Australian Journal of Crop Science

AJCS

AJCS 7(10):1442-1448 (2013) ISSN:1835-2707

Using Artificial Neural Network (ANN) technique for prediction of apple bruise damage

Vahid Rostampour[1*], Asad Modares Motlagh[1], Mohmmad Hasan Komarizadeh[1], Morteza Sadeghi[2], Iraj Bernousi[3], Tohid Ghanbari[4]

[1]Department of Mechanic of Agricultural Machinery Engineering, University of Urmia, Urmia, Iran
[2]Faculty of Mechanical Engineering, University of Tabriz, Tabriz, Iran
[3]Department of Agronomy and Plant Breeding, University of Urmia, Urmia, Iran
[4]Department of Electronic Engineering, University of Urmia, Urmia ,Iran

***Corresponding author: Rostampoor2011@gmail.com**

Abstract

Transporting vibration is a major cause of bruising damage in apples. In this study the potential of Artificial Neural Network (ANN) technique to predict bruise volume of apple was evaluated and a prediction model for bruising apple in transport condition (by truck) was developed. For this purpose, firstly significant or non-significant effects of transport vibration parameters (frequency and acceleration) and fruit properties (mass, curvature radius, acoustical stiffness) on bruising of apple in transport condition was investigated and the parameters that have significant effects identified. This parameters were considered as input variables in the develop model. In the second stage, by using of these input variables a multilayer perceptron (MLP) network trained and prediction model was developed. Results indicated that the model with 5-7-1 instruction, sigmoid transfer function in hidden layer and linear transfer function in output layer with 40000 epochs gives the best correlation between predicted and actual values, with correlation coefficient (R^2) of 0.9998 and 0.9996 in training and testing phase, respectively. It can predict the bruise volume with acceptable root mean-squared error (RMSE) of 4.21. Also a regression model for prediction with correlation coefficient (R^2) of 0.9996 was developed. These results indicated that the Artificial Neural Network technique could potentially be used to predict apple bruising in transport condition.

Keywords: Bruise volume, Prediction model, Transport vibration.
Abbreviations: ANN- Artificial Neural Network; BV- Bruise Volume; RMSE- Root Mean Square Error; MLP- Multilayer Perceptron; R^2- Correlation coefficient.

Introduction

The apple fruit is an important dietary product while it is one of the most consumed products around the world. Hence, improving apple quality and appearance is one of the most crucial challenges that the fruit industry is engaged on. Bruising is the most common type of postharvest mechanical damage that reduces the quality (Knee and Miller, 2002). Studies indicated that apple bruising can result in losses up to 50%, although typically loss levels are in the (10–25) % range, depending on consumer awareness (Studman et al., 1997). For the study of apple bruising and developing prediction model identifying the effective factors is necessary. Some of these effective factors are such as, type of contact forces, the number of contacts, maturity stage, temperature, curvature radius, firmness and fruit mass (Zarifneshat et al., 2010). The three types of forces which can cause bruising in apples are impact, compression load and vibration forces. Vibration forces that usually occur during transportation are difficult to avoid and can be repeated at 5 to 15 times each second, for many hours of the trip (Vergano et al., 1991). Detailed information about bruise prediction models of *Golden Delicious* apple reported in the references is limited, and developed models are mostly limited to the effect of two properties of fruit (either maturity or temperature of fruit), and mostly are inconsistent (Studman et al., 1997). This is due to the negation of some fruit factors in the model, such as the radius of curvature and the negation of interaction effects between fruit factors and between fruit factors and the severity of impact (Van Zeebroeck et al., 2007). Also the most previous studies that performed about the bruising susceptibility of apple are conducted using the pendulum device (with single impact). These results and developed models for transportation condition cannot be correct, because in these models the effect of tissue fatigue (caused by cyclic loading or repetitive impact) and apple mass has not been considered, while these factors in the amount of bruising volume in transportation condition are very effective. Also these models were obtained based on traditional methods. While the prediction by a well-trained Artificial neural network (ANN) model is normally much faster and less complex compared to most of the conventional simulation methodology models (Motevali et al., 2012). ANNs can model based on no assumptions concerning the nature of the phenomenological mechanisms, and understand the mathematical background of problem (Fathi et al., 2011).
Therefore, the objective of this research is: (1) Identification of significant factors on bruising damage of apple in transport condition and selection of input variables for developing prediction model (2) Evaluation of the effectiveness of ANN for predicting apple bruise volume (3) Developing a detailed prediction model for bruising of apple in transport condition.

Results

Identification of significant parameters and selection of the model input variables

Effect of frequency and acceleration

Analysis of variance indicated that the effect of frequency and acceleration on the bruising of apple at 1% probability level were significant. A relationship with negative slope and a relationship with positive slope between vibration frequency (in the constant acceleration of 0.5g) and vibration acceleration (in the constant frequency of 10 Hz) with bruise volume observed, respectively.

Effect of apple mass

The significant difference at 1% probability level was observed between bruise volume of apples with different masses (155gr, 125gr and 95gr). Generally, the small apples are less damaged than the large apples.

Effect of curvature radius

The significant difference at 5% probability level was obtained between bruise volume of two curvature radius. The results indicated that the apples with small radius of curvature (36 mm) had more bruise volume than those with a larger radius of curvature (52 mm).

Effect of acoustic stiffness

The amount of bruise volume of apples has increased with the increase of acoustical stiffness and significant difference at 5% probability level between bruise volume of two levels of acoustic stiffness (40 $Hz^2kg^{2/3}$ and 55 $Hz^2kg^{2/3}$) was observed.

Selection of the model input variables

Given this that, the effect of vibration frequency, vibration acceleration and apple mass on bruise volume were significant at 1% probability level and the effect of curvature radius and acoustical stiffness were significant at 5% probability level, therefore, these variables were selected as the Network inputs for developing prediction model (Fig 3).

Prediction model (Artificial Neural Network)

The training phase was carried on for 40000 epochs and until the cross-validation data's root mean-squared error (RMSE) was calculated by Eq. 6, did not improve for 40000 epochs. Predetermined values for the output error determined as 0.00001. For finding the best architecture different networks were built, with different neurons in hidden layer varying from 1 to 25. The lowest amount of root mean square error (RMSE) for the prediction of bruise volume during the training and testing phase was calculated. The values of RMSE for training phase are shown in Table 2. According to the results of this table, the ANN architecture with 7 neurons in hidden layer, sigmoid transfer function in hidden layer and linear transfer function in output layer seems to be appropriate for modeling bruise volume. Therefore, this architecture was chosen as the best ANN model. For this architecture (7 neurons in the hidden layer) the correlation between actual values and predicted values in training and testing phases with correlation coefficient (R^2) of 0.9998 and

Table 1. Different levels of frequency and acceleration, applied on the simulation.

Levels	frequency(Hz)	acceleration(g)
1	7.5	0.3
2	10	0.5
3	12.5	0.7

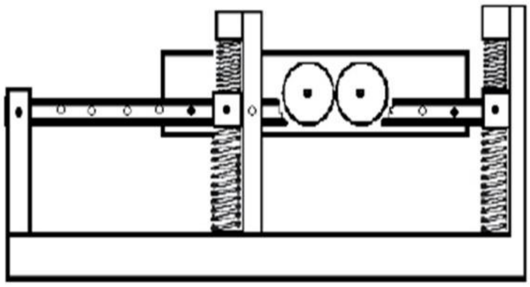

Fig 1. Vibration simulator.

0.9996, indicated in Fig 4 and 5, respectively. Also a plot of predicted values against measured values is depicted in Fig 6. Regression analysis of the predicted values by neural network model resulted in the following equation:

$$VB_{pre} = VB_{act} + 3.9$$
$$(R^2 = 0.9996) \quad (8)$$

Where VB_{pre} is predicted value and VB_{act} is actual value.

Discussion

Identification of significant parameters and selection of the model input variables

Effect of frequency and acceleration

A relationship with negative slope and a relationship with positive slope between vibration frequency and vibration acceleration with bruise volume were observed, respectively. These relationships are due to the decrease and increase in the vertical displacement amplitude of simulator table with the increase of frequency (in the constant acceleration of 0.5g) and acceleration (in the constant frequency of 10 Hz), respectively, that causes the amount of peak contact force applied to apples decrease or increase, respectively, and bruise volume change. According to Eq 2, increase the frequency of vibration without adapting the displacement amplitude leading to increase in acceleration amplitude. In our opinion, this is not the right method to test the effect of the frequency itself on the mechanical damage, because the effect of the frequency is mixed with the effect of peak acceleration. This logic is also true in testing the effect of acceleration. Timm et al. (1998) reported that changes in vibration amplitude can change the force spectral density (FSD) in fruits and reduce or increase the amount of damage. Van Zeebroeck et al. (2006) and Shahbazi et al. (2010) observed that increasing of frequency and acceleration causes the damage in fruit decrease and increase, respectively.

Effect of apple mass

The significant difference between bruise volume of apples with different masses, indicated that mass is one of the

Table 2. Errors variation with different number of neurons in the training phase.

criterion			Number of neurons in the hidden layer						
	1	2	3	4	5	6	7	8	9
RMSE	186	123	60	39	18.3	11.8	4.21	3.35	2.63
			Number of neurons in the hidden layer						
	10	11	12	13	14	15	16	17	-
RMSE	2.52	2.37	1.95	1.5	1.48	1.31	0.97	0.5	-
			Number of neurons in the hidden layer						
	18	19	20	21	22	23	24	25	-
RMSE	0.16	0.027	7e-13	6e-13	5.3e-13	5e-13	4e-13	3e-13	-

important factors in amount of bruise volume in transport condition. Generally, the large apples are more damaged than the small apples. Because, according to Newton's second law, applied force to high mass is more than low mass (in the equal acceleration). Also the large apples in comparison with small apples have a larger cell, with thinner wall (Johnson and Dover, 1990). Thus, this weaker cell wall will more easily develop bruise damage. It was observed that with increasing frequency (in the constant acceleration) and decreasing acceleration level (in the constant frequency) that, the effect of mass on bruises volume was less evident. Because, according to Eq 2, in this case the vertical displacement amplitude of the vibration table was reduced and due to the high power required for vibrant massive apples, a large percentage of applied impacts to high mass are below the critical level impact, Therefore, the amount of bruise volume for high mass should be more decreased than low mass and reduced bruise volume differences. The critical impact height can be calculated of the following equation (Baritelle and Hyde, 2001):

$$h_c = C.\sigma_f.\varepsilon_f\left(1-\mu^2\right)^4.R^3 \Big/ (mg) \tag{9}$$

Where h_c is the critical drop height; σ_f the failure stress; ε_f the failure strain; m the mass of apple and R the curvature radius. Van Zeebroeck et al. (2006) have reported that in percentage and even in absolute numbers, the small apples are less damaged than the large apples, but as a general remark, the relative importance of the apple size on bruise damage could be dependent to the vibration frequency and acceleration amplitude.

Effect of curvature radius

The apples with low radius of curvature led to more bruise damage than apples with higher radius of curvature. Also the difference between bruise volume for both the radius of curvature, at different levels of frequencies and different levels of acceleration was not the same. The following equation that is derived based on Hertz theory, by Horsfield et al. (1972) is consistent with a part of obtained results:

$$\sigma_i = C\left(mgh\right)^{\frac{1}{5}}\left(\frac{1-\nu_1^2}{E_1}+\frac{1-\nu_1^2}{E_2}\right)^{-4/5}\left(\frac{1}{R_1}+\frac{1}{R_2}\right)^{\frac{3}{5}} \tag{10}$$

Where σ_i is the peak contact stress (Pa); C the constant; m the mass of apple (kg); g the earth gravity (m/s^2); h the drop height (m); $\nu_{1,2}$ the Poisson's ratio; $E_{1,2}$ the elastic modulus

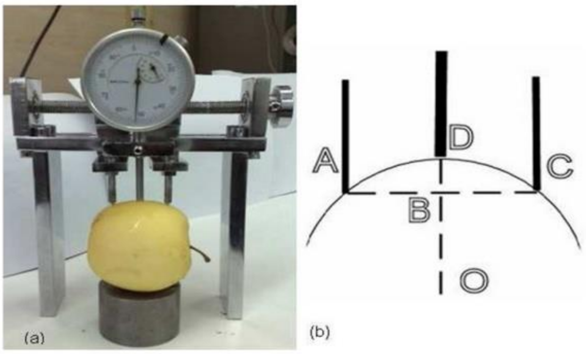

Fig 2. (a) General view of the radius meter and (b) schematic representation of geometry to calculate the radius of the apple fruit.

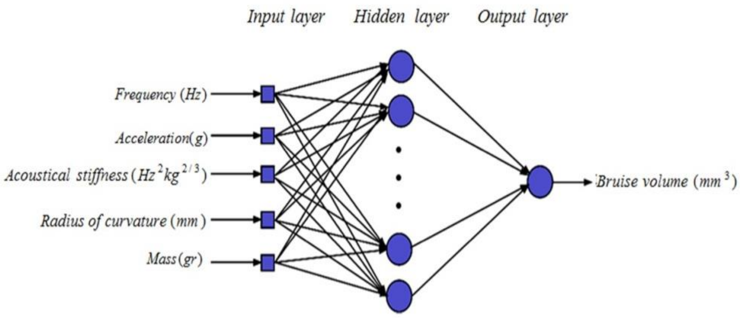

Fig 3. The schematic structure of Multi-Layer Perceptron Neural Networks model.

(Pa) and R the radius of curvature (m). From the equation, it can be seen that a large radius of curvature results in a lower peak contact stress and thus led to less bruise damage. This was confirmed by our results where small radius of curvature generally led to more bruise damage. Another equation based on Hertz theory derived by Siyami et al. (1988), shows an opposite effect of curvature radius on bruise volume. In this equation, it is assumed that the bruise surface area is similar to the contact area and is expressed based on the drop height as following:

$$BD = 4.624\left(\frac{mhR^2}{4F_{mt}}\right)^{1/5} \tag{11}$$

Where, BD is the bruise diameter (mm); m the mass of apple (kg); R the radius of curvature (m); h the drop height (mm) and F_{mt} the Magness–Taylor force (kg). This equation indicates that larger radius of curvature leads to a larger contact area and hence to a larger bruises volume. Therefore, it seems that the apple curvature radius can be a dual effect on the bruise damage, depending on severity of impact. At the low impact (low vibration amplitude), a small radius of curvature can increase the peak contact stress and increasing the amount of bruise, but in high impact contact area has dominant role. Horsfield et al. (1972) and Baritelle and Hyde (2001) concluded that a larger radius of curvature resulted in a lower impact-induced stress and thus increased a bruise threshold drop height. Van Zeebroeck et al. (2007) and Ahmadi et al. (2010) stated that at the low impact force, higher radius of curvature decreased bruise damage, but at the high impact, higher radius of curvature increased bruise damage.

Effect of acoustic stiffness

Apples with high acoustic stiffness led to more bruise damage than apples with lower acoustic stiffness. Measurement of fruit firmness is a proper manner to estimate bruising injury during harvest and postharvest transportation. According to Diezma et al. (2006); Wang et al. (2006) and Valero et al. (2007) acoustical stiffness mainly depends on the initial stiffness and correlates with Magness -Taylor firmness. While acoustical stiffness gives information about the texture of the whole fruit, Magness -Taylor firmness measurement describes only the local texture of the tissue at the penetration area. Acoustical Stiffness is mainly a measure of the mechanical stiffness of the fruit tissue that is related to the cell wall mechanical strength and cell wall turgidity (Zarifneshat *et al*., 2010). Previous studies indicated that the acoustical stiffness is positively associated to the modulus of elasticity (Duprat et al., 1997; Van Zeebroeck et al., 2006; Ahmadi et al., 2010). Therefore, reducing relative turgor (acoustic stiffness) can decrease tissue modulus of elasticity which in turn makes a specimen more self cushioning, by redistributing an applied force over a larger area of the fruit's surface, and reduces bruise volume. Also according to Baritelle and Hyde (2001) in apple and potato reduced stiffness results in the increase of failure strain (ε_f), as well as increasing tissue strength (σ_f). Therefore, according to Eq. 9 tissues that are both stronger and less stiff improve bruise threshold. In this study it was observed that increasing acoustic stiffness led to more bruise damage.

Prediction model (Artificial Neural Network)

In Fig 7 the decrease rate of error (RMSE) with increasing the number of neurons in the hidden layer is shown. As can be observed the performance of model was improved as the number of hidden neurons increased. But in this study the ANN architecture with 7 neurons in hidden layer was chosen as the best ANN architecture. Because, too many neurons in the hidden layer may cause over-fitting problems, which results in good network learning and data memorization, but lack the ability to generalize (Rohani et al., 2011). The amounts of correlation coefficient (R^2) with values of 0.9998 and 0.9996, in training and testing phases, revealed good agreement between predicted and actual values, and show that training of ANN was proper. Ahmadi et al. (2010) used statistical methods to estimate bruise volume. Their model that was built by regression method could predict bruise volume with a correlation coefficient of 0.97. But in this research by the use of artificial neural network technique,

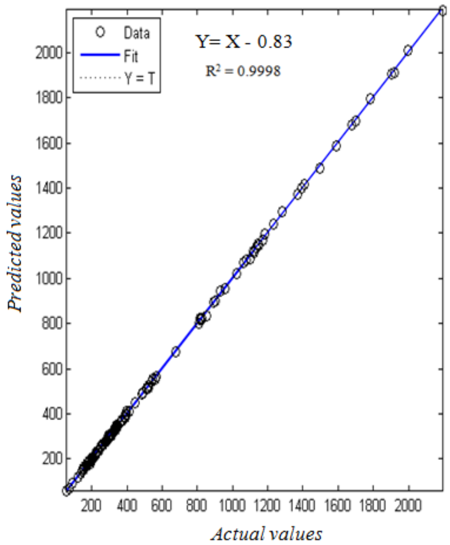

Fig 4. Correlation between actual and predicted values in training phase.

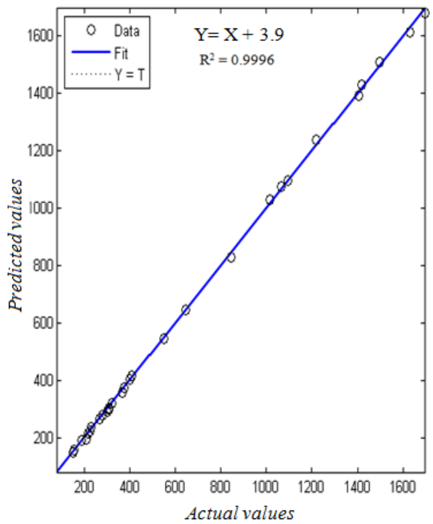

Fig 5. Correlation between actual and predicted values in testing phase.

Bruises volume could be predicted with a correlation coefficient (R^2) of 0.9996. This amount of R^2 indicated that neural network technique is more successful than statistical methods, in the application under consideration and could provide a practical solution to the problem of predicting apple bruise volume in transport condition. Also Zarifneshat et al. (2012) used artificial neural network technique and statistical methods to estimate bruise volume. Their models were built based upon impact force, impact energy, fruit curvature radius, temperature and acoustical stiffness as main independent variable. In their research bruise volume was predicted by ANN model and regression method with a correlation coefficient of 0.978 and 0.998, respectively. These results demonstrated the ability of the neural network and confirm the results obtained in our research. In our study, with using artificial neural network technique for modeling and the use of apple mass instead of fruit temperature in variables, bruise volume could be predicted with a correlation coefficient (R^2) of 0.9996, that is more accurate compared with Ahmadi et al. (2010) and Zarifneshat et al. (2012) results. The developed model in this study is an accurate model that unlike previous models, created directly upon the

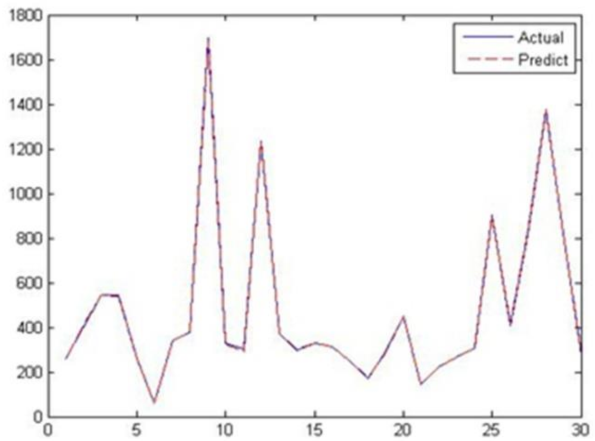

Fig 6. Comparison of actual data and the ANN prediction for bruise volume.

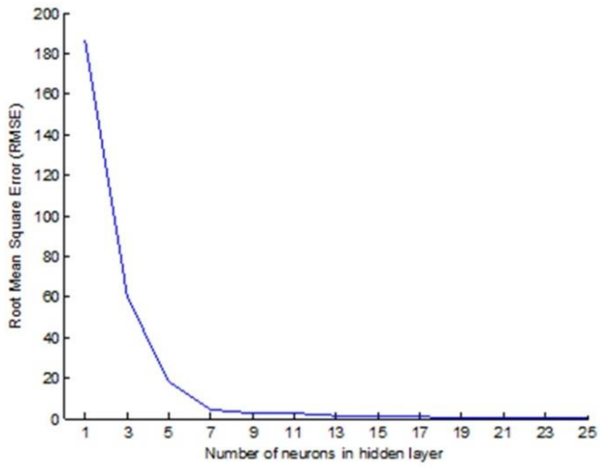

Fig 7. The decrease rate of root mean square error (RMSE) for different neurons.

road vibration parameters and can by linking to road and vehicle simulation programs, should used in research related to apple transporting damage. Also this model due to considering the effect of apple mass in bruise volume is better than previous models for transport condition.

Materials and methods

Experimental details

Variety of apple used in this study was the *Golden Delicious*. The apples were picked from the three marked and identified trees in the orchard in harvest season of 2011 from "Nazlo", Urmia region of Iran. Fruits after harvest immediately were transferred to cool storage and were stored at $3C^0$ and 85% relative humidity until being tested. Sample before the test were stored for 24 hours in the measuring room at 20 C^0. The bruise volume was used as the dependent variable and was calculated after 48 hours of damage, according to the following equation:

$$BV = \frac{\pi}{6} dD^2 \tag{1}$$

Where, *BV* is the bruise volume (mm^3); *d* the bruise depth (mm) and *D* the bruise diameter (mm). To provide vibration a laboratory vibration simulator was built and used, as the same vibrator used by Vursavus and Ozguven (2004) and Shahbazi et al. (2010) (Fig 1). This vibration simulator was consisted of a table on soft springs, and attached to it an actuating system that included adjustable weights on two counter rotating shafts (counterweights). The weights are revolving in opposite directions and about the center of gravity of the table. Their load only provides vertical vibration. Counterweights were powered by an electric motor (3.0 KW and 3000 rpm). The speed of the electric motor was adjusted by means of a speed control unit (inverter), which had a 4.0 KW power. Because the frequency of the vibration simulator table is directly related to the rotation number of the counterweights, therefore, by adjusting the speed of the electric motor the frequency of vibration simulator table was adjusted. Also by changing the value of magnitude and angular velocity of the rotating masses, the vertical displacement amplitude and acceleration of the vibration simulator table was adjusted. The acceleration was directly measured using an acceleration measurement device and a piezoelectric accelerometer.

Identification of significant parameters for selection of the model input variables

Due to the very importance of the vibration parameters and fruit properties in the effective forces on fruit and it's vulnerability, the effect of following parameters were investigated:

- Vibration frequency (F) (Hz)
- Acceleration (a) (g)
- Apple mass (m)(gr)
- Apple radius of curvature in location of impact (R)(mm)
- Apple acoustic stiffness (S)(Hz^2 $kg^{2/3}$)

The parameters that in transport condition have significant effect on apple damage were identified and were considered as independent variables in developing prediction model.

Vibration frequency and acceleration

According to the results from the vibration measurement by Shahbazi et al. (2010), the highest value of distribution percentages of vibration frequencies on the truck-beds during fruit transportation in Iran roads was 33.20%, on an interval of 5-10 Hz, and 30.17% on an interval of 10-15 Hz. The average values at intervals of 5-10 Hz and 10-15 Hz were 7.5 Hz and 13.01 Hz, respectively. Also the highest value of distribution percentages of vibration acceleration was 35.06%, on an interval of 0.25-0.50 g and 23.59% on an interval of 0.50-0.70 g. The average values at intervals of 0.25-0.50 g and 0.50-0.75 g were 0.31 g and 0.71 g, respectively. According to this report, three levels of frequency (with constant acceleration of 0.5g) and three levels of acceleration (with constant frequency of 10Hz) were used in evaluation effect of vibration parameters and apple properties (Table 1). But to develop the prediction model nine different combinations of these three levels were used.

To maintain constant acceleration and avoid the incorporation of the frequency and acceleration effects, with increasing or decreasing the vibration frequency, the vertical displacement amplitude of vibration table was adjusted. The relationship between vibration frequency, vibration acceleration and vertical displacement amplitude of vibration table is shown in the following equation:

$$\ddot{x} = -4\pi^2 f^2 X \quad (2)$$

Where, $\ddot{x}$ is the acceleration (g), *f* is the frequency (Hz) and *X* is the displacement amplitude. Due to supplant and tumble of fruits in the test with vibrator, in investigating the effects of vibration parameters and fruit properties, to increase the accuracy the results of the fruit bar was used. But for training ANN and developing prediction model, patterns obtained from the fruit boxes were used.

Apple mass

To investigate the effect of mass, the apples with mass of 100gr, 125gr and 155gr were used.

Radius of curvature

In this research to investigate the effect of curvature radius, the apples with curvature radius of 36 mm and 52 mm were used. Because a suitable device for measuring the radius of curvature (R) was not available, therefore, a non-commercial radius meter was used. This device was constructed on an analog height meter base (Fig 2a) and then the radius of curvature was calculated using the equation described by Mohsenin (1986) (Fig 2b).

$$RADIUS = \frac{(AC)^2}{8(BD)} + \frac{(BD)}{2} \quad (3)$$

Since apple cannot be considered completely spherical, the harmonic average ($2R_1 R_2 /(R_1 + R_2)$) was chosen based on circumferential (R_1) and meridian curvature Radius (R_2). Based on Hertz theory the use of harmonic mean is more acceptable than the computational mean, due to its accuracy on estimation of smaller curvature radius, which participate more to the maximum contact pressure.

Acoustic stiffness

To investigate the effect of acoustic stiffness, the apples with acoustic stiffness of 40 $kg^2/Hz^{2/3}$ and 55 $kg^2/Hz^{2/3}$ were used. For measuring the acoustical stiffness (S), acoustical impulse-response method was used. The fruits stimulated by a piece of wood on the equator and the sound signals at 180° from the impact place in a few millimeters off the apple were collected. By the microphone (ADMP401, Analog Devices) with a constant output response over the range of 100 to 10,000Hz, that was installed inside an isolated acoustic chamber to eliminate environmental noise effects. Detected sound signals after amplification were sent to a PC based data acquisition system. Signals were digitized at a sampling frequency of 44.1 kHz and were saved by using MATLAB 2011 data acquisition toolbox for subsequent analyses. By use of Fast Fourier Transform (FFT) the first resonance frequency was determined and the acoustical stiffness was calculated by following equation.

$$S = f^2 m^{2/3} \quad (4)$$

Where, *S* is the acoustic stiffness ($Hz^2\ kg^{2/3}$), *f* is the first resonance frequency (Hz) and *m* is the mass of the apple (kg).

Statistical analysis

A total of 620 apples were used for conducting the experiments. The data were processed by the statistical software package SAS version 9.1.3, where the significance level was set at 1% and 5%.

Developing prediction model (Artificial Neural Network)

In this study, fully interconnected multilayer perceptron (MLP) feed-forward network, which is the most widely used ANN for developing prediction model was used. This structure is easy to implement and any input/output map in this structure can be extracted. MLP as a multi-layer structure consists of an input layer with neurons representing input variables, an output layer with neuron representing the dependent variable and one or more hidden layers containing neuron to help capture the nonlinearity in the system. The method for training the MLP is based on the minimization of a suitable cost function. An MLP network is shown in Fig 3.
To ensure a successful modeling MLP two important factors should be considered, first the number of hidden layers and then the number of neurons in each hidden layer. Since almost all issues in neural network modeling could be solved with one hidden layer, therefore, in this research one hidden layer was used. The data were shuffled and split into two subsets: a training set and a test set. The splitting of samples plays an important role in the evaluation of an ANN performance. The training set is used to estimate model parameters and the test set is used to check the generalization ability of the model. The training set should be a representative of the whole population of input samples. In this study the training set and the test set includes 158 patterns (80% of total patterns) and 40 patterns (20% of total patterns), respectively. There is no acceptable generalized rule to determine the size of training data for a suitable training, however, the training sample should cover all spectrums of the data available (Rohani et al., 2011). Prior to any ANN training process with the trend free data, the data must be normalized over the range of [0, 1]. This is necessary for the neurons' transfer functions. If the data used with an ANN are not scaled to an appropriate range, the network will not converge on training or it will not produce accurate results. The most commonly employed method of normalization involves mapping the data linearly over a specified range, whereby each value of a variable x is transformed as follows:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times (r_{\max} - r_{\min}) + r_{\min} \quad (5)$$

Where x is the original data, x_n the normalized input or output values, x_{max} and x_{min}, are the maximum and minimum values of the concerned variable, respectively. r_{max} and r_{min} correspond to the desired values of the transformed variable range. A range of 0.1–0.9 is appropriate for the transformation of the variable onto the sensitive range of the sigmoid transfer function. To compare the performance of different ANN architectures two criteria was used, the root mean square error (RMSE) and correlation coefficient (R^2). Values of R^2 and RMSE were calculated using the following equations.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{pre,i} - y_{act,i})^2}{\sum_{i=1}^{n} (\bar{y}_{pre} - y_{act,i})^2} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_{acti} - y_{prei})^2}{N}} \quad (7)$$

Where y_{acti} is the ith actual value, y_{prei} the ith predicted value, $\overline{y}_{pre}$ the average of predicted values and N the number of data. The best ANN architecture was selected based on the highest value of the correlation coefficient (R^2) and the lowest values of RMSE. Vibration frequency, vibration acceleration, apple mass, curvature radius and acoustical stiffness were used as inputs, and bruise volume was considered as output (Fig 3). The neural network toolbox of *MATLAB R2011b* software was used for ANN design.

Conclusion

In this research artificial neural network (ANN) was used to develop a prediction model that can predict the apple bruise volume in transport condition. For reaching this purpose the first step was the selection of input variables. The effect of vibration frequency, vibration acceleration, apple mass, curvature radius and acoustic stiffness on bruise damage of apples in transport condition investigated and significant factors were considered as inputs to the neural network. It is found that neural network is more successful in the application under consideration and could provide a practical solution to the problem of predicting apple bruise volume, in a fast, inexpensive, yet accurate and objective way. We hope that the analysis conducted in this article can provide reference for the choice of ANN in such area. Finally the following conclusions are drawn: (1) The effects of vibration parameters and apple mass at 1% probability level and the effect of curvature radius and acoustical stiffness at 5% probability level were significant on bruising of apple in transport condition. (2) The ANN results were quite satisfactory, yielding R^2 values close to one, while root mean square errors (RMSE) were found to be very low. (3) The final selected model, 5-7-1 (5 neurons in input layer, 7 neurons in the hidden layer and 1 neurons in the output layer) demonstrated that it learned the relationship between the input and output parameters.

References

Ahmadi E, Ghassemzadeh HR, Sadeghi M, Moghaddam M, Zarif Neshat S (2010) The effect of impact and fruit properties on the bruising of peach. J Food Eng. 97:110-117.

Baritelle AL, Hyde GM (2001) Commodity conditioning to reduce impact bruising. Post Biol and Tech. 21(3): 331-339.

Diezma B, Valero C, Garcia-Ramos FJ, Ruiz-Altisent M (2006) Monitoring of firmness evolution of peaches during storage by combining acoustic and impact methods. J Food Eng. 77: 926–935.

Duprat F, Grotte M, Pietri E, Loonis D (1997) The acoustic impulse response method for measuring the overall firmness of fruit. J Agri Eng Res. 66: 251–25.

Fathi M, Mohebbi M, Razavi SMA (2011) Application of Image Analysis and Artificial Neural Network to Predict Mass Transfer Kinetics and Color Changes of Osmotically Dehydrated Kiwifruit. Food Bio Tech. 4:1357-1366.

Horsfield BC, Fridley RB, Claypool LL (1972) Application of theory and elasticity to the design of fruit harvesting and handling equipment for minimum bruising. Trans ASAE. 15: 746 –750.

Johnson DS, Dover CJ (1990) Factors influencing the bruise susceptibility of Bramley's seedling apples. International conference on agricultural mechanization, Zaragoza, Spain. pp: 87– 93.

Knee M, Miller AR (2002) Fruit Quality and its Biological Basis, Mechanical injury. In: Knee M (Ed.). Sheffield Academic press, Sheffield, pp: 157–179.

Landahl S, Herppich WB, Herold B, Geyer M, De Baerdemaeker J (2004) A comprehensive evaluation of the interactions between produce elasticity and water status. Eur J Horti Sci. 69: 250–257.

Mohsenin NN (1986) Physical Factors of Plant and Animal Materials. Gordon and Breach Science Publishers, New York.

Motevali A, Abbaszadeh A, Najafi GH, Minaei S, Ghobadian B (2012) Drying of jujube (Zizyphus jujube mill) fruit: comparison of prediction from mathematical models and artificial neural networks. Aust J Crop Sci. 6(2): 210-218.

Rohani A, Abbaspour-Fard MH, Abdolahpour SH (2011) Prediction of tractor repair and maintenance costs using Artificial Neural Network. Expert Sys with Appl. 38: 8999–9007.

Shahbazi F, Rajabipour A, Mohtasebi S, Rafie Sh (2010) Simulated In-transit Vibration Damage to Watermelons. J Agr Sci and Tech. 12: 23-34.

Siyami S, Brown GK, Burgess GJ, Gerrish JB, Tennes BR, Burton CL, Zapp RH (1988) Apple impact bruise prediction models. Trans ASAE. 31: 1038–1046.

Studman CJ, Brown GK, Timm EJ, Schulte NL, Vreede MJ (1997) Bruising on blush and non-blush sides in apple-to-apple impacts. Trans ASAE. 40(6): 1655-1663.

Timm EJ, Bollen AF, Dela Rue BT, Woodhead IM (1998) Apple damage and compressive forces in bulk bins during orchard transport. Appl Eng Agri. 14: 165–172.

Valero C, Crisosto CH, Slaughter D (2007) Relationship between nondestructive firmness measurements and commercially important ripening fruit stages for peaches, nectarines and plums. Post Biol Tech. 44: 248–253.

Van Zeebroeck M, Tijskens E, Dintwa E, Kafashan J, Loodts J, De Baerdemaeker J, Ramon H (2006) The discrete element method (DEM) to simulate fruit impact damage during transport and handling: Case study of vibration damage during apple bulk transport. Post Biol Tech. 41: 92-100.

Van Zeebroeck M, Van Linden V, Darius P, De Ketelaere B, Ramon H (2007) The effect of fruit factors on the bruise susceptibility of apples. Post Biol Tech. 46: 10-19.

Vergano PJ, Testin RF, Newall WC (1991) Peach Bruising: Susceptibility to Impact, Vibration, and Compression Abuse. Trans ASAE. 34: 2110–2116.

Vursavus K, Özgüven F (2004) Determining the effects of vibration parameters and packaging method on mechanical damage in golden delicious apple variety. Turk J Agri Forestry. 28: 311-320.

Wang J, Teng B, Yu Y (2006) The firmness detection by excitation dynamic characteristics for peach. Food Control. 17(5): 353–358.

Zarifneshat S, Rohani A, Ghassemzadeh HR, Sadeghi M, Ahmadi E, Javadi A, Zarifneshat M (2012) Prediction of apple bruise volume using artificial neural network. Comp Elec Agri. 82: 75-86.

Zarifneshat S, Ghassemzadeh HR, Sadeghi M, Abbaspour-Fard MH, Ahmadi E, Javadi A, Shervani-Tabar MT (2010) Effect of Impact Level and Fruit Properties on Golden Delicious Apple Bruising. Amer J Agri Biol Sci. 5 (2): 114-121.