

DETERMINATION OF MOISTURE CONTENT OF SUBGRADE SOIL USING ARTIFICIAL NEURO-ELECTRONIC CONTROL

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ABSTRACT

Moisture content of soil is of utmost importance in the progression of road construction and is absolutely crucial for making decisions concerning design and construction of pavements. Pavement sustainability depends on the performance of its individual components, which require the assurance of qualities such as evaluation of the properties of soil and constant monitoring of some soil conditions (e.g. moisture content). For pavement design the most considerable engineering factor of soil is the *strength* that is practically accomplished by *soil compaction* and *soil stabilization*. However, to achieve the required soil strength, consideration of compaction effort or stabilization ingredients should be precise, and it is inevitably related to the moisture content of soil. Hence moisture content determination is elemental and must be performed frequently as necessary. The conventional method for its determination involves oven drying and this endeavour is time consuming (requires approximately 24 hours for drying), which may affect the subsequent undertakings. Some microwave oven based fast methods have been realized recently but these require continuous manual interventions. In this paper, a new approach will be proposed in a view to suppress the limitations of existing methods while maintaining the better accuracy. This innovation embeds an automatic electronic control as well as an artificial neural network (ANN) in the framework for time optimization. Artificial neural network and automatic electronic control both together can be termed as artificial neuro-electronic control. The artificial neural network has been optimized and trained by mapping the weights of soil samples at specific time steps to the respective final moisture contents. As a result, subsequently the system can be able to predict the final moisture content by analysing fewer data samples in the very beginning of moisture content determination tests. Validation of the predictive results has also been conducted in real time for soil samples suitable for subgrade layer of a pavement to ensure the system feasibility for laboratory and field uses. Experiments show that this fully automatic system can exhibit a significant accuracy and precision for the evaluation of moisture content in about 50% reduced time compared to the standard microwave based method.

1 INTRODUCTION

Moisture content is one of the most influencing factors for evaluating the strength of soil. Roads and railway structures and its foundation planning demand an inevitable consideration of the strength of underlying soil, which comes from the test results and highly depends on moisture content. However, without knowing the moisture content, optimal strength of soil cannot be ensured reliably in the construction site by applying the so called *soil compaction method* (Budhu, 2007) and *soil stabilization technique* (Garber and Hoel, 2009).

Moisture content can be determined in accordance with any of the standards of AASHTO T-265, ASTM D2216 or ASTM D4643 for pavement design (NDOR, 2012). ASTM D2216-10 and AASHTO T-265 outline the technical knowhows for the determination of moisture content of soil and are the most widely exercised procedures. In these standards, weight of a suitable aluminium can with some soil sample is taken, which is then heated in a conventional oven at 110°C for 24 hours. After 24 hours of drying, the can with dry sample is weighed again and from the difference between this measurement and the previous one, moisture content can be found. In this procedure, a small amount of energy is actually utilized in the drying process and the remaining significant portion is lost. Therefore, this is not an energy efficient method. Moreover, spending of 24 hours time may pose detrimental effects on the construction process if its evaluation is necessary during this time and the subsequent phases. Another standard procedure is based on ASTM D4643-08, where drying process of soil sample involves microwave energy absorption. In this method, first cycle of drying process of soil sample continues for 3 minutes under a constant microwave power of 700W and after that both weighing and mixing of the sample are conducted. For subsequent cycles, drying time is reduced to 1 minute and both weighing and mixing are repeated until the two consecutive weights are differed by 0.1% or less of the initial weight of the soil (ASTM D4643-08, 2008). This microwave based moisture content determination is quite faster than the conventional oven based method, but requires frequent manual interventions and there is no automatic control for data acquisition. As a consequence, inaccuracies arise from human factors. Some variations in the test process can be found in literature (Hagerty *et al*, 1990a, Chung, 2006), but all of these methods suffer from the same drawbacks mentioned

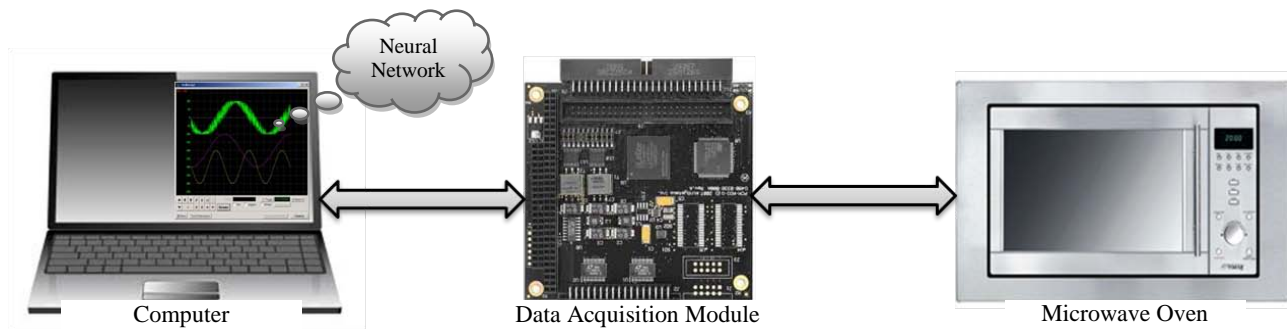


Figure 1: Illustration of the overall experimental setup

earlier. Another approach for the determination of moisture content of soil mainly used in irrigation purpose is the *neutron scattering method*. In this method, radiation is the key to measure the volumetric water content and hence *bulk specific gravity* must be considered to figure out the *gravimetric moisture content*. Moreover, this approach suffers from high instrument cost, radiation hazard and an error up to 15 percent (Zazueta and Xin, 1994), which makes this method inappropriate for this particular context.

In the last few years, artificial neural network has come to power in managing every field of modern world such as aerospace, automotive, telecommunications and transportation systems (Smith and Demetsky, 1994, Demuth and Beale, 2002, Chaturvedi *et al.*, 2004). In Geotechnical engineering, ANN has been applied successfully for the prediction of lateral load capacity of pile (Das and Bashudhar, 2006), and for the modelling of maximum dry density and optimum moisture content of soil (Alavi *et al.*, 2010). Recently, neural network has been successfully integrated in an automatic electronic controller for the determination of moisture content of soil (Shetu and Masum, 2012).

In this paper the authors are going to propose a novel approach for the determination of moisture content of subgrade soil using a custom built system depicted in Figure 1. The main components are a computer, a microwave oven and an electronic interfacing circuitry. All these components together make the system fully automatic thus evading every manual interactions and possible inaccuracies that may arise from there. The fully trained embedded neural network offers an additional flavour of predictive capability, which can provide the result in advance without going through the entire length of test period. Experiments show that time and power consumptions are lowered to about 50% compared to the these days' fast microwave oven based methods.

The next sections of this paper are organized as follows. Section 2 presents some background theories. The detail explanations of the system setup and experimental procedure are outlined in Section 3. The test results with discussions are presented in Section 4 and finally a conclusion with possible future directions is drawn in Section 5.

2 BACKGROUND THEORY

2.1 SUBGRADE SOIL

The subgrade soil is usually the inbuilt foundation soil sited at the bottom most of any pavement or railway tracks. It may also be borrowed from somewhere else. To maintain the requisite properties (e.g. strength) of soil, specific treatments such as stabilization and artificial compaction may be a viable means and this choice (e.g. chemical or mechanical stabilization, compaction effort) comprehensively depends on the existing and optimum moisture contents (Garber, 2009). Soil classified as A-1-a, A-1-b, A-2-4, A-2-5, A-2-6, A-2-7 and A-3 by the American Association of State Highway and Transportation Officials (AASHTO) can satisfactorily be used as subgrade (AASHTO M 145, 1991).

2.2 MOISTURE CONTENT OF SOIL

Soil is composed of solid particles, water and air. The ratio of the weight of water present in soil to the weight of solids is called the moisture content (Budhu, 2007) and is formulated as follows-

$$w = (W_{wc} - W_{dc}) / (W_{dc} - W_c) \times 100\% \quad (1)$$

where, W_{wc} , W_{dc} and W_c are the weights of wet and dry soil samples with container and weight of contain respectively.

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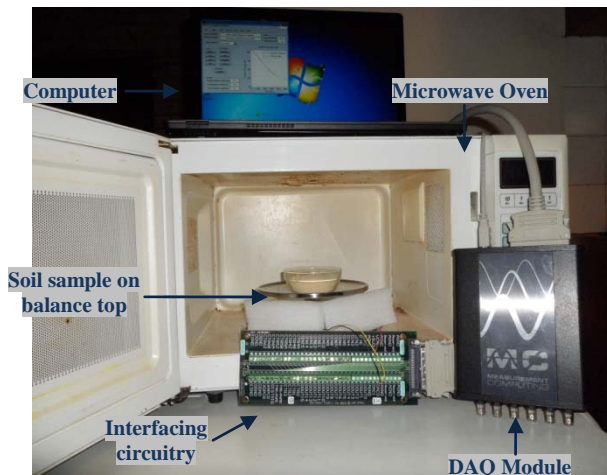


Figure 2(a): Experimental Setup

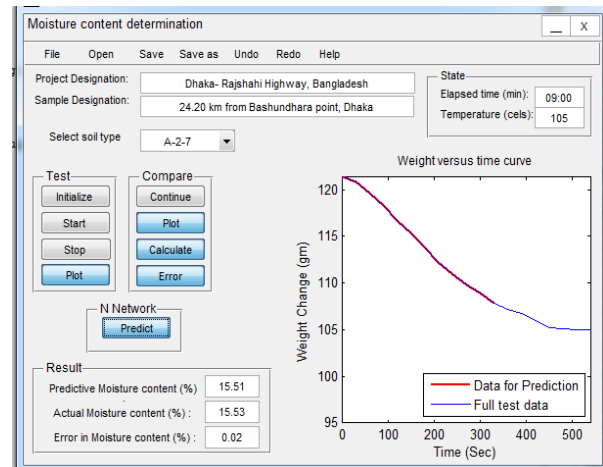


Figure 2(b): Developed GUI with a plotted sample dataset

2.3 MICROWAVE HEATING FUNDAMENTALS

Microwave occupies the frequency range of approximately 0.3 to 300 GHz in electromagnetic spectrum. The most common commercial microwave generator *magnetron* found in microwave oven having a rated frequency of 2.45 GHz. This frequency is very close to the natural frequency of water. Due to resonance, at this frequency vigorous vibration of water molecules present in soil sample causes intermolecular frictions which in turn generate heat (Cann, 2011). As a result, the temperature of the soil mass increases gradually towards the boiling point of water and eventually evaporation occurs thus allowing the sample to dry in a comparatively short time (ASTM D4643-08, 2008). According to ASTM D4643-08, in the determination process of soil moisture content, microwave oven drying gives rapid results. As microwave has to penetrate into the soil, attenuation of microwave power is occurred in every consecutive layer (Lord *et al.*, 1979). Due to the requirement of microwave penetration into the soil sample the dimensions should not be too coarse.

3 EXPERIMENTAL SETUP AND PROCEDURE

3.1 SETUP

Experimental setup consists of a microwave oven, an electronic balance, a bi-directional data communication module and a laptop computer (2.66 GHz Intel core i5 processor) is shown in Figure 2(a). A Panasonic Microwave oven NNSD691S having a dimension of 525 mm x 401 mm x 310 mm has been used. It has rated input power of 700W, which meets the power requirement of ASTM D4643-08. An electronic balance of model 'CB-V Electronic Balance' having a precision 0.01 g and capacity 2000 g has been employed for measuring the weights of samples. 'USB-1602HS' data acquisition (DAQ) module from 'Measurement Computing' has been used as an interfacing board for bi-directional communication between PC, microwave oven, balance and temperature sensor. This module can sample voltage and temperature signals up to 1 Mega samples per second (Ms/s), and also can interpret the commands issued by the developed GUI to the microwave oven using opto-coupler (MOC5007). The opto-coupler isolates high voltage (230V) side of the oven from low voltage (5V) side of the computer and DAQ module. The GUI has been designed using MATLAB software to act as an interface for the human operator to run the experiment successfully. A screenshot of the GUI is shown in Figure 2(b). The microwave oven bottom has been cut off and attached on a four-leg stand so that the balance should be placed in between the stand and the oven. All these engineering works have been done to facilitate the continuous recording of the weight signal from electronic balance as voltage using DAQ module and passing to the computer for analysis. A temperature sensor has been placed in the microwave oven to protect the oven from extra heat in case of the sample being too dry or has some mineral, which may react highly with microwave. If the temperature increases more than 110°C (which is the maximum acceptable temperature stated in the ASTM D2216) then the absorbed water is driven off from the soil mass, which is not accounted for moisture content determination. In this case the computer automatically stops the oven by analysing the data from temperature sensor to avoid any accidental damage.

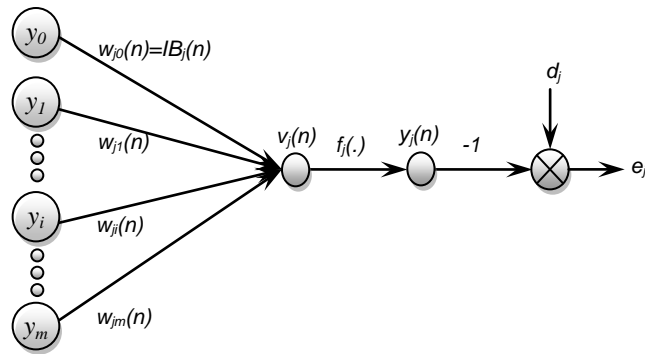


Figure 3: Signal-flow diagram of an output neuron j , adapted from 'Neural Network', Simon Haykin, 2005

3.2 PROCEDURE

3.2.1 Sample preparation

180 soil samples each of weight approximately 100 g have been collected in a 250 ml pyrex container successively following the criteria stated in ASTM D4643-00– sample weight should be 100-200 g. Another 10 sample pairs (each sample weight of approximately 100 g) have also been taken for both microwave oven and conventional oven experiments separately. A Pyrex container has been chosen because of its microwave and thermal resistance and the shape of that container favours the effective vaporization of water. These soil samples have been collected from a road construction site nearby Dhaka, Bangladesh which were A-2 as classified by AASHTO Soil Classification System.

3.2.2 Data acquisition

The proposed system has been operated algorithmically by software incorporating the GUI. The data acquisition and storing in computer memory have been done for each sample as a data set. In the beginning of the experiment, the oven and the clock have been turned on and the computer started storing the weights of the sample at every 30 seconds as it progressively losses moisture. When the two successive weights differ by 0.1% or less, the process is automatically terminated and moisture content is calculated using Equation 1. The same experiment has been repeated for next 179 soil samples. The entire length of test time in microwave oven was about 11 to 15 minute for every sample due to its different moisture content. For the last 10 samples, datasets (each set contains initial 12 records without performing full test) have been acquired by microwave oven test and moisture content with a conventional oven following the outlines of ASTM D2216-10.

3.2.3 Training neural network

For this work a two layer (i.e. a sigmoid hidden layer and a linear output layer) supervised feed-forward back propagation network has been developed. This network architecture has been chosen because of the fact that one hidden layer is sufficiently capable of resembling a function representing a continuous relationship between input and output (Heaton 2008). From a lot of available optimization algorithms, the Levenberg-Marquardt backpropagation algorithm has been nominated to optimize the errors due to its robustness, efficiency and handling capability of nonlinear problems (MATLAB Neural Network Online documentation 1984-2011). Total number of 180 sample datasets has been chosen because of the fact that the network should be capable of predicting the unknown variables (total number of network weights and biases) very reliably. And batch mode training was elected for aiming to higher accuracy. Initial 12 records (each dataset contains 22 to 30 records) from the first 180 datasets of soil sample have been considered for training the network while the training sets can be represented as

$$\mathfrak{S} = \left\{ (x_p, d_p) \right\}_{p=1}^N \quad (2)$$

where, N , x_p and d_p are the number of soil samples, a set of 12 successive weights of soil sample and the associated moisture content respectively. Figure 3 depicts the propagation path of signal flow of output layer neuron j which is fed by the outputs of the previous layer neurons. The induced local field $v_j(n)$ is the sum of weighted input nodes of neuron j at n^{th} iteration and can be expressed as

$$v_j(n) = \sum_{i=0}^m (w_{ji}(n)y_i(n)) \quad (3)$$

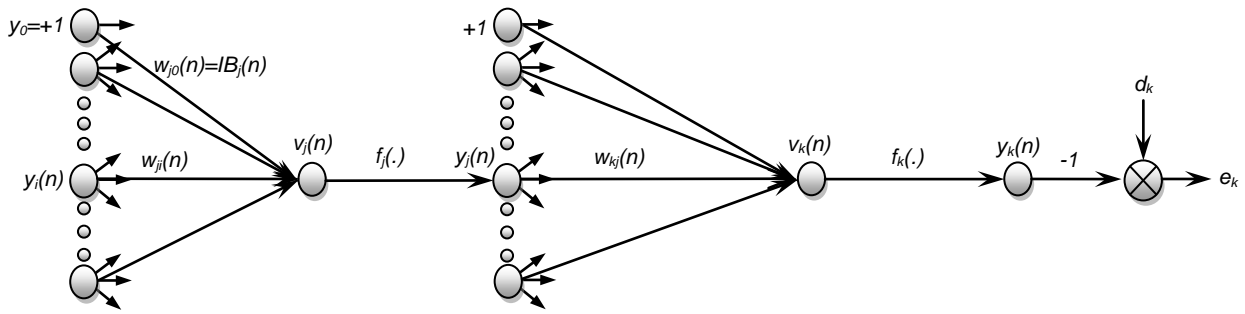


Figure 4: Signal-flow diagram of an output neuron k connected to hidden neuron j , adapted from 'Neural Network', Simon Haykin, 2005

The output of neuron j is calculated by

$$y_j(n) = f_j(v_j(n)) \tag{4}$$

f_j is the activation function of neuron j . The error for neuron j at n^{th} iteration is

$$e_j(n) = d_j - y_j(n) \tag{5}$$

Then the corrected weight is

$$w_{ji}(n+1) = w_{ji}(n) - (J(n)^T J + \mu I)^{-1} J(n) e_j(n) \tag{6}$$

where μ is the learning-rate parameter and $J(n)$ is Jacobian matrix calculated as

$$J(n) = \begin{bmatrix} \frac{\partial e_1(n)}{\partial w_{j1}(n)} & \dots & \frac{\partial e_1(n)}{\partial w_{jm}(n)} & \frac{\partial e_1(n)}{\partial w_{j0}(n)} \\ \vdots & \ddots & \vdots & \vdots \\ \frac{\partial e_N(n)}{\partial w_{j1}(n)} & \dots & \frac{\partial e_N(n)}{\partial w_{jm}(n)} & \frac{\partial e_N(n)}{\partial w_{j0}(n)} \end{bmatrix} \tag{7}$$

If neuron j is in hidden layer, there is no specified desired response for that neuron and error as well. We can consider another network shown in Figure 4 where neuron j is in hidden layer and connected to the output layer containing neuron k . The local gradient $\delta_j(n)$ for hidden neuron j can be found as

$$\begin{aligned} \delta_j(n) &= -\frac{\partial \xi(n)}{\partial v_j(n)} \\ &= -\frac{\partial \xi(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \\ &= -\frac{\partial \xi(n)}{\partial y_j(n)} f_j'(v_j(n)) \end{aligned} \tag{8}$$

In batch mode, $\xi(n)$ is average error energy and is defined as

$$\xi(n) = \frac{1}{2N} \sum_{p=1}^N \sum_{k \in C} e_k^2(n) \tag{9}$$

C is the number of neuron in the output layer. Now differentiating Equation (9) with respect to the functional signal $y_j(n)$, we get

$$\begin{aligned} \frac{\partial \xi(n)}{\partial y_j(n)} &= \frac{1}{2N} \sum_{p=1}^N \sum_k e_k \frac{\partial e_k(n)}{\partial y_j(n)} \\ &= \frac{1}{2N} \sum_{p=1}^N \sum_k e_k(n) \frac{\partial e_k(n)}{\partial v_k(n)} \frac{\partial v_k(n)}{\partial y_j(n)} \end{aligned} \tag{10}$$

From Figure 4 it is easily noted that

$$\begin{aligned} e_k(n) &= d_k(n) - y_k(n) \\ &= d_k(n) - f_k(v_k(n)) \end{aligned} \tag{11}$$

Thus

$$\frac{\partial e_k(n)}{\partial v_k(n)} = -f_k'(v_k(n)) \tag{12}$$

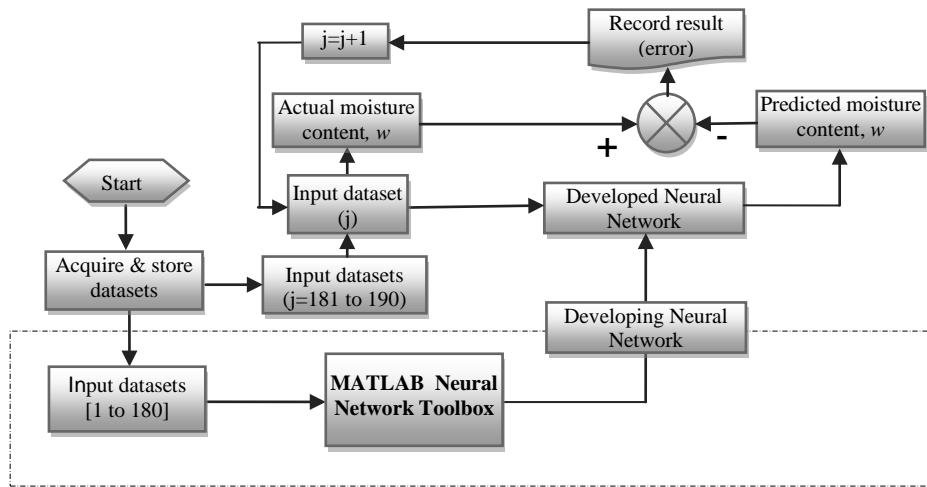


Figure 5: The algorithmic workflow of ANN development and error calculation

It is clearly seen at Figure 4 that the local induced field v_k can be regarded as

$$v_k(n) = \sum_{j=0}^m w_{kj}(n)y_j(n) \quad (13)$$

m is the total number of inputs connected to neuron k . Differentiating Equation 13 with respect to $y_j(n)$ gives,

$$\frac{\partial v_k(n)}{\partial y_j(n)} = w_{kj}(n) \quad (14)$$

Substituting Equations 12 and 14 in Equation 10 yields,

$$\begin{aligned} \frac{\partial \xi(n)}{\partial y_j(n)} &= -\frac{1}{2N} \sum_{p=1}^N \sum_k e_k(n) f'_k(v_k(n)) w_{kj}(n) \\ &= -\sum_k \delta_k(n) w_{kj}(n) \end{aligned} \quad (15)$$

$\delta_k(n)$ is the local gradient of neuron k . Using Equation 15 in Equation 8, back propagation formula for the local gradient is revealed as follows

$$\delta_j(n) = f'_j(v_j(n)) \sum_k \delta_k(n) w_{kj}(n) \quad (16)$$

The correction Δw_{ji} applied to synaptic weight connecting neuron i to neuron j is defined as follows

$$\Delta w_{ji}(n) = \mu \delta_j(n) y_i(n) \quad (17)$$

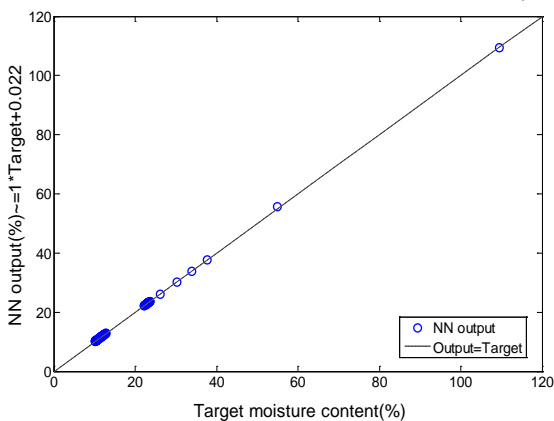


Figure 6(a): Target vs. NN Output

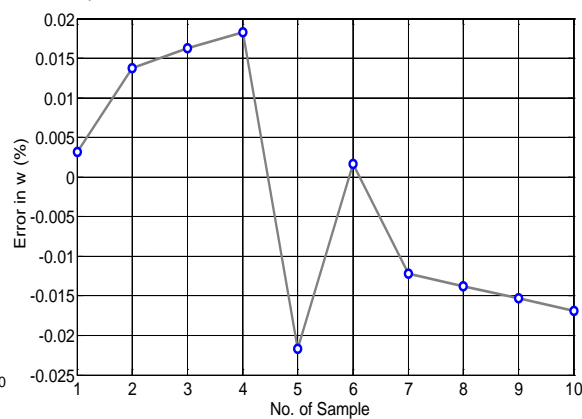


Figure 6(b): Discrepancy between actual and predicted moisture content

Then the new weight is found as

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n) \quad (18)$$

Equations 1 to 18 have somewhat been resembled as those formulated in (Haykin, 2005). Following these above steps adjustment of weights continues until the lowest mean squared error (*MSE*) and the highest regression coefficient (R^2) are reached. *MSE* and R^2 are formulated as follows

$$MSE = \frac{\sum_{p=1}^N (d_p - y_p)^2}{N} \quad (19)$$

$$R^2 = 1 - \frac{\sum_{p=1}^N (d_p - y_p)^2}{\sum_{p=1}^N (d_p - \bar{d}_p)^2} \quad (20)$$

where, y_p and \bar{d}_p are calculated moisture content and average of desired moisture content respectively. The highest regression coefficient $R^2=1$ indicates an exact relationship between predicted and actual moisture content, while the lowest value of $R^2=0$ means no relationship exists at all. The datasets have been passed through the proposed algorithm following the above equations implemented using MATLAB programming language which performed the training, validation and preliminary testing of the ANN. As a rule of thumb, the optimum number of neurons in the hidden layer should be in between two-third to twice of the number of input layer elements (Heaton, 2008). For this experiment the optimum number of neurons in the hidden layer has been found to be 16 by trading off the accuracy and computational burden.

3.2.4 Final test using microwave and conventional oven data

The ultimate validation of this system has been performed using the last 10 datasets obtained from microwave oven which has also had a counterpart attained from conventional oven drying following ASTM D2216-10 standard. Datasets acquired from microwave oven testing have been passed through the developed neural network. The outputs of the network are the predicted values of moisture contents, which have been compared with the moisture content of respective soil sample obtained from conventional oven drying process. The whole algorithmic workflow is shown in Figure 5. The discrepancy between the actual moisture contents from the conventional oven drying process and the predicted moisture contents from ANN are shown in Figure 6(b).

4 RESULTS

The performance of the developed network for all the datasets (training, validation and test) is shown in Figure 6(a). The data points represent the neural network outputs to the target moisture contents. Hence the linear dashed line indicates that the predicted moisture contents are equal to the target moisture contents. Mean squared error (*MSE*) and regression coefficient R^2 for these datasets have been found to be 0.1361 and 1 respectively. It is obvious from the relationship $R^2=1$ that there exists an exact linear relationship between the ANN outputs and targets. From this graph, it is evident that the trained network worked precisely well with the soil samples having moisture content up to 109%. And Figure 6(b) reveals the discrepancy between the actual moisture contents obtained from conventional oven and the predicted moisture contents from ANN. It should be noted that the maximum difference is only 0.022% that can be overlooked considering the huge amount of time saving (almost 50% less than the existing microwave oven based method).

5 CONCLUSIONS AND RECOMMENDATIONS

The results of this work indicate that the soil drying process for moisture content determination can be realized efficiently using a group of algorithmic actions. The implemented system presents not only the precise results in the shortest possible of time but also it automates the whole test procedure. In this study soil samples with usual properties have been tested but in real scenario it may be different. Therefore, generalization of the proposed system while considering all types of soil samples with various minerals should be the ultimate goal for future endeavour.

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