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*Full Length Research Paper*

# Modeling the terminal velocity of agricultural seeds with artificial neural networks

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**Terminal velocity (TV) is one of the important aerodynamic properties of materials, including seeds of agricultural crops that are necessary to design of pneumatic conveying systems, fluidized bed dryer and cleaning the product from foreign materials. Prior attempts to predict TV utilized various physical and empirical models with various degrees of success. In this study, supervised artificial neural networks (ANN) were used for predicting TV. Experimentally, the TV of rice, chickpea, and lentil seeds were obtained as a function of moisture content and seed size. TV was significantly influenced by seed type, moisture content and seed size. Using a combination of input variables, a database of 54 patterns was obtained for training, verification and testing of ANN models. The results obtained from this study showed that the ANN models learned the relationship between the three input factors (seed type, moisture content and seed size) and output (TV) successfully, and described the TV of seeds with different shapes extremely well. The best 4-layer ANN model produced a correlation coefficient of 0.997 between the actual and predicted TV. The ANN models compared to mathematical models were able to learn the relationship between dependent and independent variables through the data itself without producing a formula. These benefits significantly reduce the complexity of modeling for TV.**

**Key words:** Artificial neural networks, terminal velocity, prediction, back-propagation.

## INTRODUCTION

Agricultural engineers have used compressed air for separation and handling of various materials for many years. Knowledge about aerodynamic properties of agricultural materials is useful for agricultural machine and system design. One of these properties is terminal velocity (TV) of agricultural seeds as in addition to plant species, influenced by additional variables such as seed moisture (Behroozi-lar et al., 2003).

Several mathematical models have been developed for prediction of TV. These models are account for particle size, surface properties of the particle, density and shape factor. Whereas TV of agricultural seeds in addition to these factors is dependent on the other factors such as moisture content of seeds, crop variety, air temperature and relative humidity. Also, these models are defined only for some of the particular shapes of seeds (sphere, flat …). Therefore prediction the TV of agricultural seeds with these amounts of variables by using traditional mathematical models is very difficult.

ANN models, compared to mathematical models, are able to learn the relationship between dependent and independent variables through the data itself without the need to develop specific functions between them (Mittal et al., 2000). Learning is a data-driven, self-adaptive process by which experience arising from exposure to measurements of empirical phenomena is converted to knowledge, embodied in internal parameter weights of the network (Seyhan et al., 2005). It eliminates the difficulty of extracting the parameters in a statistical model. A properly trained neural network can be viewed as a function that fits the input/output data. ANN models often are used when the relationship between parameters

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is unknown or very complex. ANN is also useful in nonlinear, multivariable and nonparametric modeling, therefore, ANN has recently been utilized in modeling the physical and mechanical properties of numerous agricultural materials (Khazaei et al., 2005).

Although it has been shown theoretically that the ANN has a universal functional approximating capability and can approximate any nonlinear function with arbitrary accuracy, no universal guideline exists in choosing the appropriate model structure for practical applications. Thus, a trial-and-error approach is often adopted to find the best model. Typically a large number of neural network architectures are considered. The one with the best performance in interpolation capability is chosen as the most suitable (Park et al., 2003).

In the past few years there has been an increasing interest in ANN modeling in different fields of agriculture, particularly for some areas where conventional statistical modeling failed. The prediction by a well-trained ANN is normally faster than the statistical models. In addition, it is possible to add or remove input and output variables in the ANN. The applications of the ANN in agriculture includes the prediction of crop yield, seeding dates, biomass production, physical and physiological damage to seeds, organic matter content in soils, estimation of sugar content in fruits, characterize crop varieties, soil moisture estimation (Cerrato et la, 1990; Chen et al., 1999; Liu et al., 2001; O'Neal et al., 2002; Ingleby et al., 2001; Drummond et al., 2004; Marini et al., 2004; Jiang et al., 2004; Kaul et al., 2005; Park et al., 2005; Saberali et al., 2007; Khazaei et al., 2008).

The objectives of this research were to (I) build and evaluate the performance of ANN to predict the TV of three agricultural seeds as a function of seed type, size and moisture content, (II) comparison between ANN and mathematical models to predict the TV of agricultural crop seeds.

## MATERIALS AND METHODS

### Dataset and measurement method

Among effective factors on TV of agricultural seeds three factors were selected. For measuring TV a completely randomized design in factorial experiment was used for each experiment. The treatments were shape of seeds (cylindrical, spherical and flat), moisture content at six levels and dimensions of seeds at three levels with six replicates in each.

### *Sample preparation*

Iranian varieties of chickpea, lentil and rice (spherical, flat and cylindrical shape respectively) were selected crops. The seeds were manually cleaned to remove all foreign matters such as dust and broken seeds. Three dimensions (a, b, c) of seeds were measured by micrometer with 0.02 mm accuracy. Then geometric mean diameter of seeds was calculated from equation (1) (Storshine et al., 1998):

$$gmd = \sqrt[3]{abc} \qquad (1)$$

Where gmd is geometric mean diameters of seeds (mm), a, b and c are large, middle and small diameter of seeds (mm), respectively. Then according to gmd, the seeds were divided into three dimensional groups (Table 1). Rice and lentil were divided according to length and mean diameter, respectively, because of their shapes. Six moisture levels were selected ranging from initial moisture content of seeds to 25% w.b (Table 2). The initial moisture content of seeds was determined by using oven method. The necessary time and temperature of oven for drying rice, chickpea and lentil were 135, 105 and 135°C, respectively for 24 h (Chung, 2006; Esref et al., 2008; tang et al., 1991).

To obtain samples with higher moisture contents (Table 2), a calculated quantity of distilled water was added to the samples. The quantity of distilled water was calculated from the following equation:

$$W_2 = W_1 \frac{M_1 - M_2}{100 - M_1} \qquad (2)$$

Where $W_2$ is the mass of distilled water added (kg), $W_1$ is the initial sample mass (kg), $M_1$ and $M_2$ are the initial and desired moisture content of sample (w.b. %), respectively.

Then the samples were placed in sealed plastic bags and kept at 4°C in the refrigerator for at least 48 h to enable the moisture to distribute uniformly throughout the sample. Before starting a test, the required quantity of seeds was taken out of the refrigerator and allowed to warm up to room temperature (Deshpande et al., 1993; Carman, 1996; Dursun et al., 2005).

### Terminal velocity measurement

To measure the terminal velocity of the samples, a vertical air column was designed and constructed based on the standard methods (Tabak et al., 1998). It was contained of the electrical motor, centrifugal fan, air chamber, wind tunnel and electrically TV measurement system (Figure 1).

The sample was placed in the wind tunnel and air speed was gradually increased until the seed was floated, and air speed was measured and mean of six replications was reported as seed TV.

### Mathematical models development

The dimensional analysis method was applied to obtain the mathematical models of predicting TV. For the conditions of this research the general equation (3) can be assumed:

$$f(V, d, g, M) = 0 \qquad (3)$$

Where V is terminal velocity ($LT^{-1}$), d is diameter (L), g is gravity acceleration ($LT^{-2}$) and M is moisture content (dimensionless). The selected dimensionless parameters were $\Pi_1 = V / \sqrt{dg}$ and $\Pi_2 = M$, so the general equation containing dimensionless parameters is:

**Table 1.** Range of sizes (mm) in every dimensional group.

| | Group 1 | Group 2 | Group 3 |
|---|---|---|---|
| Chickpea | 6.4 - 6.6 | 7.1 - 7.5 | 8.2 - 8.6 |
| Lentil | 5.4 - 5.8 | 6.2 - 6.6 | 6.9 - 7.3 |
| Rice | 8.7 - 9.4 | 9.8 - 10.5 | 10.8 - 11.5 |

**Table 2.** Six moisture content levels of seeds (%).

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Chickpea | 6.37 | 10 | 13.5 | 17 | 21 | 25 |
| Lentil | 9.02 | 12.5 | 16 | 19 | 22 | 25 |
| Rice | 10.12 | 13 | 16 | 19 | 22 | 25 |

**Figure 1.** Applied vertical air column for measuring TV.

$$f\left(\frac{V}{\sqrt{dg}}, M\right) = 0 \quad (4)$$

**Artificial neural networks**

In this study a feed forward artificial neural network model was developed to model correlation between terminal velocity and three variables: seed type, seed size and moisture content of seeds. This type of neural network is mainly used for the estimation of functions and classification of patterns. The multilayer perceptron networks (MLP) are the most commonly used feed forward ANNs. Back Propagation (BP) training algorithm usually is used for MLP network training (Menhaj, 1998). In this study the multilayer perceptron ANN with back propagation (BP) algorithm was selected to develop TV prediction.

There were a total of 54 patterns, each with four components

**Table 3.** Three samples of patterns used in artificial neural networks modeling.

| Pattern no | Seed type | Seed size (mm) | Moisture content (%) | TV (m/s) |
|---|---|---|---|---|
| 1 | Chickpea (1) | 6.5 | 6.37 | 11.13 |
| 2 | Lentil (2) | 5.6 | 9.02 | 5.08 |
| 3 | Rice (3) | 11.15 | 22 | 4.92 |

($x_1$, $x_2$, $x_3$, $y$), three of which were the input variables whereas the y was the output variable. Table 3 shows three of these patterns.

Supervised ANNs are similar to conventional statistical models in the sense that model parameters (e.g. connection weights) are adjusted in the model calibration phase (training) so as to minimize the error between model outputs and the corresponding measured values for a particular data set (the training set). ANNs perform well when they do not extrapolate beyond the range of the data used for calibration. Therefore, the purpose of ANNs is to non-linearly interpolate (generalize) in high-dimensional space between the data used for calibration. Unlike conventional statistical models, ANN models generally have a large number of model parameters (connection weights) and can therefore overfit the training data (leading to memorization rather than generalization). Consequently, a separate verification set is needed to ensure that the model can generalize within the range of the data used for calibration. It is common practice that the data are divided into three sets: training, testing and verification. The training set is used to adjust the connection weights, whereas the testing set is used to check the performance of the model and the verification set is used to determine when to stop training to avoid over-fitting (Shahin et al., 2008).

The 54 patterns used in this study randomly were divided into training, verification and testing datasets: 30, 12 and 12 patterns for train, verification and test, respectively (Shahin et al., 2008). The variables of these datasets could not be trained by ANN in their original form due to the wide range of values among them. To become feasible input neurons and to achieve fast convergence to minimal RMSE, all the datasets were normalized between 0.05 and 0.95 by using the following formula (Khazaei et al., 2005):

$$X_t = 0.05 + 0.9 \times [\frac{(X_i - X_{\min})}{(X_{\max} - X_{\min})}] \qquad (5)$$

Where $X_t$ is the normalized data for $X_i$, $X_{\max}$ and $X_{\min}$ are maximum and minimum of data before normalizing. As a result of normalization, all variables acquired the same significance during the learning process.

The input and target output pairs were applied to train the weights of the networks. Training process by these networks is iterative process that includes up-dating of weights between the different layers. During training process the weights gradually proceed to stability. So, it would be minimized error between target and predicted values.

The training and prediction abilities of ANN models were considered using the root mean square error (RMSE), coefficient of determination ($R^2$), and T static's (Khazaei et al., 2008).

$$RMSE = \sqrt{\frac{1}{n}\sum_n (X_m - X_p)^2} \qquad (6)$$

$$T = 1 - \frac{\sum_n (X_m - X_p)^2}{\sum_n (X_m - \bar{X})^2} \qquad (7)$$

Where $X_m$ and $X_P$ are measured and predicted data respectively, $n$ is the number of data and $\bar{X}$ is mean of output data.

Various ANN structures were investigated, including three and four layers with different number of neurons in each hidden layers, different values of learning coefficient and momentum, different learning coefficients and transfer functions. Once a given neural network was trained by using the appropriate training dataset, its performance was evaluated using the testing dataset. The best ANN structure and optimum values of network parameters were obtained on the basis of lowest error on training and test sets of data, by trial and error.

The neural network professional ii/plus simulator, version 5.23, mstat-c and excel softwares were used in this study.

## RESULTS AND DISCUSSION

The terminal velocities (TV) of rice, chickpea, and lentil seeds were obtained as a function of moisture content (at six levels) and seed size (at three levels). TV of rice, chickpea, and lentil seeds varied within the 4.25 - 5.01, 11.13 - 15.08, and 5.08 - 6.41 m/s, respectively. TV was influenced significantly by seed type, moisture content and seed size. The regression equations of terminal velocity and their $R^2$ values are listed in Table 4.

### Mathematical models

Equations (5 - 7) show the results of applied dimensional analysis method to obtain the mathematical models for chickpea, lentil and rice respectively. Figures 2 to 4 show the coefficient of determination ($R^2$) for mathematical models.

$$TV = (d.g)^{1/2}(24.67M^2 + 12.86M + 44.75) \qquad (5)$$

$$TV = (d.g)^{1/2}(80.15M^2 - 0.033M + 20.46) \qquad (6)$$

$$TV = (d.g)^{1/2}(-9.85M^2 + 16.25M + 12.11) \qquad (7)$$

**Table 4.** Regression equations of terminal velocity.

| Seed type | Seed size (mm) | Equation | $R^2$ |
|---|---|---|---|
| | 6.5 | $TV = 0.03384M_C + 10.92$ | 0.961 |
| Chick-pea | 7.3 | $TV = 0.0444M_C + 11.819$ | 0.91 |
| | 8.4 | $TV = 0.0861M_C + 12.988$ | 0.962 |
| | 5.6 | $TV = 0.064M_C + 4.4899$ | 0.986 |
| Lentil | 6.4 | $TV = 0.0719M_C + 4.5373$ | 0.982 |
| | 7.1 | $TV = 0.0676M_C + 4.7102$ | 0.984 |
| | 9.05 | $TV = 0.0366M_C + 3.8485$ | 0.967 |
| Rice | 10.15 | $TV = 0.0408M_C +3.8678$ | 0.931 |
| | 11.15 | $TV = 0.0434M_C + 3.9585$ | 0.966 |

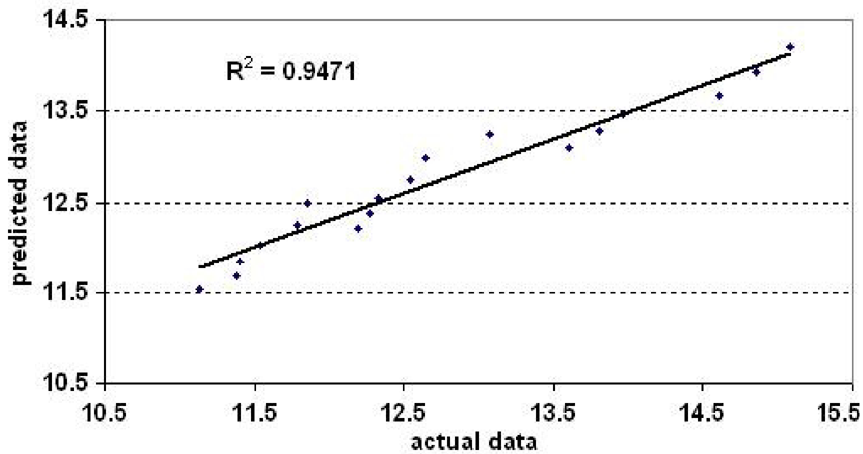


**Figure 2.** Correlation between the actual and predicted TV data of pea by mathematical model.

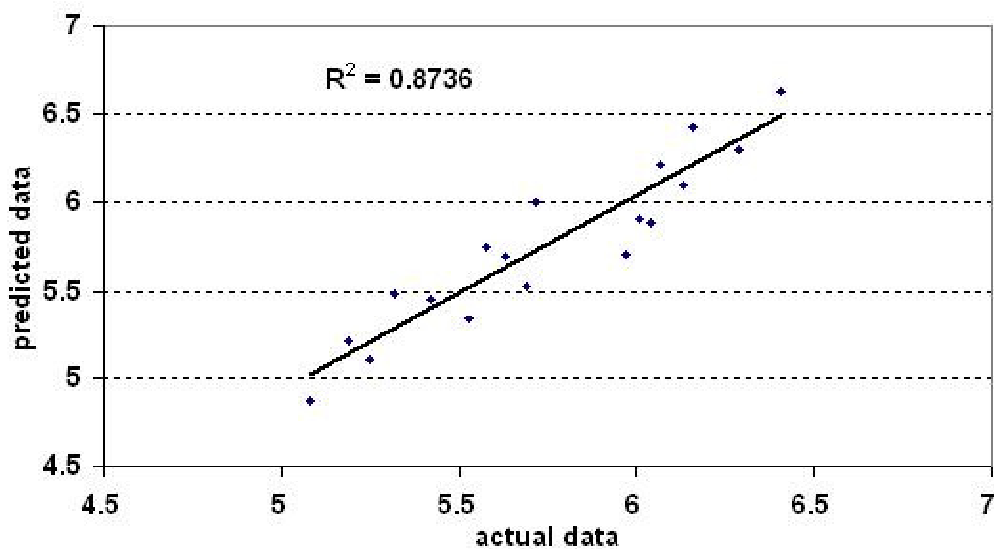


**Figure 3.** Correlation between the actual and predicted TV data of lentil by mathematical model.

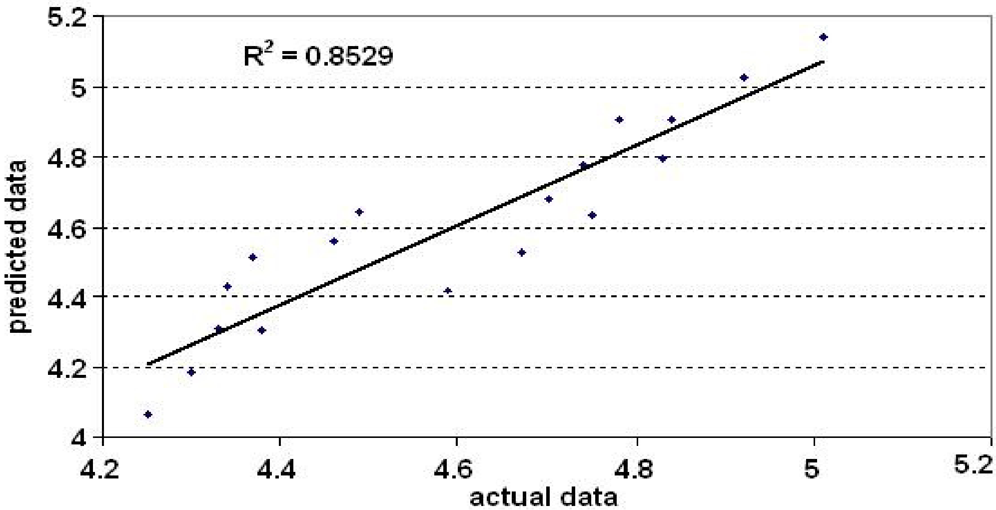


**Figure 4.** Correlation between the actual and predicted TV data of rice by mathematical model.

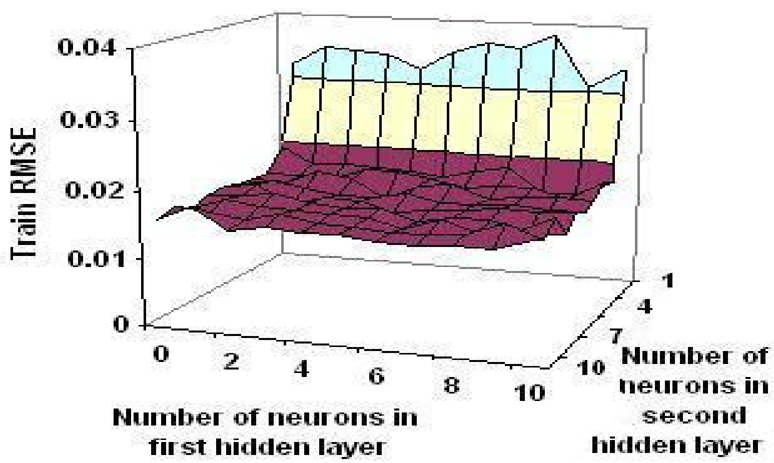


**Figure 5.** Training RMSE of ANN as a function of the number of neurons in the first and second hidden layers.

Where $M$ is the moisture content, $d$ is size of seed (mm) and $g$ is the gravitational acceleration (m/s$^2$).

## Artificial neural networks model

Preliminary trails indicated that two hidden layer networks performed better results than one hidden layer ANN to learn and predict the correlation between input and output parameters.

To determine the optimal number of neurons in hidden layers, training was used for 3-$n_1$-$n_2$-1 architectures. The number of neurons in the first hidden layer ($n_1$) was studied from 1 - 10 and from 0 - 10 for second hidden layer ($n_2$). Figure 5 shows the training performance of ANN as a function of the number of neurons in the first and second hidden layers. Results show that among the various structures, the best training performance to predict TV was belong to the 3-4-4-1 structure. Figure 6 illustrated this structure.

On the basis of the lowest error on training and test sets of data, by trial and error, the best transfer function and learning rule (Figure 7) for predicting TV were sinusoidal and delta rule.

The results obtained from this research showed that the network parameters including learning coefficient and momentum values affected the ANN performances significantly but the choice of suitable learning coefficient

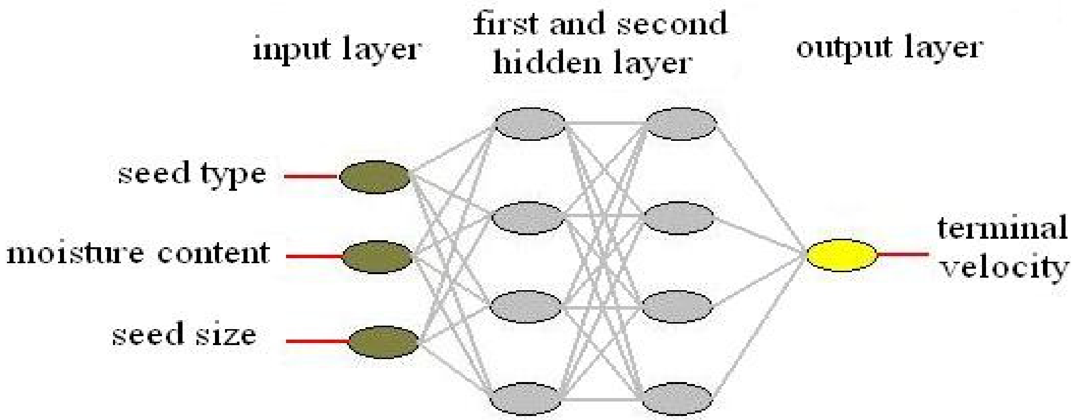


**Figure 6.** The topology of four layers, feed-forward back-propagation ANN for predicting TV based on three input variable.

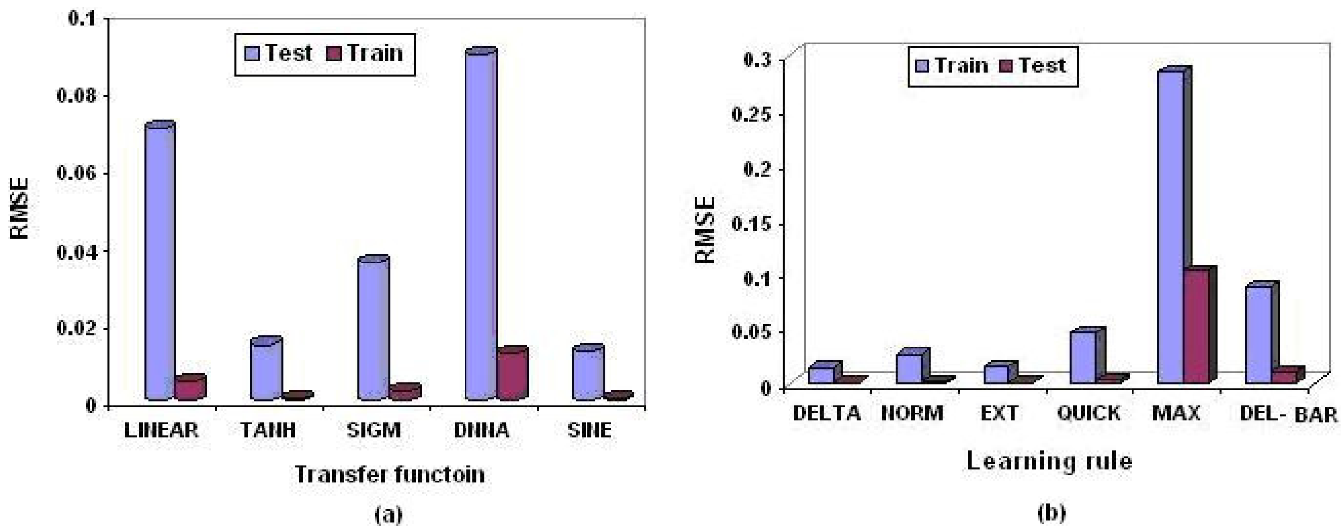


**Figure 7.** Comparison of training and test RMSE for several transfer functions(a) and learning rules (b).

and momentum is an important problem. The values of 0.5 for learning coefficient and 0.1 for momentum were desirable (Figure 8), so that the achieved result was as precise as possible.

For 3-4-4-1 structure the number of epochs was increased from 4 x $10^2$ - 4 x $10^4$ and the amount of RMSE was calculated for train and verification datasets. As Figure 9 shows the error on training data generally decreases with increasing number of epochs, with an initial large drop in error that slows down as the network begins to learn the patterns representing the training data set. A well-trained ANN model is the key to design and analysis of the input and output relations. However, if training is allowed to continue beyond the point at which the error reaches the global minima, overfitting (or overtraining) may arise, where memorization of the training data occurs (Khazaei et al., 2008). Because of this overfitting, if a network performance is monitored by training data alone, the network will perform with little error on the training data but will not be able to generalize well for testing data. In several neural network applications, this has been handled by monitoring verification set performance during training and picking the network where performance on the verification set was optimal. In this study for the epochs in the range of 11 x $10^3$ - 4 x $10^3$, the errors on both training and verification sets were in the acceptable range (Figure 9). The number of epochs was limited to 17 x $10^3$.

Table 5 shows the best structure and optimum parameters used to predict TV and Figure 10 shows its performance. As Figure 10 shows the linear adjustment between the actual and predicted values gives a slope

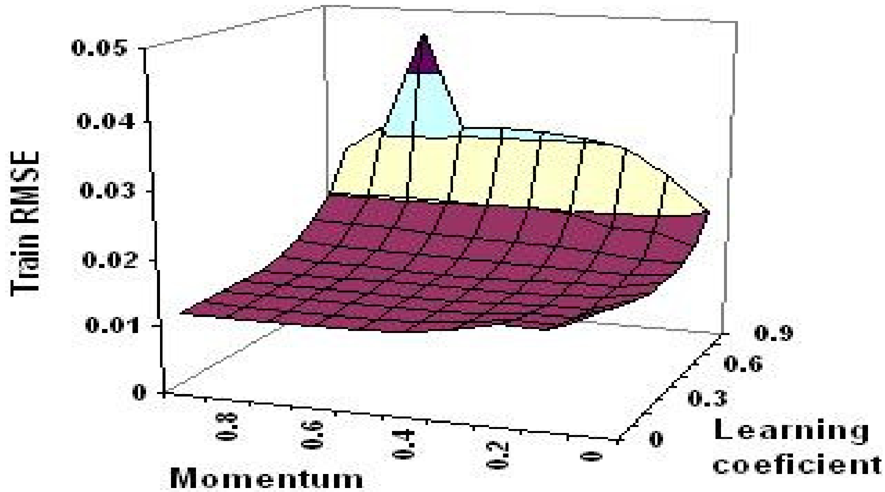


**Figure 8.** The effect of learning coefficient and momentum values on training performance of the ANN model.

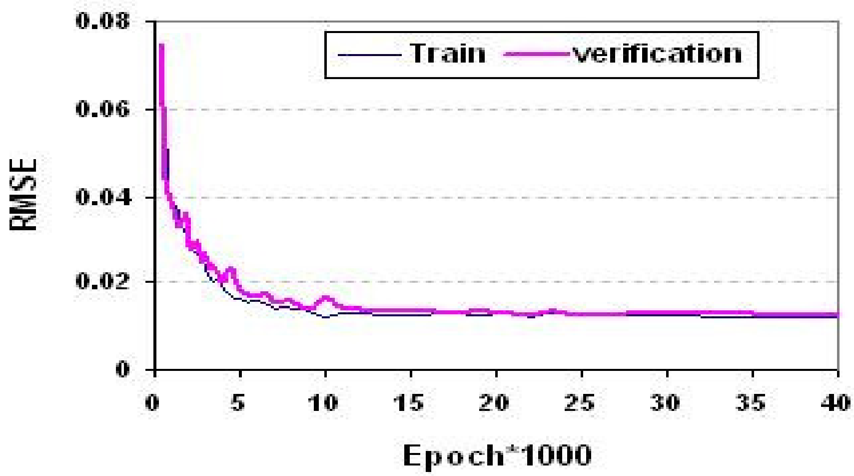


**Figure 9.** The training and verification RMSE as a function of the number of epochs.

**Table 5.** The best structure and optimum parameters used to predict TV.

| Multi layer perceptron ANN with back-propagation algorithm | | | | | |
|---|---|---|---|---|---|
| **Structure** | **Learning rule** | **Transfer function** | **Learning coefficient** | **Momentum** | **Epoch** |
| 3-4-4-1 | Delta rule | sinusoidal | 0.5 | 0.1 | $17*10^3$ |

equal to 0.9903 (y = 0.9903x + 0.0005). The resulting coefficient of determination ($R^2$) was 0.9968 for the regression between actual and predicted values. The ANN model was able to predict TV data with training and test RMSE of 0.018747 and .0128, respectively. Also the T coefficient and $R^2$ value of model were 0.9966 and 0.9968, respectively.

## Conclusion

The results obtained from this study show that the ANN models learned the relationship between the three input factors (seed type, moisture content and seed size) and terminal velocity as output successfully. ANN models compared to mathematical models were able to learn the

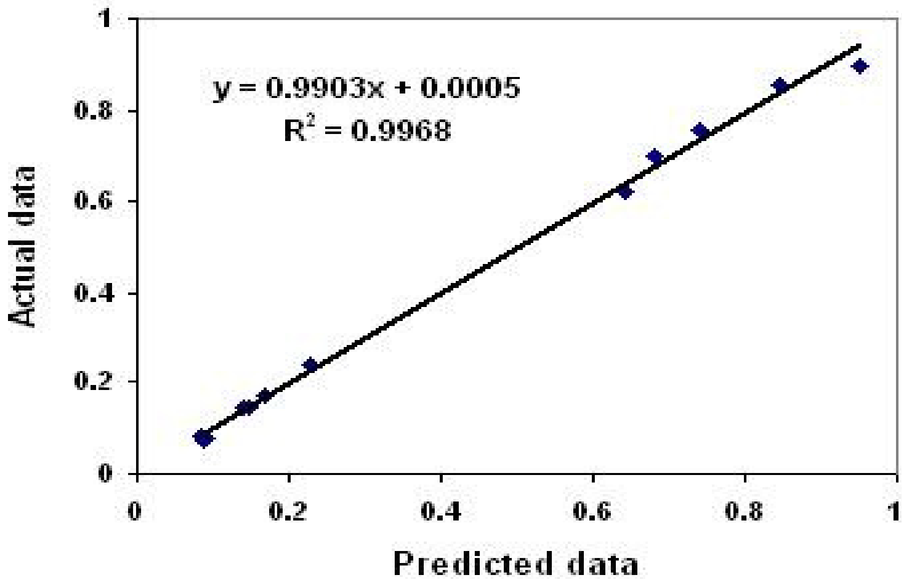


**Figure 10.** Correlation between the actual and predicted TV data by the ANN model.

relationship between dependent and independent variables through the data directly without producing a formula; therefore, ANN eliminates the difficulty of extracting the parameters for a mechanistic model.

The results also showed that one ANN model can be used to predict terminal velocity of several seeds with different shapes, whereas empirical models for predicting TV of every seed at least one model is needed. Also the accuracy of the ANN model is very better than mathematical models.

The number of patterns in the training dataset in this research was not very much (30 patterns) nevertheless the ANN models were able to successfully predict TV (acceptable values for RMSE, $R^2$ and T), whereas the empirical models need a large amount of data for reliable training results and to validate trained models.

If new data for TV are available, the ANN models can easily relearn the relationship between them. The higher performance, higher prediction accuracy, and ability to relearn are important to create a powerful model.

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