

Study on Firmness and texture changes of pear fruit when loading different forces and stored at different periods using artificial neural network

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Received: 2018.09.30 Accepted: 2019.05.06

Abstract

This study evaluated the effect of different dynamic and static loadings and different storage periods on the firmness of pear fruit. Pear fruit was first segregated into three groups of 27 pear in order to undergo three loadings: static thinedge compression loading, static wide-edge compression loading and dynamic loading. All loaded pears were stored in accordance with three storage period designs: 5-day storage, 10-day storage, and 15-day storage. Following each period, the variations of pear texture were scanned by using the CT-Scan technique as a non-destructive test. Then, the firmness of pear texture was measured using a penetrometer. Data were simulated and evaluated using MLP and RBF artificial neural networks. The results showed that with increasing storage time and loading force , the firmness significantly decreased (1% level) in all three types of loading, In addition, pear texture was destructed under dynamic compression loading in order to compare with other two loadings. Best value artificial neural network for wide edge loading (12 neuron-RBF) was (R² Wide edge= 0.9738–RMSE Wide edge= 0.170977- MAE Wide edge = 0.268) and for thin edge loading (4 neuron-RBF) was (R² _{Dynamic loading} = 0.9946– RMSE _{Thin edge} = 0.170977- MAE _{Thin edge} = 0.133), also for dynamic loading (8 neuron-RBF) was (R² _{Dynamic loading} = 0.9933– RMSE _{Dynamic loading} = 0.230- MAE _{Dynamic loading} = 0.187).

Keywords: Artificial Neural Network, Firmness, Loading Pear, Storage.

Introduction

Pear fruit is cultivated in more than 70 countries across the world. When pear matures, it becomes a fruit with a buttery texture. The dense texture of pear is dependent on the specifications of its cells and in turn, depend on different factors including cell size, cell wall thickness and strength and the water content. Generally, consumers assess a fruit texture by chewing and hand touching and these are important factors in buying fruits and evaluate the sweetness, freshness, and maturity of fruits. Therefore, the texture is a key factor of quality and is widely used as a measure to assess and accept the quality of products in fresh and recycled food industries (Yan et al., 2018)(W. Zhang et al., 2014). Today, fruits play an important role in human health as they carry a considerable content of biological compounds with physiological and biochemical functions (Tavarini et al., 2008). On the other hand, the increased demand for high-quality fruits in developed countries is an important challenge.

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Therefore, different non-destructive techniques are used to assess fruits quality (Khalifa et al., 2011). Fruit firmness is an important qualitative variable. It is the indirect measurement of maturity so that suitable storage intervals and ideal transportation conditions can be predicted by the accurate evaluation of this factor (Zhang et al., 2018, Mirzaee et al., 2009). Today, many inspections are carried out in commercial markets to assess fruits quality in order to determine whether they are high-quality fruits. Firmness is an important factor. Fruit softness is the most prevalent drawback that wastes fruits (Moggia et al., 2016). Mechanical and shear damages are among factors affecting the qualitative and chemical properties of fruits and result in bruised fruits. The measurement of fruit firmness is an important factor by which this drawback can be predicted and avoided (Mazidi et al., 2016). The mathematical models of predictions face different limitations including the selection of parameters and applying defaults for solving equations.

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Artificial neural network addresses mathematical methods and can process software and hardware structures and models (Leśniak and Juszczyk, 2018). Neural networks are used in different sectors such as prediction, approximation, control. communication. classification, pattern identification and data sorting (Leśniak and Juszczyk, 2018; Read et al., 2017). Different studies have been conducted by different researchers on the impact of loading and storage period on fruits firmness.

Moggia et al. (2017) studied the firmness and internal browning of blueberries induced by mechanical damages and compared them with undamaged blueberries. Their results showed that blueberries with lower firmness have higher internal damages. They concluded that during the storage period, the percent of total soluble solids, the acidity of the fruit and fruit firmness can be used to estimate the harvesting time and storage potential of fruits (Moggia et al., 2017). Mazidi et al. (2016) evaluated mechanical damages of oranges and their firmness variations during the packing process. They showed that damaged fruits showed a 9% change in firmness compared to control group. However, statistical analysis showed that this effect is not significant (Mazidi et al., 2016). Montero et al. (2009) evaluated the effect of impact loading on two orange types. They reported that impact has no effect on the appearance and firmness of oranges and the imposed damage reduced the sweetness as well as vitamin C content of the oranges (Montero et al., 2009). Afsharnia et al. (2017) studied the effect of dynamic loading on the scratch and tear of mulberry. They reported that dynamic damages and storage decrease the firmness of mulberry (Afsharnia et al., 2017). Jahangiri et al. (2016) conducted a test on the effect of storage on the mechanical properties of viola cucumber under compressive loading. Their results showed that the firmness of this fruit reduced by 49% during storage compared to its initial state (Jahangiri et al., 2016).

Since the different forces generated during transportation, handling, and harvesting processes, definitely affected the texture of fruits and decrease their firmness. The aim of this study was to evaluate the firmness and texture of pear fruit under static and dynamic loadings in order to assess the variations of firmness and texture during storage as both factors affecting storage period and result in the degradation and wastage of fruits. In addition, this study evaluated and simulated data and calculated the sensitivity factor for different loadings.

Materials and Methods Sample Preparation

Pears (Spadana variety) was prepared from the markets of Gorgan, Golestan province, Iran.. They were placed in an oven at 103°C for 16 hours and their moisture content was measured. The moisture content of the pears was calculated to be 77.92% (w.b %). Environmental conditions for testing were conducted at a temperature of 18°C and relative humidity of 72%.

Quasi-Static test

To perform the wide and thin edge compression mechanical test, a pressuredeformation device (the Santam Inestrone -STM5-Made in Iran) with a load cell of 500 N was used. The compression test was performed at a speed of 5 mm/s with three forces of 70, 100, and 130 N and three replications. In this experiment, the pear was horizontally placed between the two plates and pressed, with the duration of the measurement recorded. Concerning thin edge compression test, we designed a double-jaw of plastic with a rectangular cross-section dimension of 0.3×1.5 cm. The test was performed at a speed of 5 mm/s with three forces of 15, 20, and 25 N and three replications (Fig. 1).

Impact Test

First, the pendulum and the required masses were made in a workshop in Gorgan Biosystem Mechanics Group (Fig. 2). The fruits were placed in the desired position and then the device arm was raised to the desired angle (90°), and in the controlled state of the arm impact the pear. The pendulum had a 200 g arm and three different attachment masses of 100, 150, and 200 g for knocking. It should be noted that air resistance and friction were neglected through this procedure.

Imaging via CT scan method

After the quasi-static and dynamic loading and 5, 10, and 15 days storage, each pear was scanned with the Siemens Compute Tomography (CT) Scans of the SOMATOM Emotion 16-slice model, made in Germany. This device is a third-generation CT device in which the tube and detector are placed opposite to each other 360° around the pears in a series of turns to create the image. Also, the pitch was locked for the test; i.e., pitch 1. Images were recorded at 80 kV and 120 mAh current, and 1 mm slices were used to create full images. The images created by the Syngo CT 2012 software were recorded and extracted in the form of twodimensional and gravscale images. Convolution kernel, which shows image resolution level, was B31Smooth and the images were created by 512×512 matrixes. The interval between bruises and imaging was applied to allow bruises to reduce their moisture content and be better fixed on the fruit. Such a difference in moisture can increase the absorption of X-rays between healthy and unhealthy texture (Diels et al., 2017).

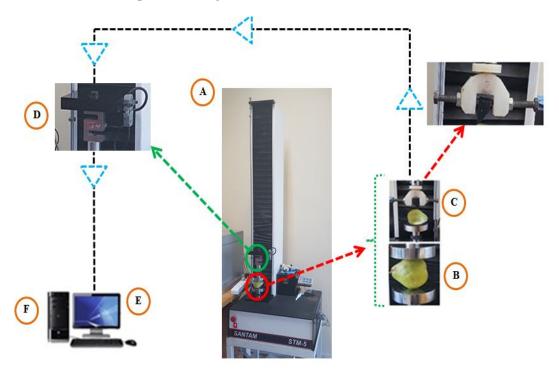


Fig. 1. Static quasi-load diagram of pear A: The force-deformation device (Inestrone), B: Jaw wide edges, C: Jaw thin edges D: Load Cell, E: Computer, F: Information Extract.

Evidence (Control) Treatments

Four evidence (Control) pear groups were firstly taken into account for the investigation and comparison of the experimental data obtained for pear firmness. The firmness of pear texture was then measured using a penetrometer (Effeg FT327- Made in Italy with a diameter of 8 mm). The first evidence group was called zeroth day and its pear firmness was measured on the first day, on the day before being subjected to the specified loads and on the day before being stored. Then, besides measuring the firmness of each of the pears subjected to loads, the firmness of the evidence pears that had only been stored was evaluated during each specified periods. The evidence pears were labeled 5-day, 10-day, and 15-day evidence pears, respectively.

Statistical Analysis

Samples were stored for 5, 10, and 15 days after quasi-static and dynamic loading, pear

firmness was measured. All experiments were performed in three replications and the results were analyzed using a factorial experiment in a completely randomized design with SAS statistical software.

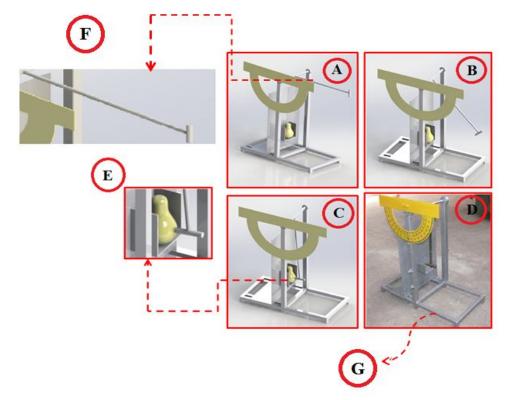


Fig. 2. Schematic of the impact machine.

A: Pendulum at a 90-degree angle, B: Walking along the path, C: Collapse pendulum to pear, D: Main device profile, E: Place the pear, F: Pendulum blow, G: the base of the device.

Artificial Neural Network Modeling

In this research, the artificial multilayer perceptron (MLP) and radial basis function (RBF) neural network were used for modeling the examined pear firmness during storage and different loading by two hidden layer and 4, 8, and 12 neurons using the Neuro Solution 5 software. Hyperbolic tangent activation functions (Eq. 1), which are the most common type of activation functions, were used in the hidden input and output layer. In this study, the Levenberg- Marquardt algorithm was used to learn the network(Taheri Garavand et al., 2018). Additionally, 80% of the data were used

for training, and 20% of the data were used for testing the network (Testing data) (Table 2). The loading value and storage time as network inputs and firmness was the considered network outputs. Five replications were considered to achieve the minimum error rate and maximum network stability as a mean of 4000 Epoch for the network. The error was estimated using an algorithm with back propagation error. Statistical parameters including, Root Mean Square Error (RMSE), R², and Mean Absolute Error (MAE) were calculated for inputs and relationships were calculated using the formulas shown in Table 1.

Table 1. Neural Network Relationships					
Formula	Formula Number	Reference			

$Tanh = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$	(1)	(Soleimanzadeh et al., 2015)
$R^{2} = 1 - \frac{\sum_{i=1}^{n} (P_{i} - O_{i})^{2}}{(P_{i} - O)^{2}}$	(2)	(Azadbakht et al., 2016)
$r = \sqrt{1 - \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{(P_i - O)^2}}$	(3)	(Salehi and Razavi 2012)
$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n}}$	(4)	(Khoshnevisan et al., 2013)
$MAE = \frac{\sum_{i=1}^{n} P_i - O_i }{n}$	(5)	(Azadbakht et al., 2017)

Equations 2, 3, 4 and 5 include the predicted values (Pi) and the actual values (Oi) and the mean value of data (O).

	Table2. Optimization values for artificial neural network parameters							
	Number of	Learning rule	Type of activation	The number of hidden	Testing	Training		
	hidden layers	Learning rule	function	layer neurons	data %	data %		
MLP	2	Levenberg Marquardt	Hyperbolic tangent	4,8,12	20%	80%		
RBF	2	Levenberg Marquardt	Hyperbolic tangent	4,8,12	20%	80%		

Results and Discussion

Table 3 presents an analysis of variance (ANOVA) results for the effect of loading force (Wide and Thin edge– dynamic Loading) and storage period on pear firmness. According to the Table (3), all loading forces and storage periods had significant effects at 1% level on pear firmness. Moreover, considering the results, the interaction of loading force (thin edge and dynamic loading) and storage period

on the pear firmness at 5% level and the insignificance of interaction was evidenced for wide edge loading. In addition, considering the significance of the interaction of pear firmness for thin-edge and dynamic loading, mean comparisons were made using the least significant difference (LSD) test the results of which have been illustrated in Figures (3) and (9).

 Table 3. Analysis of variance (ANOVA) results for the effect of loading force (Wide and Thin edge-dynamic loading) and storage period on pear firmness

	loading) and storage period on pear infiliness							
	Variables	DF	Mean Squares	F value				
Thin edge	Storage	2	32.7600	563.39**				
hin lge	Loading	2	5.0011	86.01**				
_	Storage× Loading	4	0.1877	3.23*				
	Error	18	0.0581					
Wi Lo	Storage	2	18.1417	97.62**				
Wide ed Loading	Loading	2	7.1095	38.26**				
	Storage× Loading	4	0.1678	0.90 ^{ns}				
ge	Error	18	0.185					
Dy Lo	Storage	2	38.6233	327.93**				
Dynamic Loading	Loading	2	13.9511	118.45^{**}				
	Storage× Loading	4	0.4194	3.56*				
0	Error	18	0.117					

** Significant at level 1%, * Significant at 5% level, ns insignificant

Static Loading

Thin-edge compression loading

Fig. 3 shows the interaction of storage× loading on the firmness of fruits during thinedge compression loading. According to the obtained results, firmness decreases as the loading and storage period increase. Fig. 3 shows that within 5 day storage, this effect was not significant compared to the 5 day storage of the control group but, as the storage period increases, the firmness of pear fruits decreases. The maximum firmness was obtained in pears underwent 15 N compression loading and stored for 5 days (11.03 N) while the minimum one was obtained in pears underwent 25 N compression loading and stored for 15 days (5.8 N). Fig. 4 shows the destruction of the texture of the studied pear during storage. According to Figure 4, the density of texture decreases during storage. One reason may be the degradation of

the healthy texture of fruit whereas loading force increases, the internal damages increase and this, in turn, decreases the firmness of pears and changes their texture. Our results are comparable with the results of Moggial *et al.* (2017) for blueberries (Moggia *et al.*, 2017).

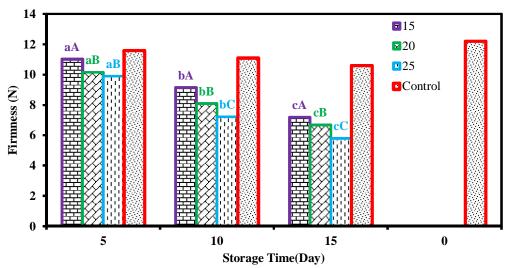


Fig. 3. Interaction effect of loading force during storage period on pear firmness at thin edge pressure Lower cases stand for the no significance of the loading force while capital letters stand for the significance of storage period

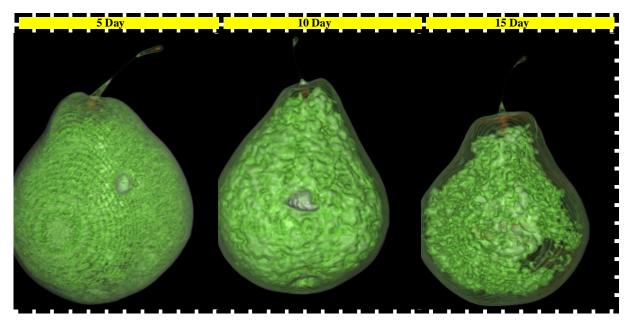


Fig. 4. Extraction images of fruit tissue, by CT in Thin edge Loading

Figures 5 and 6 show firmness reduction in pear fruits under the loading force and storage

periods compared to the pears of the control group on day 0 and in each storage period,

respectively. Both comparisons show that firmness reduction (compared to control pears in each period and control pears of day 0) increases in each storage period. The maximum reduction compared to control pears of day 0 is 60.37%, which corresponds to the 15-day storage and loading force 25N. For the same storage period and loading force, this reduction was 52.45% compared to control group pears stored for 15 days. On the other hand, the minimum firmness reduction belongs to loading force 15N and 5-day storage period where the firmness reduced by 9.59% compared to the control pears of day 0 while for the same period and loading force, firmness reduction compared to the control pears stored for 5 days was only 0.63%. This indicates that in negligible loading forces and in short-term storage periods, firmness reduction was not significant compared to control.

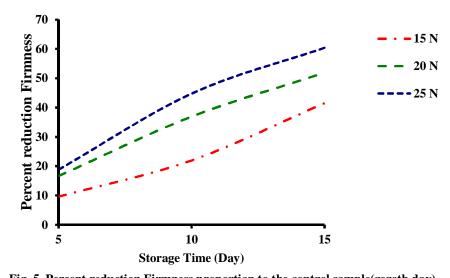


Fig. 5. Percent reduction Firmness proportion to the control sample(zeroth day)

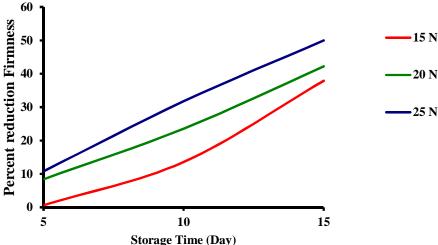


Fig. 6. Percent reduction Firmness proportion to the control sample for each storage period

Table 1 shows the effect of storage and wide-edge compressive force on pear firmness. Fig. 7 shows firmness reduction during the

Wide-edge compression loading

storage period and under loading forces compared to control pears in each storage period. According to fig. 7, as storage period and loading force increase, firmness decreases. Within the 5-day storage period, the effect of storage on firmness reduction was higher than that of the loading force. However, by the lapse of time, firmness was more affected by loading force than storage. Fig. 8 shows the variations of pear texture during wide-edge compression loading at different storage periods. Storage matures pears. This, in turn, changes the type of cell wall texture and breaks its beneficial enzymes. Moreover, the increased loading force increases the enzyme activities of cell walls. This, in turn, reduces firmness during the storage period. Our results are comparable with the reports of Jahangiri *et al.* (2016) about the viola cucumber under loading (Jahangiri *et al.*, 2016).

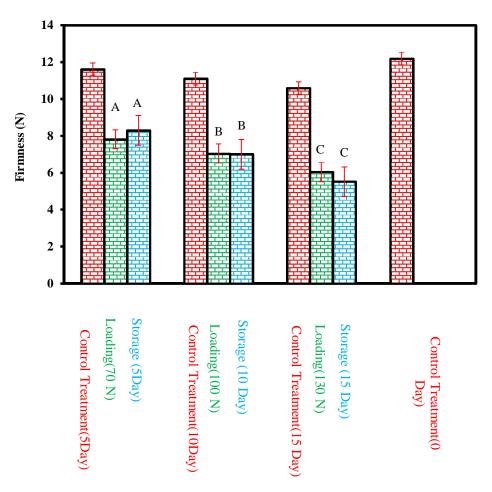


Fig. 7. Effect of loading force in storage period on pear firmness at wide edge pressure



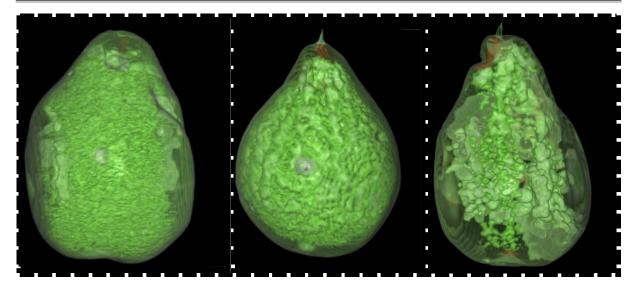


Fig. 8. Extraction images of fruit tissue, by CT in Wide edge loading

Dynamic Loading

Fig. 9 shows the interaction of storage \times loading on the firmness of fruits during dynamic loading. According to the obtained results, firmness decreases as the loading and storage period increase. The maximum firmness was obtained in pears underwent Weight of 300 grams and stored for 5 days (9.2 N) while the minimum one was obtained in pears underwent Weight of 400 grams and stored for 15 days (2.43 N). According to the results, as the number of loading weights increases, the magnitude of impact increases. This increases the energy absorption of pear fruits and, in turn, damages cell wall and scratches the external texture of fruits. On the other hand, this impact increases the phenolic activity of fruits and, in turn, bruises pears disrupts the functions of the structural cells and reduces firmness. Fig. 10 shows the variation of pears texture during storage where the effect of impact after storing for 15 days is shown. Our results are comparable with the results of Afsharnia et al. (2017) for mulberry (Afsharnia et al., 2017).

Figures 11 and 12 show firmness reduction in pear fruits under the impacts of loading force

and storage periods compared to the pears of the control group on day 0 and in each storage period, respectively. Both comparisons show that firmness reduction (compared to control pears in each period and control pears of day 0) increases in each storage period. The maximum reduction compared to control pears of day 0 was 92.17%, which corresponds to the 15-day storage and Weight of 400 grams. For the same storage period and loading force, this reduction was 79.02% compared to control group pears stored for 15 days. On the other hand, the minimum firmness reduction belongs to loading force with Weight of 300 grams and 5day storage period where the firmness reduced by 24.54% compared to the control pears of day 0, while for the same period and loading force, firmness reduction compared to the control pears stored for 5 days was only 17.11%. This indicates that in negligible loading forces and in short-term storage periods, firmness reduction was not significant compared to control pears. Percent reduction Firmness indicated high destruction of the internal tissue and decreased firmness of the fruit due to loading weights and storage period.

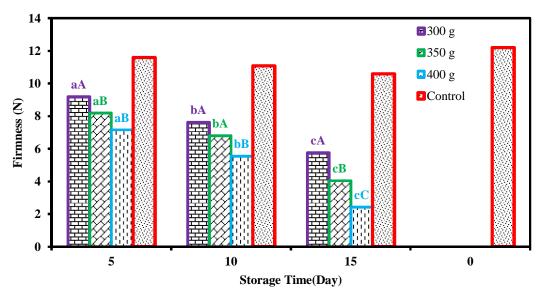


Fig. 9. Interaction effect of loading force during the storage period on pear firmness at dynamic loading Lower cases stand for the no significance of the loading force while capital letters stand for the significance of storage period

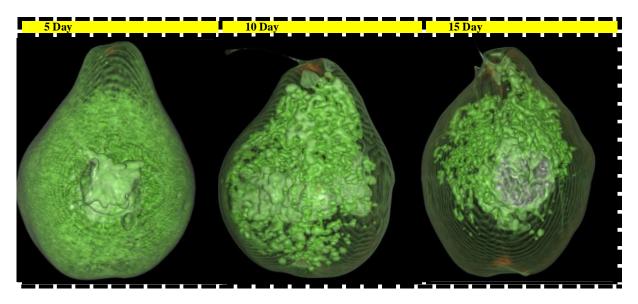


Fig. 10. Extraction images of fruit tissue, by CT in dynamic loading

Artificial Neural Network

The quasi-static results showed for error values for the quasi-static (thin and wide edge) and dynamic loading in predicting experimental data using the optimal artificial neural network in Table 4. Also some of the best MLP and RBF neural network topologies to predict training values presented in Table 4.

Table 5 shows the best network between input data and data simulated by the network for each of the neurons in the hidden layer. The lower value of Epoch indicates that the number of neurons in the layer has been able to have learned from the neural network compared to another number of neurons. The results for thin edge Loading showed that neural network has 4 neurons in the hidden layer and RBF network for firmness ($R^{2}_{Thin edge}$ = 0.9946– RMSE _{Thin edge} =0.170977- MAE _{Thin edge} =0.133) can predict firmness in different loading and storage time (Table 4). In addition,

the neural network with 12 neurons in the hidden layer and RBF network has the best neural network topologies to predict training (Run= 1, Epoch= 11). Also, according to the results, the RBF network is faster than the MLP (Table 5).

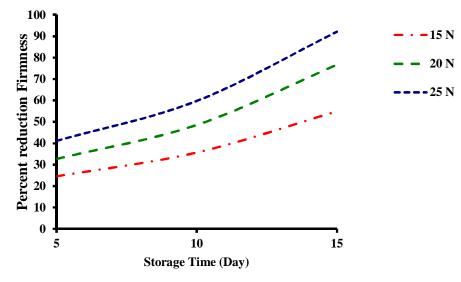


Fig. 11. Percent reduction Firmness proportion to the control sample(zeroth day)

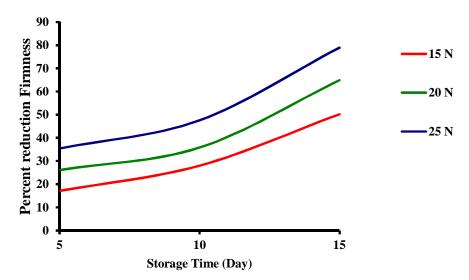


Fig. 12. Percent reduction Firmness proportion to the control sample for each storage period

	experimental data using optimal artificial neural network									
	Netw ork	Neuron	MSE		RMSE		MAE		\mathbb{R}^2	
TI	k tw	number	Training	Test	Training	Test	Training	Test	Training	Test
Thin		4	0.120	0.115	0.3464	0.3391	0.30658	0.273	0.9907	0.987
edge	MLP	8	0.02931	0.134	0.17129	0.3660	0.13786	0.317	0.9942	0.986
9 0		12	0.0335	0.0765	0.18303	0.2765	0.13787	0.23	0.9937	0.990
Loading		4	0.02924	0.133	0.17099	0.3646	0.1333	0.3	0.9946	0.977
adi	RBF	8	0.0399	0.0485	0.19975	0.2202	0.15909	0.18	0.99305	0.997
ng		12	0.036	0.058	0.18973	0.2408	0.1575	0.19	0.99307	0.993
		4	0.1177	0.2786	0.34307	0.5278	0.2717	0.472	0.9675	0.9618
LA	MLP	8	0.12	0.231	0.34641	0.4806	0.2810	0.365	0.9732	0.9873
ide 0a		12	0.440	0.421	0.66332	0.6488	0.515	0.59	0.874	0.986
Wide edge Loading		4	0.1363	0.103	0.36918	0.3209	0.306	0.23	0.967	0.9872
a ia	RBF	8	0.1380	0.0926	0.37148	0.3043	0.297	0.245	0.9621	0.9948
		12	0.1169	0.3800	0.34190	0.6164	0.268	0.480	0.9738	0.04
Dy		4	0.085	0.375	0.29154	0.6123	0.253	0.21	0.98953	0.958
Dynamic	MLP	8	0.0687	0.1645	0.26210	0.4055	0.2166	0.37	0.99100	0.8771
		12	0.0554	0.3820	0.23537	0.6180	0.1939	0.199	0.9919	0.9821
		4	0.0771	0.134	0.27766	0.3660	0.225	0.269	0.9912	0.9744
yad	RBF	8	0.05318	0.071	0.23060	0.2664	0.187	0.18	0.9933	0.996
Loading		12	0.085	0.074	0.29154	0.2720	0.251	0.58	0.9887	0.9911

Table 4. Error values for the quasi-static (thin and wide edge) and dynamic loading in predicting experimental data using optimal artificial neural network

Table 5. Some of the best MLP and RBF neural network topologies to predict training values

	Activation function	Neuron Numbers	Run	Epoch
	MLP Netw k	4	2	26
Ξ	MLP Networ k	8	1	13
Thin edge Loading		12	1	16
ed	RBF Networ k	4	1	17
ad ad	two	8	1	15
		12	1	11
	MLP Networ k	4	1	16
LÅ	P	8	1	18
Wide edge Loading		12	1	19
lin ed	RBF Networ k	4	2	15
19 19 19	F	8	1	10
	ř	12	1	9
Dy	Ne	4	2	14
na	, P	8	1	10
mic	irk	12	1	11
Dynamic Loading	ALP RBF Vetwork Network	4	1	15
adi	two ^F	8	1	11
ing	ork	12	1	11

For wide edge showed best values in neural network is 12 neuron in the hidden layer and RBF network for firmness (R^2 wide edge = 0.9738- RMSE wide edge = 0.3419- MAE wide edge = 0.268) and the neural network with 12

neurons in the hidden layer and RBF network has best neural network topologies to predict training (Run= 1, Epoch= 9)

For dynamic loading best value was shown in the hidden layer by 8 neurons and RBF network (R^2 _{Dynamic loading} = 0.9933– RMSE _{Dynamic loading}= 0.230- MAE _{Dynamic loading}= 0.187). Best neural network topologies to predict training was in hidden layer with 8 neurons and MLP network

Also, Figures (13, 14 and 15) illustrate the output amounts between the real and predicted data. Based on the figures, it can be observed that the neural network well capable of predicting and comparing the given numbers and it can be stated considering the closeness and similarity of the numbers outputted from

the ANN to the real data that the neural network possesses an appropriate competency for data prediction. Moreover, considering the R^2 value, the RBF network has the best overlap with the experimental data for all loading. For thin edge loading was showed the best overlap in a hidden layer by 4 neurons for training data (Fig. 13).

Figure 14 showed the best overlap for wide edge loading and the best overlap between experiments data with network output is in the hidden layer by 12 neurons.

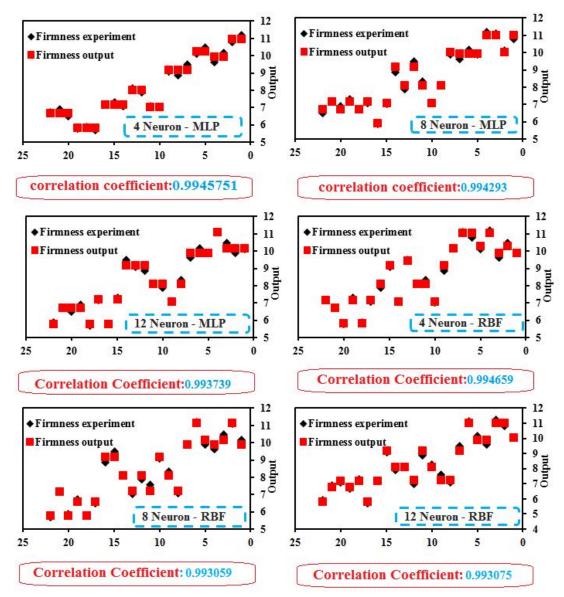


Fig. 13. Compare experiment data with network output data for thin edge loading

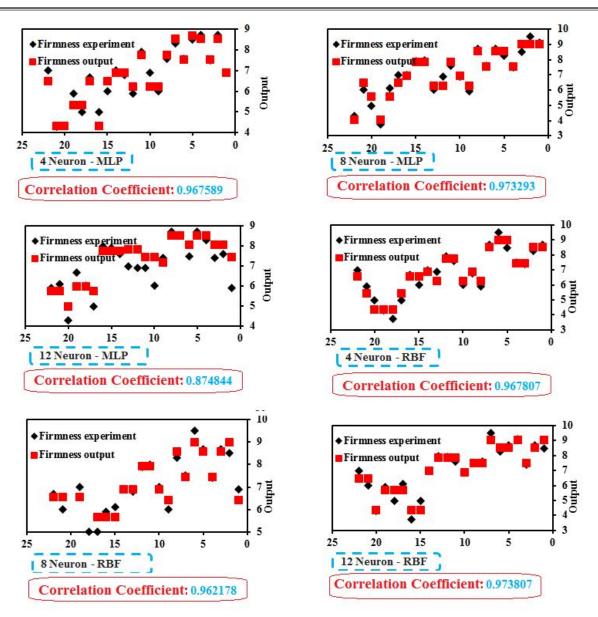


Fig. 14. Compare experiment data with network output data for wide edge loading

Figure 15 showed the best overlap for dynamic loading and the best overlap between experiment data with network output is in the hidden layer by 8 neurons.

Sensitivity Coefficient for quasi-static (Wide and thin edge)

The results of the sensitivity analysis for firmness (Wide and thin edge) are shown in Figure 16. Based on this figure, the highest sensitivity for training data was obtained for the loading in hidden layer by 4 neuron (Thin edge loading) and 8 neuron (Wide edge loading) with RBF Network and for storage time in the hidden layers with 4 neuron and RBF Network (Thin edge loading) and 8 neuron in hidden layer and MLP Network (Wide edge loading) (Figure 16).

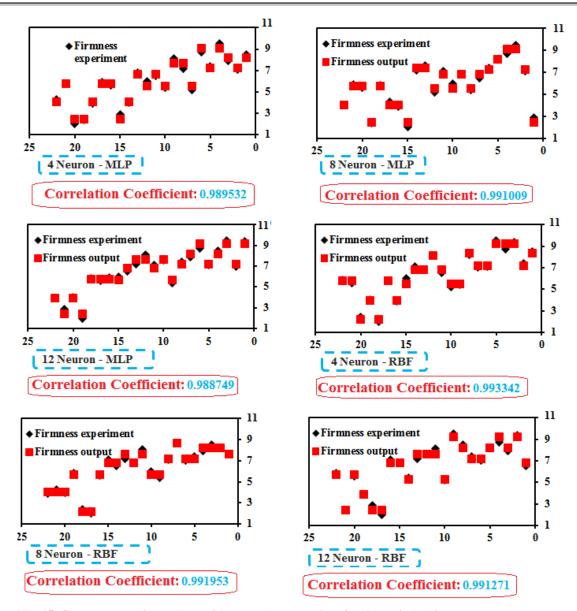


Fig. 15. Compare experiment data with network output data for dynamic loading

The lowest sensitivity analysis for firmness (Wide and thin edge) are shownin Figure 16. According to the figure for a thin edge, loading had lowest value for firmness in a hidden layer by 8neuron and RBF network for loading and for storage in a hidden layer by 4 neurons and MLP Network. For the wide edge, loading was obtained for loading and storage in the hidden layers with 12 neurons by MLP Network. The result for Test Data showed that highest sensitivity for a thin and wide edge in hidden layer 12 neuron and RBF and MLP Network for loading respectively and in storage time for thin and wide edge loading had lowest firmness in a hidden layer by 4 neurons and MLP Network and 12 neurons and RBF Network.

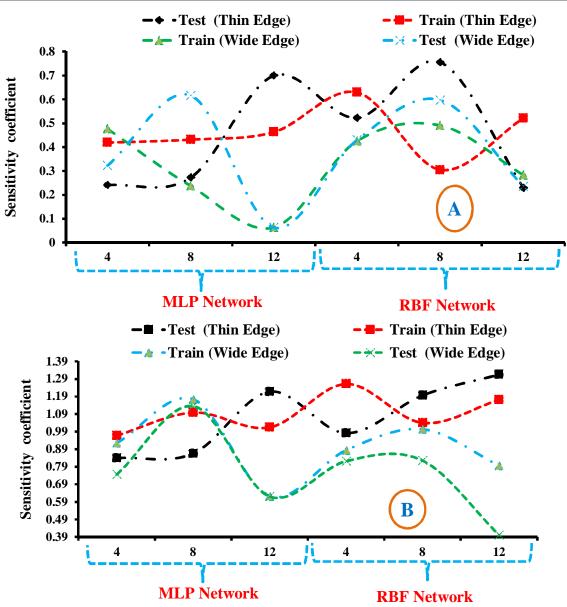


Fig. 16. Sensitivity coefficient (Thin and Wide edge) for firmness A: Loading B: Storage time

Sensitivity Coefficient for quasi-static (Dynamic Loading)

The results of the sensitivity analysis for firmness (Wide and thin edge) are shown in Figure 17. The highest sensitivity for training and Test data was obtained for the loading in a hidden layer by 4 Neuron with MLP Network and 12 Neuron in hidden layer with RBF network respectively. for storage time in the hidden layers with 12 neurons and MLP Network (Training Data) and 12 neurons in the hidden layer and MLP Network (Test data) (Figure 17). The lowest sensitivity analysis for firmness (Dynamic Loading) is also shown in Figure 17. According to the Figure, for loading lowest value was for firmness in hidden layer by 4neuron and RBF network (Training Data) and 12 neuron in hidden layer by MLP Network (Test Date) and for storage, Lowest firmness was in hidden layer by 4 neurons and RBF Network (Training Date) and 8 neurons in hidden layer by MLP network (Test Data).

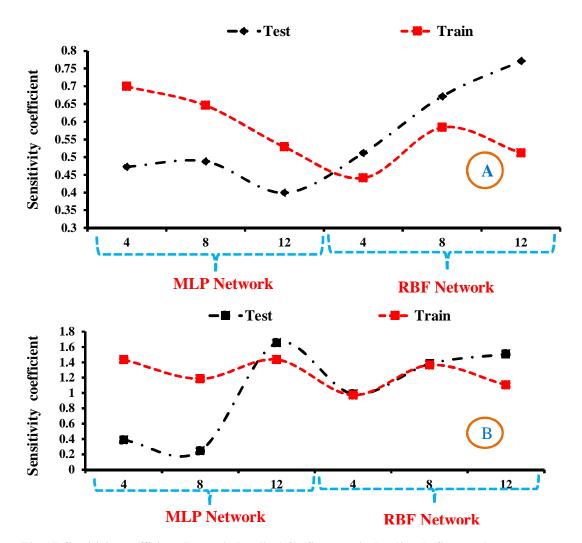


Fig. 17. Sensitivity coefficient (Dynamic Loading) for firmness A: Loading B: Storage time

Conclusion

- The maximum firmness reduction was obtained in dynamic loading where firmness reduced by 92% compared to the firmness of pears on day 1. Moreover, the minimum firmness reduction was obtained in wide-edge compression loading where firmness reduced by 60.37% compared to the firmness of pears on day 1. This reduction was obtained in the 15-day storage period.

- The effect of loading and storage on firmness reduction in static and dynamic loading states was significant.

- During the storage period, dynamic loading more destructs pear texture than static loading.

- Considering R^2 value obtained for training and test, RBF is the most accurate neural network. However, R^2 is acceptable for MLP too.

- In static loading, RBF is the fastest network for learning neural network.

- In dynamic loading, MLP is the fastest network for learning neural network. The epoch of MLP and RBF is 10 and 11, respectively which is negligible considering the high accuracy of RBF. - Considering experimental and simulated data, there is an acceptable overlap between data. This implies the capability of the employed network in predicting pear firmness.

- In static loading, the highest sensitivity factor was obtained in thin and wide-edge compression loading in an RBF network with 4 and 8 neurons in a hidden layer respectively. Moreover, considering the storage period of both loadings, the maximum sensitivity factor was obtained in an RBF network with 4 neurons in the hidden layer and in an MLP network with 8 neurons in a hidden layer respectively.

- Considering the storage period and loading, the maximum sensitivity factor was obtained in an MLP network with 4 and 12 neurons in a hidden layer respectively.

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بررسی تغییرات سفتی و بافت میوه گلابی در بارگذاری نیروهای مختلف و دورههای متفاوت انبارداری با شبکه عصبی مصنوعی محمد واحدی ترشیزی¹- محسن آزادبخت^{2*} تاریخ دریافت: 1397/06/08 تاریخ پذیرش: 1398/03/21

چکیدہ

در این تحقیق به بررسی اثر نوع بارگذاریهای دینامیکی و استاتیکی و دوره انبارداری بر میزان سفتی گلابی پرداخته شد. برای این کار ابتدا گلابیها به سه گروه 27 تایی برای سه بارگذاری استاتیکی لبه نازک، استاتیکی لبه پهن و دینامیکی دستهبندی شده و بارگذاری شدند. هر یک از گروههای بارگذاری شده در سه دوره 5. 10 و 15 روزه انبار دار شده و بعد از هر دوره انبارداری با استفاده از آزمون غیرمخرب CT-Scan از تغییر بافت گلابیها عکس برداری شد و سپس میزان سفتی بافت گلابی با استفاده از هر دوره انبارداری با استفاده از آزمون غیرمخرب CT-Scan از تغییر بافت گلابیها عکس برداری شد و سپس میزان سفتی بافت گلابی با استفاده از هر دوره انبارداری با استفاده از آزمون غیرمخرب CT-Scan و MLP و RBF شبیه سازی و مورد بررسی قرارگرفت. سفتی بافت گلابی با استفاده از سفتی سنجی بافت گلابی با استفاده از موره در بررسی قرارگرفت. نتایج نشان داد که با افزایش دوره انبارداری و میزان نیروی بارگذاری در هر سه نوع بارگذاری میزان سفتی بهطور معنی داری (سطح 1%) کاهش یافت. همچنین بافت گلابی در بارگذاری دیامیکی به شدت نسبت به دوبارگذاری دیگر تخریب شده است. بهترین مقادیر شبکه عصبی مصنوعی باری کاهش یافت. همچنین بافت گلابی در بارگذاری دینامیکی به شدت نسبت به دوبارگذاری در هر سه نوع بارگذاری میزان سفتی بهطور معنی داری (سطح 1%) کاهش یافت. همچنین بافت گلابی در بارگذاری دینامیکی به شدت نسبت به دوبارگذاری دیگر تخریب شده است. بهترین مقادیر شبکه عصبی مصنوعی برای فشار لبه پهن (12 نرون - RBF) (RBF) (RBF) (RBF) و RBF) (RBF) و برای فشار لبه نازک(4 نرون -RBF) (RBF) (RBF) (RBF) (RBF) (RBF) و برای فشار لبه نازک(4 نرون -RBF) (RBF) (RBF) (RBF)) و در نهایت برای بارگذاری دینامیکی (8 نرون -RBF) (RBF) و در نهایت برای بارگذاری دینامیکی (8 نرون -RBF) (RBF) و در نهایت برای بارگذاری دینامیکی (8 نرون - RDF) و RDF) و در نهایت برای بارگذاری دینامیکی (8 نرون -RBF) (RBF) و در نهایت برای بارگذاری دینامیکی (8 نرون - RDF) و در نهایت برای بارگذاری دینامیکی (8 نرون - RDF) و در نهایت برای بارگذاری دینامیکی (8 نرون - RDF) و در نهایت برای بارگذاری دینامیکی (8 نرون - RDF) و RDF) و در نهایت برای بارگذاری دینامیکی (8 نرون - RDF) و RDF) و در نهایت برای بارگذاری دینامیکی (8 دون - RDF) و RDF) و در نهایت برای بارگذاری دینامیک

واژههای کلیدی: انبارداری، بارگذاری گلابی، سفتی، شبکه عصبی.

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