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Three Term Back Propagation Network for Moisture Prediction

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Abstract. This paper introduces Three Term Backpropagation Network model for prediction of moisture content on maize with a better prediction result. Improvement on Two Term Back propagation leads to the addition of an extra term, the proportional factor (γ), which increases the convergence speed and reduces learning stalls in the conventional neural network. The experimental results are conducted using semi-annual datasets obtained from a maize thermal dryer, andthe results shows that our proposed model out-performs the Two Term Back propagation as a prediction tool by attaining quantitatively a higher precision result with Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) of 0.00145 and 0.00001 respectively.

Keywords: Three Term Back propagation neural network, maize, moisture content, proportional factor.

1. INTRODUCTION

Maize (Zea mays) is a cereal crop that is grown widely throughout the world in a range of agro ecological environments, rich in vitamins, carbohydrates, and essential minerals and contains 9% protein. All parts of the crop can be used for food and non-food products, but this study will concentrate on the food part which is the maize seed.

Moisture content is the level of water (moisture) in maize and is one of the most important factors in quality control of maize especially in controlling fungus infestation. Maize with high moisture content will not keep for extended periods in storage, so it is important, therefore, to have accurate determination of the moisture content and also for future storage planning after the harvesting season. During this period aflatoxin contamination in maize is of major concern; the necessity for suitable methods to determine moisture content with less time and higher accuracy assumes greater importance.After shelling maize is stored in silos, the storage life of maize is greatly affected by the moisture content and temperature of the stored maize seeds. An increase in moisture results in respiration and enzymes production. This will lead to maize decay and greatly reduce the storage period of maize [1].

The level of moisture content is one of the most important marks in maize quality evaluation and overall in grain evaluation. The most commonly used method in measuring moisture content in maize is the direct method which involves the use of moisture meters before and after thermal drying. Not only is the measurement period time consuming but also there exists some defects of low measurement precision and instability due to the application of single sensor measurement [2]. Therefore the use of multi-sensor measurement and neural network methods of data processing, grain moisture measurement accuracy have been greatly improved.

With the purpose of improving the accuracy of moisture prediction, Artificial Neural Network (ANN) has been chosen as the basis of prediction in this study. Hence this study will investigate the use of Three Term Backpropagation (BP) Neural Network to predict the levels of moisture content of a particular

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agricultural product i.e. Maize, and by using datasets obtained from a multi-sensor moisture meter after thermal drying.

By the use of Three Term BP algorithm, it translates to stability and robustness in choice of initial weights, especially when relatively high values for the learning parameters are selected [3].There are various methods for prediction of moisture levels for agricultural products. The simplest way is to use the available empirical correlations. However this approach generally fails for different agricultural products since such kind of correlations are not general since they are usually based on data obtained from a particular product [5]. That is, as the products changes, the equation alternates.In another study, [6] proposed to use Tanks-in-series (analytical model) to predict the average moisture content of solids. However, the solutions of these analytical models are very complicated and time consuming. Consequently, researchers have been using soft computing techniques among which artificial neural networks (ANN) and genetic algorithm (GA) have received much interest due to their ability to dynamic modelling of the drying characteristic of agricultural products [7]. However, they [7] pointed out that the ANN outperforms GA in predicting the experimental drying characteristics.

Standard Backpropagation (BP) algorithm has major limitations which are the existence of temporary, local minima resulting from the saturation behaviour of the activation function and the slow rates of convergence especially for networks with more than one hidden layer [8].Standard BPhas been improved by adding an extra term, the proportional factor which is used to speed-up the weight adjusting process by increasing the convergence rate and decreasing learning stalls whilst maintaining the simplicity and efficiency of the standard two-term BP algorithm [8].

Adnan Topuz [9] proposed the prediction of moisture content of agricultural products using standard Back propagation neural network (BPNN). However, BPNN method was preferred due to its simplicity and reliability but the existence of drawbacks within the BP training algorithm hinders a more accurate prediction result [4]. Thus, there is need for a prediction model that will predict more accurate moisture content for agricultural products using Three Term BP without the existence of drawbacks within the BP training phase [4].

2. BACKGROUND

2.1. Artificial Neural Network Model

Artificial Neural Network (ANN) uses a mathematical model for information processing which is based on the approach of computation inspired by the structure and operation of biological neurons organized into layers. Namely, there are three layers in a neural network; Input layer, Hidden layer and Output layer as shown in Fig. 1, where, X_i and X_j represents two input signals; drying time and drying temperature, W_{ij} represents weight from i^{th} input to j^{th} hidden node, V_{jk} represents weight from j^{th} hidden unit to k^{th} output node and Y_k represents output signal from the output node i.e. moisture content. There are many algorithms to fine-tune the weights, and Back propagation (BP) algorithm is widely used by the practitioners.

Back propagation (BP) algorithm is a supervised learning method used for training artificial neuron networks (ANN). Training is usually carried out by iterative updating of weights based on the error signal. Then the error signal is back propagated to the lower layers. Back propagation is a descent algorithm which attempts to minimize the error rate at each iteration. By the use of 3-Term Back propagation algorithm it translates to stability and robustness in choice of initial weights, especially when relatively high values for the learning parameters are selected [3]. Learning is a fundamental and essential characteristic of ANN. It is capable of learning through the network experiences to improve their performance. When ANN is exposed to a sufficient number of samples, it can generalise well to other data that they have not yet encountered [4].

The input data is trained by the ANN and the results of the training process is an appropriate output according to the desired target. At first all weights are initialized to produce small random numbers. This prevents the network from being saturated by very large weight values. Back propagation (BP) is a gradient descent technique used to minimize the error for a particular training pattern; it is the most famous training algorithm for multi-layer perceptions [3].

From the training datasets a training input pattern is presented to the input layer, and then it is forward propagated from layer to layer until output pattern is determined from the output layer.

$$Output = \int(net_i) \quad , \tag{1}$$

$$net_i = \sum W_{ij} O_j + \vartheta_j \quad , \tag{2}$$

where W_{ij} is the weight connected between node i and j , θ_i is the bias of node i and O_j is the output of node j

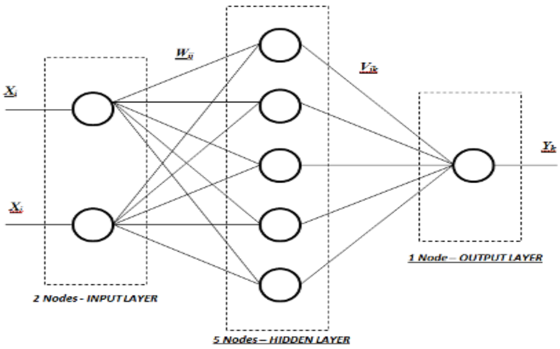

Fig. 1: ANN model

2.2. Modelling of Three Term BP Network for Moisture Prediction

Modification done by researchers to the standard BP algorithm was meant to improve efficiency and convergence rate of the algorithm. Zweiri [3] proposed a new term called the proportional factor (PF) which speeds up the weight adjustment process. This new proposal came to be known as Three Term Back propagation. This new approach showed that it out performs the standard BP algorithm in terms of both convergence rate and also escapes the local shallow minimum [8].

The BP algorithm is modified by adding an extra term called proportional term. It is as shown below:

$$\Delta W(k) = \alpha(-\Delta E(W(k))) + \beta \Delta W(k-1) + \gamma e(W(k)) \tag{3}$$

where α is learning rate, $\Delta E(W(k))$ is gradient of E at $W = W(k)$, with $k = 1,2,3,..,N$, being the iteration number, β is momentum term, $\Delta W(k-1)$ is a previous weight change , γ is proportional term and $e(W(k))$ is the difference between the output and the target at each iteration.

Note that BP algorithm given by Eq. (3) above has three terms. α is proportional to the derivative of $E(W(k))$, while β is proportional to the previous value of the incremental change of the weights and γ is the Proportional Factor that is proportional to $e(W(k))$.The proportional term increases the learning speed of back propagation algorithm. This term is proportional to $e(W(k))$. This represents the difference between the target and output result at each iteration.

However, in our study, we use modified cost function as proposed by Shamsuddin [10] to improve speed of convergence of Three Term BP. This cost function will be used to calculate the error signal to measure the performance of the Three Term network. The selection of a good cost function helps in improving accuracy by iteratively updating weights thus minimizing error and giving a more accurate output. Also getting stuck into the local minima is a common problem and whereby researchers have stated that a good selection of cost functions can overcome this problem [11].This has led to researchers coming up with cost functions so as to avoid the local minima. Hence, good cost function is important to ensure stable learning of the network [12]. The modified cost function (mm) is defined implicitly below as in [10]:

$$mm = \sum k \, \rho^k \tag{4}$$

with

$$\rho^k = E_k^2 / 2a_k(1 - a_k^2) \tag{5}$$

where,

$$E_k = t_k - a_k \tag{6}$$

And E_k error at output $unit_k$, t_k target value of output $unit_k$ and a_k an activation of $unit_k$.

3. EXPERIMENTAL RESULTS

Maize datasets are normalized before the training process. After the process of data normalization, the data is divided into 10% for testing and 90% for training. Thus the number of instances for training was 90 and 39 for testing; this kind of selection is mainly done to avoid over-fitting problems.The network structure will consist of 2 input nodes, 5 hidden nodes and 1 output node. Using Two Term Backpropagation as a benchmark model, the selection of values for Learning and Momentum factor is done through trial and error (80 trials) and these values are increased in each case and the number of epochs. Hence the best parameters for learning and momentum rate are obtained from the test with the best error rate and lowest convergence speed.

In Three Term Backpropagation, an additional term i.e. proportional factor is required; hence the values for each parameter (momentum, learning and proportional factor) were identified after 80 trials with different combination of proportional, momentum and learning rate.The stopping criterion is the number of epochs which are executed between 10 to 1000 epochs in each of the experiments and an error threshold value of 0.005 [18]. The selection for initial weights is done randomly between weight values of -1 and 1 and the minimum and maximum number of iterations is 10 and 1000 iterations respectively. The predicted moisture content obtained from Three Term Backpropagation isshown in Table 2.

To evaluate the performance of the model, three statistical tests are employed as given in Equations (7-9), namely;

Root Mean Square:

$$RMSE = \sqrt{\sum_{i=1}^{n} \left(de_i - o_i\right)}^{\,2} \tag{7}$$

Mean Absolute Percentage Error:

$$MAPE = \sum_{i=1}^{n} \left[\frac{de_i - o_i}{de_i}\right] \times \frac{100}{n} \tag{8}$$

Mean Absolute Deviation:

$$MAD = \sum_{i=1}^{n} \left(\frac{de_i - o_i}{n}\right) \tag{9}$$

where, n is the number of periods, de_i is actual values and o_i are forecasted values. The measurements are calculated using testing data. The error rate is assumed to be better if the value is very small or the value is near to zero. Statistical results tests which were obtained are given in Table 1.

Table 1: Statistical results for individual neural networks

Method	2-term Back propagation	3-term Back propagation
RMSE	0.03162	0.00118
MAD	0.01037	0.00145
MAPE	1.03692	0.00001

Table 2: Test Error for moisture samples obtained using 3-Term Back propagation

Samples	1	2	3	4	5	6
Known Moisture	12.78	11.25	10.9	11.95	13.1	11.4
Predicted Moisture	12.7798	11.2498	10.8998	11.9498	13.0998	11.3998

Table 2, is graphically represented as shown in Fig.2, this shows that the values for actual moisture prediction has a very small difference from the predicted moisture content.

4. CONCLUSION

The main purpose of the present study is to investigate the applicability of Three Term Back propagation neural network as a prediction tool for moisture content in maize. The experimental results shows that the newly proposed model outperforms Two Term Backpropagation in all of the three commonly used quantitative error measurements and in terms of both convergence rate and also escapes the local shallow minimum [3].Hence, it can be concluded that the Three Term Backpropagation model without the existence of drawbacks within the Backpropagation training phase [12] can be effectively utilized as a prediction tool for moisture prediction in maize as shown in Fig. 2.

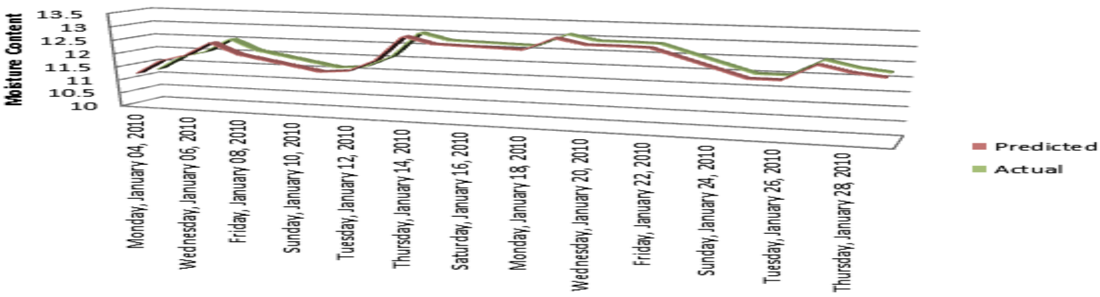

Fig. 2: Comparison of predicted and actual moisture

5. ACKNOWLEDGEMENT

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