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Original article

Employing an intelligence model and sensitivity analysis to investigate some physicochemical properties of coated bell pepper during storage

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Summary The objectives of this work were to study the effects of three different coatings (gum Tragacanth, sesame oil and gum Tragacanth–sesame oil), temperature and time on shelf life of bell pepper. Moisture reduction, shrinkage as well as firmness and colour changes were studied during 30 days at 4, 10, 15 and 23 °C. Results of this study showed that bell peppers treated with gum Tragacanth at higher temperatures, such as 10 °C, had good quality up to 30 days of storage. However, sharp changes in physicochemical characters were observed in bell peppers stored at 23 °C. In order to predict moisture reduction, shrinkage, firmness and colour changes genetic algorithm–artificial neural network model was developed. It was found that artificial neural network with eight hidden neurons truly could predict the physicochemical changes of bell pepper during storage ($R^2 > 0.9598$). The results of sensitivity analysis showed that shrinkage percentage and also changes of firmness and colour were very sensitive to storage time, while storage temperature had the most effect on moisture reduction.

Keywords Artificial neural network, bell pepper, coating, genetic algorithm, storage.

Introduction

Bell pepper (*Capsicum annuum* L.) is one of the most important commercial vegetables. After detachment from the plant, bell peppers commonly encounter postharvest problems, for example strong physiological activities, rapid loss of nutritive components, and fast physical or physiological decay. Therefore, maintaining freshness of green bell peppers has been a challenge in the fresh produce industry (Xie *et al*., 2004).

The main quality index of vegetables is colour, which is related to its maturation. Fruit firmness is also an important quality attribute and is directly related to improvement of storability potential and causing greater resistance to decay and mechanical damage (Barret & Gonzalez, 1994). Therefore, weight loss, colour changes, softening and surface pitting are the most important signs for detecting quality reduction (Martinez-Romero *et al*., 2006).

There are many methods for preservation of the vegetables. Among these, the coating is well-accepted method of vegetable preservation. Coatings successfully reduce weight loss in green peppers, zucchini and cucumbers (Habeebunnisa *et al*., 1963; Avena-Bustillos *et al*., 1994). Other quality improvements related to edible coatings include slower softening and texture changes and likewise increased colour retention, all of which have been illustrated on bell peppers (Habeebunnisa *et al*., 1963).

Some of the lipids that have been used effectively in coating formulations are beeswax, mineral oil, vegetable oil, surfactants, acetylated monoglycerides, carnauba wax and paraffin wax (Kester & Fennema, 1986).

When Durkex, a vegetable oil blend, coated on tomato fruit, ripening, oxygen uptake and ethylene production reduced significantly compared with controls (Baldwin *et al*., 1997).

Sesame oil is a source of vitamin E. Vitamin E is an anti-oxidant and has been correlated with lowering cholesterol levels. As with most plant-based condiments, sesame oil contains magnesium, copper, calcium, iron, zinc and vitamin B_6 (Gokbulut, 2010).

Also, polysaccharide-based coatings have been used widely to prolong the shelf life of fruits and vegetables. These coatings are excellent oxygen, aroma, and oil barriers and supply strength and structural integrity (Sonti, 2003). Many works have focused on the use of polysaccharide-based coatings to extend and improve

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the shelf life of fruits and vegetables (Ribeiro *et al.*, 2007). For example, chitosan reduced water loss, respiration and fungal infection in bell peppers and cucumbers (Ghaouth *et al.*, 1991).

Gum Tragacanth is a polysaccharide widely used in the industrial sector as a common food additive such as stabilizer, emulsifier and thickener in food, pharmaceutical, cosmetic industries and in technical applications for many years (Weiping *et al.*, 2005).

In recent years, the concept of artificial neural network (ANN) has gained wide popularity in many disciplines of engineering and science. ANN has appeared as an effective data-processing system based on the structure of biological neurons. Unlike simulation modelling where previous knowledge of relationship between process parameters is required, ANN has the ability to learn from examples and re-learn when new data are utilised. It is especially useful in managing the uncertainties and nonlinear relationships in data. ANN has been successfully applied in the past for predicting food quality (Singh *et al.*, 2009). The ANN is made up of a group of interconnected artificial neurons. Each neuron transforms an input and sends its output to other neurons to which it is connected. The receiving neuron determines a weighted sum of the inputs. Each artificial neuron transforms its input through a system of linear equations, which may include logarithmic or hyperbolic tangent functions. The network is trained with a subset of observations and optimised based on its ability to predict a set of known outcomes (Kerdpiboon *et al.*, 2006).

Artificial neural network has been used to predict thermal conductivity of food as a function of moisture content, temperature and apparent porosity (Sablani & Rahman, 2003); to predict thermal inactivation of bacteria (Lou & Nakai, 2001); and to design and optimise high-pressure processes in the food industry (Torrecilla *et al.*, 2005). Finding the efficient values for a neural network, or any nonlinear model, is not an easy job certainly not as easy as parameter estimation with a linear approximation. A neural network is a highly complex nonlinear system. There may be a multiplicity of locally optimal solutions, none of which delivers the best solution in terms of minimising the differences between the model predictions and the actual values and minimising the error function. To minimise the error function, there are several techniques such as back propagation, simulated annealing and genetic algorithm (GA; El-Henawy *et al.*, 2010).

Genetic algorithm can be used for overcoming this limitation of neural network. It is a combinatorial optimisation technique, which searches for an optimal value of a complex objective function by simulation of the biological evolutionary process based, as in genetics, on crossover and mutation. An optimal value can be searched, in parallel, with a multi-point search procedure (Izadifar & Zolghadri Jahromi, 2007). It has been applied in food engineering for achieving optimal solutions to many complex optimisation problems (Morimoto *et al.*, 1997a) developed an ANN-GA intelligence approach for optimal control of fruit-storage process (Morimoto *et al.*, 1997b) used GA for optimisation of heat treatment for fruit during storage.

The aim of this work is to elucidate the effects of gum Tragacanth, sesame oil and gum Tragacanth–sesame oil coatings on quality and shelf life of bell peppers and employing an ANN trained with a GA to model some physicochemical properties of the coated bell peppers during storage. Besides sensitivity analysis was carried out to examine the contribution of each factor during this process.

Materials and methods

Plant material and experimental design

The green bell peppers (*Capsicum annuum cv. Cardio*) harvested in a commercial grower near Mashhad were visually inspected for freedom from defects and blemishes and were placed in card-board boxes, and taken to a laboratory within 10 h after harvest. The fruits were sorted according to uniformity of the size and green skin colour, and finally, those with defects or diseased ones were discarded. The selected fruits were separated into four batches. Four different treatments were used, which are as follows: (i) control; (ii) gum Tragacanth coating (10%w/w); (iii) Sesame oil treatment (10%w/w), and (iv) gum Tragacanth–sesame oil (10%w/w) coating and the ratio of the two components 50:50. Peppers were dipped into the solutions for 5 min. Samples dipped in distilled water were used as control. In this study, 72 peppers were treated with each coating and with two replications. Treated peppers were kept over a plastic sieve for 1 h and a fan generating low-speed air was used to accelerate drying for removing surface moisture. After the treatments, bell peppers were air-dried for removing surface moisture at room temperature and then were stored at 5, 10, 15 and 23 °C for 30 days. In first 2, 6, 10, 14, 18, 22, 26 and 30 days of storage, the bell peppers were taken out. Thirty-six peppers were treated simultaneously for every treatment in each replication. At first, all the peppers were coded according to temperature and time, and all factors such as weight loss, volume, firmness and colour were measured in defined days.

Weight loss analysis

The weight of each bell pepper was recorded using a balance (Sartorius AG, Göttingen, Germany). Each bell pepper was weighed on the first and second days of storage and then every 4 days (i.e. 2, 6, 10, 14, 18, 22, 26 and 30). The results were expressed as the percentage loss of initial weight.

Shrinkage

In this study, the decrease in volume of the bell pepper during storage is considered as shrinkage. When moisture is removed from food during storage, there is a pressure imbalance between inside and outside of the bell pepper. This generates contracting stresses leading to material shrinkage or collapse (Mayor & Sereno, 2004). To measure the shrinkage in defined days, one pepper was used for each replication.

Each bell pepper was weighed on the scale in the air and then was forced in to water by means of a sinker rod. The second reading of scale with the bell pepper submerged minus the weight of the container and water was the weight of the displaced water which is used to calculate volume. Apparent shrinkage (S_{app}) is defined as the ratio of the apparent volume at given moisture content (V_{app}, m^3) to the initial apparent volume of materials before processing (V_{0app}, m^3; Sahin & Sumnu, 2005):

$$S_{app} = \frac{V_{app}}{V_{0app}} \times 100. \quad (1)$$

Firmness determination

Texture of green pepper fruit walls was analysed using a puncture test performed on Texture Analyzer (QTS25; CNS Farnell, Borehamwood, Hertfordshimre, England, UK) interfaced to a personal computer. These pieces were 30 × 30 mm cut from the side walls of the fruit. The pepper was punctured with a 3 mm diameter stainless steel cylindrical probe. The probe was attached to the texture analyzer and the speed of loading head was set at 40 mm min^{-1}. The maximum amount of force (load kg) needed to puncture the pepper sample was recorded from each fruit being compressed to 3 mm deformation and then unloaded (Thompson *et al.*, 1982). Two samples per pepper were tested and analysed as subsamples and for the texture measurements, two samples of each treatment were used. The results were expressed as the loss of initial firmness (N). At first day, firmness of all peppers was similar; therefore, three peppers were randomly selected for measurement. Then in each day, the peppers related to same day were evaluated for firmness.

Image acquisition and colour analysis

In order to investigate the effect of the treatments and storage time on colour changes of bell peppers, the following procedure was applied:

1 A computer vision system generally consists of four basic components: illumination, a camera, computer hardware, and software. In this research, sample illumination was achieved with four fluorescent lights (Opple, 8 W, model: MX396-Y82, 60 cm in length; Taipei city, Taiwan) with a colour index (Ra) close to 95%. The illuminating lights were placed in a wooden box, 45 cm above the sample and at the angle of 45° with sample plane to give a uniform light intensity over the bell pepper sample (Quevedo *et al.*, 2009). The interior walls of the wooden box were painted black to minimise background light. To achieve stabilization of the lighting system, it was switched on for about 30 min prior to acquiring images. A colour digital camera (Canon Powershot, Model A520; Tokyo, Japan) with 4 Mega pixels of resolution was located vertically at a distance of 25 cm from the sample. The angle between the camera lens axis and lightening sources was around 45°. The iris was operated in manual mode, with the lens aperture of 4 and speed 1/10 s (no zoom, no flash) to achieve high uniformity and repeatability. Images were captured with the mentioned digital camera at 2272 × 1704 pixels and connected to the USB port of a computer. Canon Digital Camera Solution Software (version 22) Ōta, Tokyo was used to acquire the images in the computer in JPEG format.

2 Image preprocessing: Improvement of background's contrast of images and segmentation (to separate the true images of the bell peppers from background) were performed using Adobe Photoshop (Adobe, v.8.0) American Computer Software company, San Jose, California, United States.

3 Conversion of red, green, blue (RGB) chromatic space into $L^*a^*b^*$ units:

As the $L^*a^*b^*$ colour is device independent and providing consistent colour regardless of the input or output, the images taken were converted into $L^*a^*b^*$ units. In the $L^*a^*b^*$ space, the colour perception is uniform, and therefore, the Euclidean distance between two colours is almost in agreement with the colour difference perceived by the human eye (Pedreschi *et al.*, 2007). The net colour difference (ΔE) was calculated with the relation

$$\Delta E = \sqrt{\left(L_2^* - L_1^*\right)^2 + \left(a_2^* - a_1^*\right)^2 + \left(b_2^* - b_1^*\right)^2}. \quad (2)$$

where L^* is referred to as the lightness or luminance, while a^* is defined along the axis of red–green, and b^* is defined along the axis of yellow–blue. A positive value of a^* indicates that red is the dominant colour, while a negative value suggests the dominance of green. The same applies the b^* component on the yellow–blue axis, a positive value indicates that yellow is dominant, while a negative value suggests the dominance of blue (Sun, 2008). Where L_1^*, a_1^* and b_1^* represented the readings at time zero, and L_2^*, a_2^* and b_2^* represented the individual readings at any storage condition. In this study, the image analysis was managed using IMAGEJ software (National Institutes Health, Bethesda, MD, USA) version 1.40 g. For measurement of the colour of bell peppers in defined days, one of them was used for each replication.

Neural network modelling

In this study, a multi-layer perceptron (MLP) network based on back propagation learning rule was used to model moisture reduction, shrinkage as well as firmness and colour changes of bell pepper during storage.

The MLP network is probably the most popular neural network in engineering problems in the case of nonlinear mapping. It consists of an input layer, one or more hidden layers and an output layer. The input nodes receive the data values and pass them to first hidden layer nodes. Each one sums the inputs from all input nodes after multiplying each input value by a weight, attaches a bias to this sum, and passes on the results through a nonlinear transformation function. This forms the input either for the second hidden layer or the output layer that operates identically to the hidden layer. The resulting transformed output from each output node is the network output. The network needs to be trained using a training algorithm such as back propagation. Basically the objective of training patterns is to reduce the global error. The goal of every training algorithm is to reduce this global error by adjusting the weights and biases (Kashaninejad *et al.*, 2009).

The working variables of (coating, storage temperature and storage time) were used as inputs, whereas moisture reduction, percentage of shrinkage, the firmness change and ΔE were considered as the outputs (Fig. S1). Hyperbolic tangent activation function (eqn 3) was selected to be used in the hidden layer, while linear function was used in the output layer.

$$\tan\mathrm{h}\ (x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \quad (3)$$

First, the data were divided into three partitions. Thirty percentage of them were used to perform training of the network. To evaluate the prediction quality of the network during the training, 30% of data were considered as cross-validation. Finally, to estimate the performance of the trained network on new data, the surplus data, which never was seen by the neural network during the training and cross-validation process, were used for testing. The applied learning algorithm was Levenberg–Marquardt which, an iterative technique that locates the minimum of a function expressed as the sum of squares of nonlinear functions. It is a standard technique for nonlinear least-squares problems and is a combination of steepest descent and the Gauss–Newton method (Fine, 1999).

Therefore, mean-squared error (MSE), normalised mean-squared error (NMSE), and mean absolute error (MAE) each output were calculated by using eqns 4–6 (Amiryousefi & Mohebbi, 2010) based on testing data.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N} (O_i - T_i)^2}{N}, \quad (4)$$

$$\mathrm{NMSE} = \frac{1}{\sigma^2}\frac{1}{N}\sum_{i=1}^{N} (O_i - T_i)^2, \quad (5)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |O_i - T_i|. \quad (6)$$

where O_i is the ith actual value, T_i is the ith predicted value, N is the number of data and σ^2 is the variance.

The objective of a sensitivity analysis is to define which parameters have the greatest impact on given model outputs (Lurette *et al.*, 2009). The sensitivity analysis was run by batch testing on the developed network first started by varying the first input between the mean ± one standard deviation, while all other inputs are fixed at their respective means. The network output was computed for fifty steps above and below the mean. This process was then repeated for each input. Finally a report, summarising the variation of each output with respect to the variation of each input, was generated (Cheung *et al.*, 2006).

Genetic algorithm

When GAs are used for solving optimisation problems, a population composed of possible solutions (individuals) is randomly selected. Each individual in the population is represented by a string of symbols called chromosomes. The quality of the chromosomes in the population is evaluated over a fitness function. Once the fitness values are assigned to the chromosomes, a selection procedure is applied. A selection operator evaluates the population according to fitness function and chooses the best individuals. After the selection, in crossover step, two individuals are chosen randomly and are reproduced into two new individuals. The mutation operation consists of randomly altering the value of each element of the chromosome according to the mutation probability. Mutation enhances the GA ability by intermittently injecting a random point in order to better search the entire parameter space, which allows the GA to possibly escape from local optima. These three operations are repeated until desired convergence on optimal or near-optimal of the solutions is achieved (Fig. S1; Morimoto, 2006; Koc *et al.*, 2007).

$$F = \begin{bmatrix} -0.3986 & 1.3200 & 0.4657 & 1.5690 & -0.0671 & 0.8158 & 0.0315 & 7.0866 \\ -0.2307 & 0.0462 & 6.4780 & 0.2163 & -0.0292 & 0.2537 & 0.8382 & 5.3706 \\ 2.4888 & -0.3307 & 0.2090 & 3.0140 & 0.8512 & 0.1273 & -0.0353 & -1.4081 \end{bmatrix},$$

$$H = \begin{bmatrix} -0.1208 & 0.3025 & -2.3845 & 2.6516 \\ -0.4344 & 0.0314 & 0.5779 & -0.2402 \\ -0.1590 & 0.2202 & -3.3449 & 3.6290 \\ -0.4244 & -0.0563 & 1.0488 & -0.1036 \\ 0.2366 & 0.1083 & -4.5277 & 4.8268 \\ -1.9402 & -0.0166 & 0.9796 & -1.9287 \\ -0.2725 & 0.0511 & -3.4300 & 3.7647 \\ -0.2319 & -0.0473 & 1.0121 & -0.0468 \end{bmatrix}, B = \begin{bmatrix} 0.4060 \\ -1.6925 \\ 4.9659 \\ 5.0226 \\ 1.0721 \\ -2.4908 \\ -2.8491 \\ -1.9750 \end{bmatrix}, B_{\text{out}} = \begin{bmatrix} -0.1079 \\ 0.3088 \\ -0.6923 \\ 0.0282 \end{bmatrix}.$$

In this study, neural network structure and training parameters were represented by haploid chromosomes consisting of 'genes' of binary numbers. Each chromosome had three genes. The first gene represents the number of neurons in the hidden layer of the network, which could range from one to twenty-five neurons. The second and third genes depict the learning rate and momentum with which the network was trained. Table S1 depicts specification of the algorithm applied in this research.

In this work, the ANN modelling and GA optimisation and also sensitivity analysis were performed by Neurosolutions for Excel software release 5.0, produced by NeuroDimension, Inc., Gainesrille, Florida, USA.

Results and discussion

In this study, ANN with eight neurons in the hidden layer gave the lowest prediction error. Table S2 reports the performance of the optimised network in terms of MSE, NMSE, MAE, minimum absolute error (Min Abs Error), maximum absolute error (Max Abs Error) and the linear correlation coefficient (R^2) between experimental data and neural network outputs for testing data set.

The best fitness attained during each generation of the optimisation is illustrated in Fig. S2. The best fitness, which is the lowest MSE value calculated across all the networks within the corresponding generation, is decreased crosswise generations until it becomes relatively constant after thirty generations.

The matrixes of weights (F matrix of 3×8 between input and the hidden layer and H matrix of 8×4 between the hidden layer and output layer) and bias values (B matrix of 8×1 for the hidden layer and B_{out} matrix of 4×1 for output layer) of the selected network are as follows:

Sensitivity analysis was used to determine how the optimised model would react to changes in input parameters. Sensitivity analysis is acknowledged as mandatory for valid modelling practice, and is an implicit part of any modelling field. Additionally, it investigates how decision-making might change with different input data. Furthermore, sensitivity analysis gives important information about the 'robustness' of the parameters involved in the models which further helps in the decision-making process. In this way, the models can be analysed to determine the dependence of the results on the initial assumptions (Jaiswal *et al.*, 2005).

Sensitivity of each variable in the optimised model is shown in Fig. S3. Except for moisture reduction, other outputs of the network especially the changes of firmness were very sensitive to storage time compared with other input variables. Storage temperature had the most effect on moisture reduction which shows temperature during storage, and was mainly important to the changes of moisture reduction. Furthermore, it could be comprehended that different coatings had the minimum effect on outputs of the optimised network.

Variance analysis (ANOVA) of the studied parameters is given in Table S3. The individual effects of storage temperature, time and coating on physiochemical properties of the bell peppers were highly significant ($P < 0.01$). Moreover, the interactions of the mentioned variables, except for two items were significant ($P < 0.01$).

Effect of coating treatment, storage time and temperature on weight loss (%), shrinkage (%), firmness changes, changes of three chromatic parameters (L^*, a^* and b^*) and ΔE is illustrated in Tables S4–S7, respectively. In general, coating application reduced moisture loss of bell peppers during storage. Among the experimental coatings, gum Tragacanth coating decreased moisture loss slightly compared with the uncoated samples, sesame oil and gum Tragacanth–sesame oil coatings during 30 days of storage. After that, gum Tragacanth–coated fruits showed 16.15% moisture loss at 4 °C, as compared to 26.80%, 25.12% and 22.73% moisture loss for control fruit, sesame oil and gum Tragacanth–sesame oil-coated bell pepper, respectively. As expected, larger changes in moisture loss were observed at higher temperatures. Shrinkage percentage increased at higher temperature. Among treated bell peppers with coating, gum Tragacanth had the lowest values of shrinkage percentage at all temperatures. Sesame oil and gum Tragacanth–sesame oil-coated bell peppers had similar shrinkage with the control samples. Firmness of bell peppers decreased with the passage of time at different storage temperatures, and higher temperatures caused a faster rate of change. Lower storage temperatures (4–10 °C) delayed the changes and no excessive softness was noticed in bell peppers stored at these temperatures. Gum Tragacanth and gum Tragacanth–sesame oil-coated bell peppers showed beneficial results on firmness retention of bell pepper wedges during the entire storage period, and sesame oil-coated bell peppers had similar behaviour with the control samples at all temperatures during storage.

The lowest and highest changes of ΔE showed in bell peppers treated with gum Tragacanth and control samples. However, in this study, all coatings reduced colour changes in the peppers during storage compared with control samples.

The performance of the optimised ANN model with eight neurons in hidden layer for prediction of moisture reduction, shrinkage, ΔFirmness and ΔE of bell pepper during storage based on test data that never was used for training was inspected and the consequences are shown in Table S2. This Table reveals that the ANN estimated the outputs fitted with the experimental data ($R^2 > 0.95$) and displayed high power of designed genetic-neural network model for prediction of physicochemical changes of bell pepper during storage.

Results of this study showed that bell peppers treated with gum Tragacanth in higher temperatures, such as 10 °C, had good quality up to 30 days of storage and the physicochemical characters of changes in this temperature were almost similar to those stored at 4 °C. However, sharp changes in physicochemical characteristics were observed in bell peppers stored at 23 °C. So, bell peppers treated with gum Tragacanth can be stored at 10 °C and it could reduce energy consumption and warehousing costs during storage.

Conclusion

This study revealed that several physicochemical quality changes of stored bell peppers were dependent on the storage conditions and type of coating. Elevated temperature had adverse influence on quality attributes of bell peppers especially during long time storage. Most changes were accelerated at higher temperatures, and hence, lower temperatures offered better choices for storage. Gum Tragacanth had beneficial effects in retarding the ripening process. These treatments were effective as physical barriers and thus reduced the weight loss during postharvest storage. In addition, gum Tragacanth delayed colour changes, softening and shrinkage. On the basis of these data, we recommend the use of gum Tragacanth to maintain the quality of bell peppers during long-term storage. In this study, GA–ANN model was developed for estimation of moisture reduction, shrinkage, firmness changes and ΔE of bell pepper during storage. It was found that ANN with eight hidden neurons could predict the physicochemical changes of bell pepper during storage with high coefficient of determination ($R^2 > 0.9598$). Sensitivity analysis was used to determine how the optimised model would respond to changes in input parameters. Shrinkage percentage and also changes in firmness and colour were very sensitive to storage time while storage temperature had the most effect on moisture reduction.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Schematic of optimisation procedure for artificial neural network using genetic algorithm.

Figure S2. Best fitness (lowest mean-squared error, MSE) versus generation of optimal neural network.

Figure S3. Sensitivity analysis on the optimised neural network.

Table S1. Applied genetic algorithm properties

Table S2. Performance of genetic algorithm-artificial neural network for modelling moisture reduction, shrinkage, ΔFirmness and Δ*E* of bell pepper during storage

Table S3. Successive mean squares from the analysis of variance of the %water loss, %shrinkage, changes of firmness, colour changes and changes of three chromatic parameters (L^*, a^*, and b^*)

Table S4. Effect of coating treatment and storage time on moisture loss (%) at different temperatures

Table S5. Effect of coating treatment and storage time on shrinkage (%) at different temperatures

Table S6. Effect of coating treatment and storage time on firmness changes (*N*) at different temperatures

Table S7. Effect of coating treatment and storage time on colour changes (Δ*E*) at different temperatures

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