Determining Moisture Content of Wheat with an Artificial Neural Network from Microwave Transmission Measurements

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***Abstract*— An artificial neural network (ANN) was used to determine the moisture content of hard, red winter wheat. The ANN was trained to recognize moisture content in the range from 10.6% to 19.2% (wet basis) from transmission coefficient measurements on samples of wheat. The measurements were made at 8 microwave frequencies (10 GHz to 18 GHz) on wheat samples of varying bulk densities (0.72 g/cm^3 to 0.88 g/cm^3) at 24°C. The trained network predicted moisture content (%) with a mean absolute error of 0.135 (compared with oven-dried measurements).**

***Index Terms*— Dielectric, microwave measurements, moisture content, neural networks, permittivity.**

I. Introduction

MOISTURE content is an important factor that affects the quality, price, and storage of grain. Moisture content, in percent, wet basis, is defined as follows:

$$MC = ((m_t - m_d)/(m_t)) \times 100 \tag{1}$$

where m_t is the total mass of the grain sample and m_d is the mass of the dry material. The wet and dry weights of grain samples are determined by weighing with an analytical balance and standard oven drying procedures [1]. This technique is time consuming and destructive. For unground wheat, the recommended drying time is 19 h. Although oven moisture determinations are important for reference data, the technique has no potential for configuration into an on-line process.

Classical nondestructive techniques for determining moisture content of grain consist of measuring the electrical properties of the grain in a sample holder and relating these properties to the moisture content. These techniques have their roots in the early part of the century when Briggs [2] studied the possibility of rapidly determining the moisture content of grain by measuring the dc resistance of two brass rod electrodes inserted into the wheat sample. This resistance was found to vary with moisture content. More recent works in this field are summarized by Nelson [3]. Modern techniques typically involve placing the wheat in an appropriate sample holder and determining the permittivity-related characteristics of the wheat from measurements made on the sample holder. The sample holder can be a parallel plate or coaxial capacitor, a resonant cavity or a transmission line. A relationship between the moisture content and the permittivity measurements can be established [4], [5]. Some researchers have chosen other parameters as a basis for this relationship [6]–[10]. These techniques are generally dependent on the measurement system.

The major drawback to these classical approaches is the fact that these parameters are not only a function of moisture but also of bulk density, frequency, and temperature [4], [11]. Successful implementation of these techniques usually depends on making independent measurements of the other quantities for accurate determination of moisture content. Of these quantities, bulk density is the most difficult to determine when the grain is flowing. This situation is of particular interest because of the desirability of measuring the moisture content of grain when it is being transferred or stored. Several researchers have reported density independent moisture measurement techniques [12]. Because of the complex nature of the interaction between the applied electromagnetic field and the grain, air, and moisture mixture, empirical techniques are typically employed.

This complexity makes the Artificial Neural Network (ANN) an attractive candidate as a solution to this problem. The ANN was also viewed as a candidate solution because of previous successes in applying ANN's to other biologically based systems [13]–[16]. In this study, an ANN was trained to predict the moisture content of hard, red winter wheat. The input to the ANN consisted of free-space transmission coefficient measurements on a layer of wheat placed between two antennas.

II. Methods and Techniques

A. Measurement Method

The measurement technique used to obtain the free-space transmission coefficients, the problems associated with such measurements, and the description of the wheat samples have previously been reported in detail [5]. The sample holder was placed between two microwave horn antennas that were connected to a network analyzer. The sample holder was a rectangular polyethylene container that provided a layer of wheat (kernels and air space mixture) with a sample thickness of 10.4 cm. Fig. 1 illustrates such an arrangement. The system was calibrated by measuring the empty sample holder. The wheat was then placed into the sample holder. The data collected were the ratio of the wheat sample measurements to

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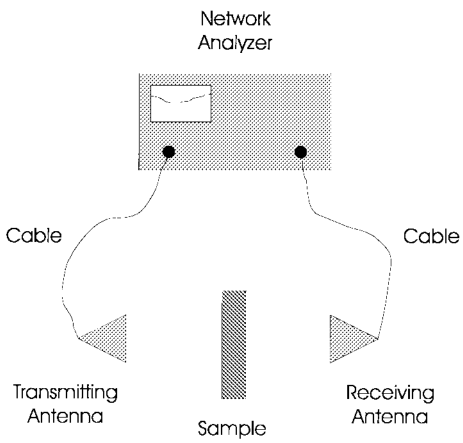

Fig. 1. Transmission coefficient measurement configuration.

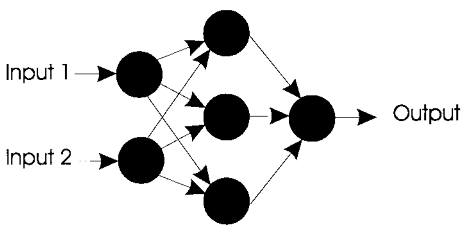

Fig. 2. Artificial neural network.

the calibration measurement. The bulk densities varied from 0.72 g/cm^3 to 0.88 g/cm^3 (loosely packed to compacted). Samples were measured at moisture contents ranging from 10.6% to 19.2%. The eight measurement frequencies ranged from 10 GHz to 18 GHz. All measurements were taken at 24°C.

B. Artificial Neural Network Fundamentals

An ANN is a collection of simple interconnected analog signal processors. The purpose of the ANN is to provide a mathematical structure that can be trained to map a set of inputs to a set of outputs. Fig. 2 illustrates an ANN similar to the one used in this study.

This ANN has three layers: the input layer, one hidden layer, and the output layer. Each layer consists of nodes or neurons. Each node has a sigmoid activation function associated with it. Each interconnection between the nodes has a weight associated with it. The nodes in the hidden and output layers sum the weighted inputs from sending nodes and apply this net input to the activation function. The output of the network is determined by applying the inputs and computing the output from the various node activations and interconnection weights. The differences between the ANN shown in Fig. 2 and the network used are the number of inputs and number of neurons in the hidden layer.

The feedforward, backpropagation method was used to train the ANN [17]. This method consists of initializing the network with random activation levels and weights. Training is accomplished by adjusting the weights to minimize the error between the predicted ANN outputs and the observed values.

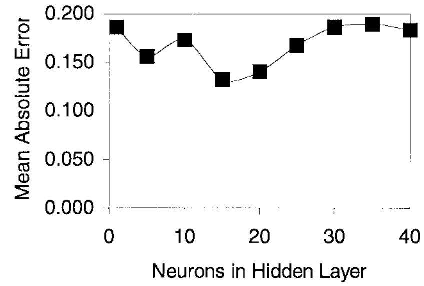

Fig. 3. Mean average error of test set as a function of number of hidden neurons.

The activations and weights are adjusted by using a gradient-descent technique. In this study 179 sample measurements were available. These samples were divided into a training set of 70 measurements, a test set of 48 measurements, and a production set of 61 measurements. The training set was used to train the network. The test set was used in the feed-forward mode only during training to determine the optimal point to stop training. This was done to avoid overfitting the training set. The trained ANN was evaluated based on the production set exclusively.

C. ANN Design and Training

The number of neurons in the input layer was determined by the number of inputs. Each of the transmission coefficients contains two parts—an amplitude and a phase. This results in 16 inputs. The number of neurons in the output layer was one, the moisture content. The number of hidden layers and the number of neurons associated with each hidden layer is somewhat arbitrary. One hidden layer was selected. The number of neurons associated with this hidden layer was determined by training the network for varying numbers of neurons. Fig. 3 is a plot of the mean average error of the test set versus the number of neurons in the hidden layer. Of the configurations considered, 15 hidden nodes delivered the best prediction.

III. RESULTS

The effectiveness of applying the trained network to the production set of measurements is shown in Table I. As illustrated, there is a strong correlation between the measurements and moisture content provided by the trained ANN ($r^2 = 0.99$). Fig. 4 shows the results obtained when all the data (training, test, and production sets) were applied to the trained ANN. The statistics, to the precision shown in Table I, were identical.

Next, the ANN was trained using only the amplitude of the transmission coefficient measurements as the inputs. The statistical results of processing the production set with the trained ANN are also listed in Table I. Even though the mean absolute error (compared to the oven-dried measurements) is larger than the one obtained when both the amplitude and phase of the transmission coefficients were used as inputs to the ANN, this configuration is attractive. Implementing such a system would require significantly less sophisticated hardware

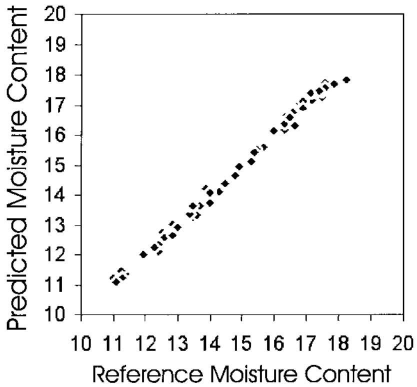

Fig. 4. Moisture contents predicted by trained ANN compared to oven-dried reference moisture determinations.

TABLE I
STATISTICS OF PRODUCTION SET MEASUREMENTS PROCESSED BY TRAINED NEURAL NETWORK WITH INDICATED INPUT

Statistics	Transm. Coeff.	Ampl. Transm. Coeff.	Permittivity
r squared:	0.993	0.982	0.992
Mean squared error:	0.028	0.073	0.032
Mean absolute error:	0.135	0.219	0.142
Min. absolute error:	0.004	0.005	0.001
Max. absolute error:	0.441	0.634	0.440

than one requiring both amplitude and phase measurements. Simple diode detection could be used.

Finally, the procedure was then repeated with values of permittivity calculated from the transmission coefficient [5] as inputs to the ANN. This has the appeal of making the determination of moisture content independent of the sample holder and the measurement technique used to determine permittivity. The statistical results obtained when the production set of permittivities was processed by the trained ANN are shown in Table I.

IV. CONCLUSIONS

An ANN can be used to make density-independent moisture content measurements on hard red winter wheat from free-space transmission coefficient measurements with a resultant mean absolute error of 0.135 (%) compared to oven dried measurements. The mean absolute error increased to 0.219 (%) when only the amplitude of the transmission coefficient measurements were used as inputs to the ANN. Eliminating the need for the phase measurements greatly reduces the complexity of the hardware required to make the measurements. Furthermore, this study indicates that the same level of accuracy (0.142) can be obtained with calculated values of permittivity. This permits the use of measurement techniques and sample holders other than those reported. Since grain permittivity is dependent on temperature, provision for temperature effects would need to be incorporated for practical application. Training an ANN for each temperature of interest or including temperature as an input to the ANN could accomplish this. Even though the measurements reported were made on static samples, the system has potential for on-line, nondestructive moisture content measurement for flowing grain.

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