x_i + c \tag{3}$$

where a_1-a_7 and c are the regression coefficients. The independent variables are F&Y percentage (x_1), A&S percentage (x_2), MC (x_3), FC (x_4), TOM (x_5), HCV (x_6), and pH (x_7). The regression coefficient (R^2) for the model was 0.490 (Table 1).

5.2. Artificial neural networks

The main objective of this section is to develop an ANN model that predicts the C:N ratio given F&Y percentage, A&S percentage, MC, FC, TOM, HCV and pH. When designing an ANN it is important to choose the proper network size. If the network is too small, it may not have enough free parameters to represent the data adequately. If the network is too big, it can either failing to classify the data into meaningful categories or reject new patterns as too dissimilar from the training set. In general, finding a suitable network structure is a matter of trial and error, although an educated guess can be made by comparing the size of the training dataset to the number of free parameters in the network. As shown in Fig. 2, a three-layer, and feed-forward network is selected for this study. Each layer is fully connected to the next, but no connections exist between neurons in the same layer. The first and third layers contain the input and output data respectively. The single output node is interpreted as the C:N ratio (y). The order of variables in the input layer is F&Y, A&S, MC, FC, TOM, HCV, and pH.

The 52 weekly data are divided into 42 training and 10 testing patterns. Input values for some of the testing data and all of the training data are listed in Table 2.

Before they can be used to train the network, the input data need to be normalized to a suitable range. A hyperbolic tangent sigmoid as the first transfer function (input layer → hidden layer) and a logistic sigmoid as the second transfer function (hidden layer → output layer) are used within the network. Both transfer functions are designed to present most of their variation over the range [0, 1]. Therefore, input data is normalized to the range [0.1, 0.9] as follows:

$$\text{Normalized value}=\left[\frac{\text{Raw value-Minimum value}}{\text{Maximum value-Minimum value}}\right]\times(0.9-0.1)+0.1 \tag{4}$$

TABLE 1 - Regression coefficients and R^2 value for the MLR

a_1	a_2	a_3	a_4	a_5	a_6	a_7	c	R^2
0.0628	0.1626	-0.0796	0.3526	0.6617	-0.0008	2.5726	-53.6996	0.490

TABLE 2 - Weekly data used in the ANNs model

The 52 weekly data: March 2004 - February 2005																									
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
▲	x	x	x	▲	x	x	x	x	x	x	▲	x	▲	x	x	x	x	x	▲	x	x	x	x	x	▲
27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52
x	▲	x	x	x	▲	x	x	x	x	x	x	x	x	x	▲	x	x	x	▲	x	x	x	x	x	x

x : training set
▲ : testing set

The selected network size represents a compromise between generalization and convergence. Convergence is the capacity of the network to learn the patterns in the training set, and generalization is its capacity to respond correctly to new patterns. The idea is to implement the smallest possible network that is able to learn all patterns in the data while retaining the ability to generalize its rules to new patterns. One hidden layer is sufficient for most applications. As determining the number of nodes in the hidden layer is not an exact science, several networks with different numbers of hidden nodes are tested. The parameters of the optimum ANN structures are given in Table 3.

TABLE 3 - Parameters used for different ANNs structures.

Number of hidden layer unit	Learning rate (α)	Momentum (η)
5 10 15 20 25 30 35 40	0.10 0.25 0.50 0.75 1.00	0.10 0.25 0.50 0.75 1.00

To begin the training process, all of the training patterns are introduced to a network initialized with random weights and the corresponding outputs are recorded. Then the network error (E) is computed according to Eq. (2), and increments to the generalized weights are computed by Eq. (1). The weights are updated, and the training set is presented to the network again to compute a new set of errors E. The process continues until the network error converges or drops below a specified tolerance.

The increment used to update a given weight depends on two derivatives: that of the upper node's transfer function and that of the lower node's transfer function. For this reason, it is important to avoid initial weights that would make derivative close to zero. In this study, the weights are initialized to random values between –0.5 and +0.5, according to commonly accepted procedure. The factors α and η in Eq. (1) also influence the convergence. The learning rate (α) is the constant of proportionality for the generalized back-propagation rule. The larger its value, the greater the changes in the weights at each iteration. The momentum term (η) is used to prevent the network from oscillating around a local minimum in the parameter space. Several combinations of α and η are tested in order to find a neural network with good convergence (Table 3).

Memorization is a fundamental problem encountered in training of artificial neural network. To prevent this, the training is cut when the network begins to memorize. In this situation, training set error continues to decrease, although testing set error does not change. Because training of the network is cut before memorizing, error values of the training set may be greater than the testing set in models [27, 35].

The rate of convergence during training is monitored as follows. In a single iteration or 'epoch', each training pattern is introduced to the ANN five times, as shown in the 4th column (Cycle) of Table 4. The patterns are presented in the same order each time. The learning process was stopped after 100,000 epochs, and which epoch number resulted in the minimum TSSE of the testing set was determined. Table 4 shows the structures of the ANNs giving the best results.

6. RESULTS AND DISCUSSION

The performance of a network may be enhanced by increasing the number of training samples, the length of training (number of epochs), or the number of hidden layer nodes. Choosing different values for the learning rate (α) and momentum (η) may also change the performance of a network. However, all of these methods increase the computation time required to train the network. It is very important to strike a balance between performance and training time.

TABLE 4 - Characteristics of the ANNs giving the best results

Number of hidden layer unit	α	η	Cycle	Epoch	Training error[1]	Testing error[1]	Maximum relative error in testing set (%)	Average relative error of testing set (%)
20	0.1	0.75	5	6251	1.071	0.0206	9.528	6.376

[1] : The error values were calculated from Eq. 2

In this research, the smallest average relative error (ARE) over the testing set (6.376 %) was obtained from the network with $\alpha = 0.1$ and $\eta = 0.75$ (Table 4). The maximum relative error (MRE) in the testing set was 9.528 %. There are several possible ways of reducing the MRE, which is of interest in practical applications. One way is to simply increase the number of training iterations, or to look for versions of the network during training that minimize the MRE while requiring the ARE to remain in an acceptable range. Another option is to use the conjugate gradient or scaled conjugate gradient learning methods, instead of generalized delta rule.

Relative error is calculated as

$$e_{rel}=\left(\frac{|O_{ANN}-O_{real}|}{O_{real}}\right)*100 \quad (5)$$

where O_{ANN} and O_{real} are the computed and real C:N ratios, respectively. The ten testing data sets are used to evaluate relative error and the performance of the trained network. Fig. 3 displays the learning results (O_{ANN} vs. O_{real}) of the network; each lozenge stands for one of the testing vectors. The results obtained from MLR are plotted with triangles in the same figure. The closer the points are to the diagonal, the better the learning result. The maximum relative errors computed for the ANN and MLR methods are 9.528 % and 31.294 %, respectively. Their average relative errors are 6.376 % and 11.002 %, respectively. Thus, the ANN method gives significantly better results, and does better at controlling the maximum error involved in interpreting new patterns.

A completed network can be fed a series of artificial inputs in order to reveal aspects of the nonlinear model. To complete the present study, the effect of TOM on the C:N ratio is simulated using the trained ANN model. The effect of varying TOM values while holding all other inputs constant is shown in Fig. 4. The TOM values in a set of 13 samples are all incremented or decremented by 4 percentage points, which is the coefficient of variation for this variable. The 13 samples start with the 3rd sample of the full dataset, and are then selected at four-week intervals. As the Fig. 4 shows, the C:N ratio increases and decreases with the TOM value.

The effects of changing the A&S percentages on the C:N ratio was also investigated. This input variable was 0 % between the 14th and 33rd weeks of the study. The ANN model was used to simulate a scenario where the A&S component remained at 0 % in all weeks after the 33rd, and the resulting variation in the C:N ratio is shown in Fig. 5. The C:N ratio decreases with the A&S percentage. Then, a scenario in which the A&S percentage was 41.5 % (the average of all non-zero weeks in the study) between the 14th and 33rd weeks was tested. The results are given in Fig. 6, and clearly show that the C:N ratio increases along with the A&S percentage.

Finally, the effects of changing the F&Y percentages were investigated. This scenario was tested only between the 14th and 33rd weeks, when the A&S component was 0 %. Forty percentage points, corresponding to the coefficient of variation of the F&Y component, was added to or subtracted from the actual values of F&Y during this period. The results of the ANN are given in Fig. 7. The C:N ratio increases along with the F&Y component, except in a small number of cases.

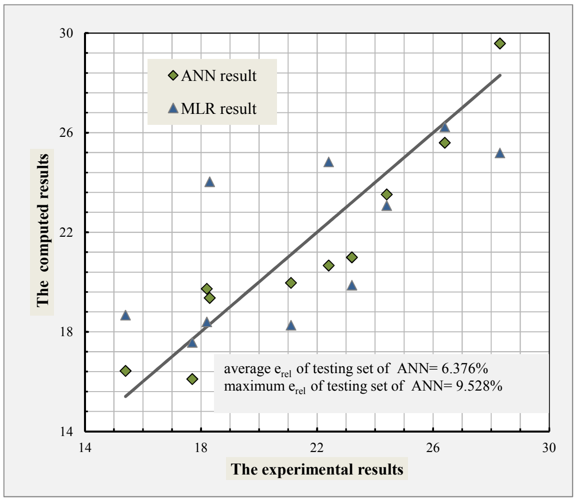

FIGURE 3 - Comparison of the computed results with the experimental results for the C:N ratio

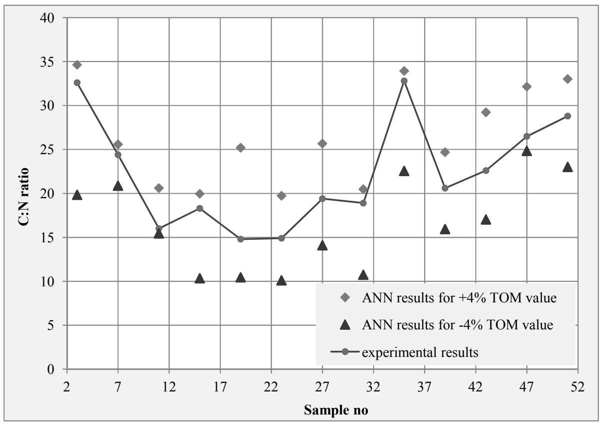

FIGURE 4 - Effects of the variation in TOM content data on the C:N ratio

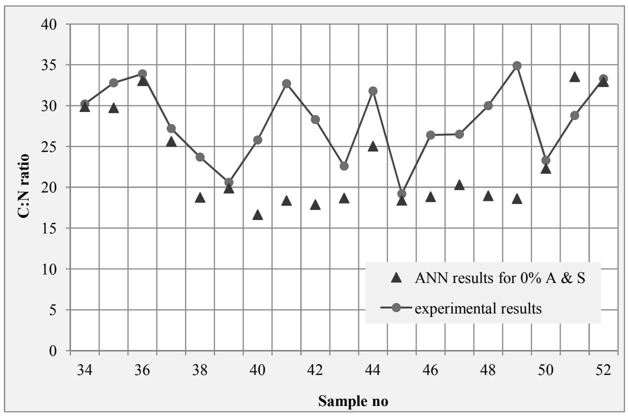

FIGURE 5 - Effects of the variation in the A&S percentages (34th-52th samples) on the C:N ratio

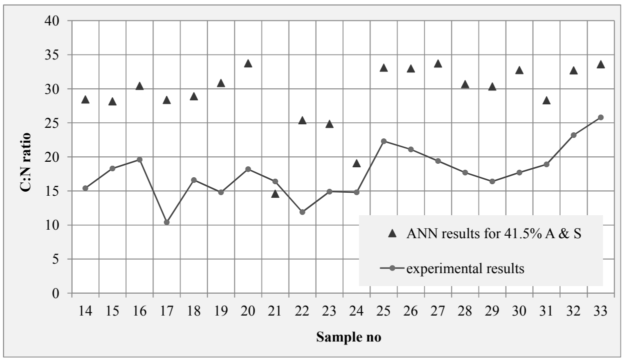

FIGURE 6 - Effects of the variation in the A&S percentages (14th-33th samples) on the C:N ratio

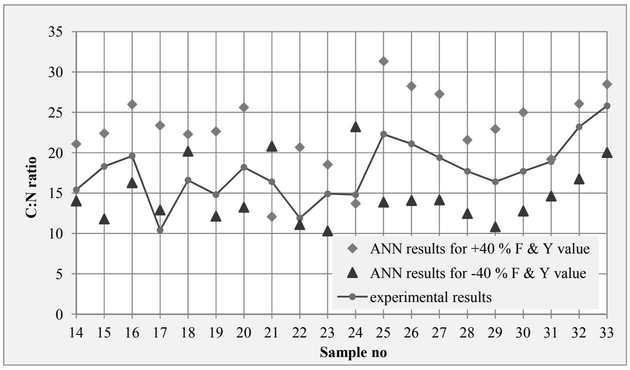

FIGURE 7 - Effects of the variation in the F&Y percentages (14th-33th samples) on the C:N ratio

7. CONCLUSION

This study investigated the ability of an ANN to estimate the C:N ratio of compostable MSW based on seven input variables representing the environment and composition of the waste. A weekly series of 52 waste samples from a MSW collection site, Gümüşhane Province, Turkey, was collected and analyzed to provide accurate training data for the ANN model. The ANN model produced satisfactory estimates of the C:N ratio, and therefore appears to be a useful forecasting tool for the solid waste composting process. The ANN model also performs significantly better than a MLR model derived from the same training data. This application of neural networks to environmental data has great potential in future research on the estimation of C:N ratios, and provides a useful tool for environment managers.

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