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ORIGINAL PAPER

Comparison of adaptive neuro-fuzzy inference system and artificial neural networks (MLP and RBF) for estimation of oxidation parameters of soybean oil added with curcumin

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Abstract A analysis of soybean oil oxidation in presence of different concentrations of active substrate of turmeric rhizome (curcumin) (0.012, 0.016 and 0.02 %) at 25 and 55 °C based on oxidation parameters including peroxide value (PV), acid value (AV) and iodine value (IV) at specific time interval, was performed. Adaptive neuro-fuzzy inference system (ANFIS) and multilayer perceptron (MLP) and radial basis function (RBF) functions of artificial neural network (ANN) with three inputs (temperature and concentration, time of sampling) and three outputs (PV, AV and IV) were used for the construction of models that could predict the oxidation parameters and were compared to multiple linear regression (MLR). It was shown that the ANFIS model ($R^2 = 0.98$, 0.85 and 0.99 for PV, AV and IV, respectively) performed better compared to ANN (MLP and RBF) and MLR. Sensitivity analysis based on ANFIS model suggested the high sensitivity of oxidation parameters on temperature and concentrations of curcumin due to its high antioxidant activity to enhance soybean oil shelf life.

Keywords Adaptive neuro-fuzzy inference system · Artificial neural network · Curcumin · Lipid oxidation · Sensitivity analysis · Soybean oil

Introduction

Soybean oil is known as a non-fish source of omega-3 polyunsaturated fatty acids which have so many beneficial effects on health due to favorable fatty acid profile [1]. Also, Omega-6 fatty acids, found naturally in soybean oil, may also decrease risk of heart attack and reduce blood cholesterol. However, Soybean oil is highly susceptible to oxidation due to high amounts of polyunsaturated fatty acid (57–58 %) and linolenic acid (7 %) [2]. Lipid oxidation is a challenging problem in food production and storage which causes nutritional losses and produces undesirable taste, color, and toxic compounds, which make foods less acceptable to consumers. Auto oxidation is a thoroughly spontaneous free radical chain process which involves unsaturated lipid and oxygen without light and catalyst. This type of oxidation requires considerable time to produce a sufficient quantity of peroxides (the main initial product of auto oxidation) and develop unpleasant flavors in oil. Indeed, the oxidation rate of oil is dependent on temperature, the presence of antioxidant and the nature of the reaction environment [3–5]. Antioxidant addition is one the most effective means to retard oxidation and extend oil shelf life. Synthetic antioxidants are more effective and less expensive than natural ones [6]. However, recently due of health hazards, use of TBHQ is forbidden in many countries. And BHA and BHT have been suspected of many adverse side effects, such as liver damage and carcinogenesis. As a consequence, natural antioxidants in fruits and vegetables have been interested among

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consumers and the scientific community which are trying to identify safe source of dietary antioxidants [7]. Curcumin, a yellow pigment from the rhizome of turmeric (Curcuma longa L.) prevents a various kind of cancers, premature aging, liver fibrosis, atherosclerosis by reducing the formation of bloods clumps and protects biomembranes against peroxidative damage by the scavenging of free radicals mechanism which can be used as an antioxidant [8, 9]. The structural formula of curcumin is shown in Fig. 1.

An artificial neural network (ANN) is a machine-learning model whose structure and function are inspired by behavior of human brain. The primary elements of a neural network are the neurons. These neurons are arranged in input, output and one or more hidden processing layers. The multilayer perceptron (MLP) and radial basis function (RBF) are widely used approaches of ANN [10]. Both types of neural network structures are used for regression or classification problems. General difference between these two networks is that RBF is a section of input space, whereas, MLP is a more distributed approach. The hidden layer of RBF network, hidden nodes map distances between input vectors and center vectors to outputs through a nonlinear kernel or radial function. However, the output of MLP network is produces by linear combinations of the outputs of hidden layer nodes in which every neuron maps a weighted average of the inputs through a sigmoid function [11]. Adaptive neuro-fuzzy inference system (ANFIS) model is a combination of a neural network and a fuzzy inference system in such an approach that the neural network is used to determine the parameters of the fuzzy inference system. The fuzzy logic also enhances the generalization capability of a neural network by providing more reliable output when extrapolation is needed beyond the limits of the training data [12]. Intelligent network has been successfully used to predict property and quality changes of food products during processing and storage. These networks have already been applied to simulate processing such as fermentation, drying behavior of different foods, osmotic dehydration and cross flow microfiltration [13]. Also, to predict the Menhaden fish oil oxidation during storage [14], rheological properties of Iranian bread dough [15], freshness index of modified atmosphere packed rice snack during storage period [16].

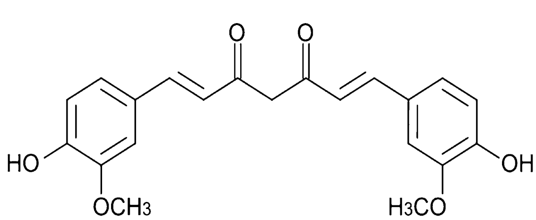

Fig. 1 Molecular structure of curcumin

Given the fact that antioxidants have an important role in human life and that conventional methods for their determination are expensive and time-consuming, many food model studies have been performed to determine the antioxidative effects of different plant extracts, phenolic compounds and carotenoids in a model of oil system [7, 17]. However, there is no report in the literature on a model to examine the antioxidant effects of curcumin in soybean oil. So this study aims to propose and evaluate the possibility of using intelligent systems to estimate the effect of curcumin to improve soybean oil shelf life.

Materials and methods

Materials

Soybean oil with no added components was supplied from Damoon (Fariman, Iran). Rhizome of turmeric provided by local market and standard curcumin provided from sigma company. All chemicals and solvents used in this study were of analytical reagent grade and purchased from Merck and Sigma Chemical Companies.

Methods

Extraction of curcumin

After peeling, powdering and sieving of the rhizomes of turmeric (Curcuma longa L.), 500 g dried powder was steeped for 48 h in hexane in a shaker with 750 rpm. After filtration and evaporation of hexane solution, the turmeric oil was obtained. For increasing the extraction yield, this operation was done twice. The powder from the hexane extraction was further steeped overnight in 95 % ethanol in a shaker (750 rpm) and this process was repeated. The concentrated mixture of alcoholic extract was kept in room temperature in darkness to eliminate solvent, then 1:5 mixture of water: ethanol added to sediment. After filtration and drying at room temperature, curcumin powder was obtained [18].

Identification of the curcumin

A dichloromethane solution (5 %) of the extracted curcumin and its standard (50 mg/plate) was streaked using a thin-layer chromatography (TLC) applicator on a precoated silica gel plate 2 × 10 cm which had been activated for 15 min at 100 °C. Then the plate was developed in the ascending direction for 10 cm with the solvent system dichloromethane: methane (9.9: 0.1, by volume) [19]. The NMR spectra were recorded by an NMR instrument (Bruker AC-80) at 300 MHz at room temperature, using methanol as a solvent. A solution was prepared by dissolving 10 mg of curcumin in 0.5 mL of methanol to NMR tube. The samples were prepared freshly and carefully protected from light during the NMR experiments.

Preparation of oil samples

The soybean oil was mixed for 15 min separately with 0.012, 0.016 and 0.02 % of the curcumin then oil samples containing different concentrations of curcumin were stored in 25 and 55 °C in incubator. Progress of oxidation was monitored by determination of the PV following the AOCS official methods Cd 8-53 (AOCS 1989) [20], AV according to the AOCS (1993) Official Method Cd 3d-63 [21] and IV according to the AOAC Official Method 920.158 (Hanus method) in determined time interval (0, 7, 14, 21, 28, 60, 90 days) [22].

Intelligent techniques for modeling oxidative parameters of soybean oil including curcumin

In the present study, three widely used techniques including ANN (MLP and RBF) and ANFIS, were used for modeling the relationship between time of storage, concentration of curcumin and temperature and oxidation parameters including PV, AV and IV. The number of samples at both 25 and 55 °C and 0, 0.012, 0.016 and 0.02 % concentration of curcumin during 90 days of storage time (7 interval points) was 169. To find the best technique for modeling the oxidative parameters, these techniques were evaluated using neurosolution (Neurodimension, Inc.) software (version 5.0).

Multilayer perceptron structure

MLP network models are the popular network approach used in most of the research applications in engineering, medicine and mathematical modeling [23]. Vallejo-Cordoba et al. (1995) used MLP to predict the shelf life of milk applying interpretation of flavor compounds and sensory data [24]. Moreover, Cabrera and Prieto (2010) applied MLP for the antioxidant activity of essential oils prediction [25] and Yalcin and Tasdemir (2007) for α-linolenic content of eggs obtained from hens fed diatery flax seed and the results indicated that MLP was a reliable data-modeling tool that could be used in food systems [26]. MLP belongs to the class of feed forward networks, meaning that information passes among the network nodes exclusively in the forward direction the network includes an input, hidden layers and an output layer. The inputs to a neuron include its bias and the sum of its weighted input the output of a neuron depends on the neuron's inputs and on its transfer function [11].

Radial basis function (RBF) structure

RBF network is a mathematical model to solve the serious problems. This network consist of three layers: a transparent input layer, a hidden layer with sufficiently large number of nodes, and an output layer. RBF network refers to radially symmetric basis function which is used as activation functions of hidden nodes is a non-linear one [11].

In this study, the two different architectures of ANN (MLP and RBF) were also used to estimate the effect of curcumin in soybean oil shelf life. The data of curcumin concentration (0.012, 0.016 and 0.02 %), the temperature (25 and 55 °C) and the time intervals of sampling (0, 7, 14, 21, 28, 60, 90 days) were used as input data for the ANN calculation. And PV, AV and IV, were used as output data. All data were first normalized and divided into three data sets such as: training (60 % of all data), test (30 % of all data) and cross validation (10 % of all data). In this study neurosloution (Neurodimension, Inc.) version 5.0 software was used in neural network analyses having a three-layer feed-forward network that consists of an input layer, one hidden layer and one output layer. Neuron numbers in hidden layer were selected from a series of trial runs of the networks in order to obtain the neuron number in the network having minimum error. In these analyses, network parameters of learning rate and momentum were set to 0.01 and 0.9, respectively. Variable learning rate with momentum as networks training function and the transfer function used in hidden layer was sigmoid axon and the transfer function used in output layer was linear axon.

Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS model combines knowledge that can be explained through fuzzy system and the knowledge that can be acquired by learning through neural network [12]. Indeed, this form of neuro-fuzzy approach provides a means of training a family of membership functions to emulate a nonlinear, multidimensional mapping function. The two generalized bell membership function (Eq. 1) or a gaussian membership function (Eq. 2) are mentioned bellow:

$$\mu_{A_i}(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \tag{1}$$

$$\mu_{A_i}(x) = \exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \tag{2}$$

where a_i, b_i and c_i are premise parameters. Also, x is the input to node i and a_i is the linguistic label associated with this node function. The ANFIS approach integrates the basic functions of a fuzzy inference system into the neural network connective structure, which distributes the learning ability to obtain the membership functions and fuzzy logic rules. Five transfer functions including linear tangent axon, linear sigmoid axon, softmax axon, bias axon, linear axon and axon were performed and momentum rule was used as learning method using neurosolution (Neurodimension, Inc.) software (version 5.0).

Selection of optimal model

For comparison of developed models and selection of the optimal one, the performance of models was evaluated using mean-squared error (MSE), normalized mean-squared error (NMSE), mean absolute error (MAE) and coefficient of determination (R^2) of testing set, between the predicted and experimental values as follows:

$$MSE = \frac{\sum_{i=1}^{N}(O_i - T_i)^2}{N} \tag{3}$$

$$NMSE = \frac{1}{\sigma^2}\frac{1}{N}\sum_{i=1}^{N}(O_i - T_i)^2 \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - T_i| \tag{5}$$

where N is the number of data, σ^2 is data variance and O_i is the observed oxidation parameters and T_i is the predicted oxidation parameters used as output.

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}[O_i - T_i]^2}{\sum_{i=1}^{n}[O_i - T_m]^2}} \tag{6}$$

The coefficient of determination is the correction coefficient between two variables O_i and T_i whose n pairs are available. Also the T_m is calculated from following equation:

$$T_m = \frac{\sum_{i=1}^{N} O_i}{N} \tag{7}$$

The lower the MSE, NMSE and MAE, the better the accuracy of the model in predicting the parameters. Also, the highest R^2 values showed that the model performed the best [27].

Sensitivity analysis

In order to assess the predictive ability and validity of the models, a sensitivity analysis was performed using the best network selected. The sensitivity analysis conducted to compare relative importance between input variables (curcumin concentration (0.012, 0.016 and 0.02 %), the temperature (25 and 55 °C) and the time intervals of sampling (0, 7, 14, 21, 28, 60, 90 days)) on output parameters (PV, AV and IV). Sensitivity analysis provides insight into the usefulness of individual variables. With this kind of analysis it is possible to judge what parameters are the most significant.

Results and discussion

The results of identification of curcumin

The purity of extracted curcumin was accomplished by TLC on silica gel and the NMR spectra which were provided on a Brucker (Ac-80). The NMR and TLC results were in agreement with the obtained results from standard curcumin.

ANFIS and ANN modeling and comparison of their performance

To estimate the performance parameters of ANFIS, ANN (MLP and RBF) and MLR models for oxidation parameters including PV, AV and IV of soybean oil with different concentrations of curcumin addition, different training of the experimental data were used. In the ANN modeling, MLP and RBF were chosen and to determine the optimum network configurations that gave the best predictive power, the errors of the oxidation parameters with different numbers of neurons in one hidden layer at both model structures were determined. The optimized MLP structure was obtained with 10 neurons in one hidden layer. Also, at RBF structure, the lowest MSE, NMSE and MAE and the highest R^2 for the oxidation parameters were found with eight numbers of neurons in one hidden layer. The performance of oxidation parameters of MLR, optimized structure of MLP and RBF and ANFIS models constructed for the estimation of PV, AV and IV of soybean oil with 0, 0.012, 0.016 and 0.02 % added curcumin are shown in Table 1. Moreover, Table 2 lists the errors of the prediction of PV, AV and IV with different membership and transfer functions in hidden layer. As can be seen from the Table 2, the best fit was observed in the ANFIS model with gaussian membership function and linear axon as transfer function in hidden layer which shows high performance for all data sets of each output parameters. Comparison the optimized models of ANFIS, MLP and RBF in Table 1, the best fit was observed in the ANFIS model with high performance for all data sets for each oxidation parameter. The lowest MSE, NMSE and MAE means that a good fit was observed in the ANFIS model, whereas, the highest MSE, NMSE and MAE value were in MLR. So that, the MSE, NMSE and MAE values for PV were 3.973, 0.045, 0.876 in the ANFIS model, but were calculated to be 15.202, 0.173, 2.222 and 30.203, 0.343, 0.954 for ANN structures (MLP and RBF), respectively. Whereas, MLR showed the lowest accuracy among the constructed models,

Table 1 Errors in the prediction of oxidation parameters of optimized MLR, MLP, RBF and ANFIS models

Models	Performance	Peroxide value	Acid value	Iodine value
MLR	MSE	13.97	0.0008	12.02
	NMSE	0.3	1.01	0.31
	MAE	0.29	0.0202	0.27
	R^2	0.676	0.59	0.667
MLP	MSE	15.202	0.0003	0.964
	NMSE	0.173	0.298	0.015
	MAE	2.222	0.008	0.763
	R^2	0.935	0.724	0.984
RBF	MSE	30.203	0.0003	6.237
	NMSE	0.343	0.339	0.097
	MAE	0.954	0.009	1.448
	R^2	0.820	0.702	0.939
ANFIS	MSE	3.973	0.0003	0.475
	NMSE	0.045	0.317	0.007
	MAE	0.876	0.0086	0.539
	R^2	0.984	0.720	0.993

with rather high MSE, NMSE and MAE (13.97, 0.3 and 0.29) and low R^2 (0.676). The ANFIS model showed a rather high coefficient of determination ($R^2 = 0.984$) compared to MLP ($R^2 = 0.935$), RBF ($R^2 = 0.820$) and MLR ($R^2 = 0.676$) in modeling of PV, the most important oxidation parameters. A similar trend was observed for the other oxidation parameters. For the prediction of AV, ANFIS also performed better compared to the others, with the highest R^2 (0.72) and the lowest MSE, NMSE and MAE (0.0003, 0.317 and 0.0086, respectively). The highest MSE (0.0008), NMSE (1.01) and MAE (0.0202) and the lowest R^2 (0.59) values were obtained using MLR, as expected for AV. Also, for IV, the ANFIS model performed better than ANN (MLP and RBF) and MLR. As can be seen from the Table 1, the MSE, NMSE and MAE of IV in the ANFIS modeling is 0.475, 0.007 and 0.539 while, 0.964, 0.015 and 0.763 for MLP and 6.237, 0.097 and 1.448 for RBF and 12.02, 0.31, 0.27 for MLR model. It is obvious that MLR with R^2 0.667 cannot successfully predict the IV.

Figure 2 illustrates the measured and predicted PV, AV and IV in the form of a scatter-plot for ANFIS as a best predictive model. ANFIS estimates are closer to measured PV compared to those of MLP ($R^2 = 0.935$), RBF ($R^2 = 0.820$) and MLR ($R^2 = 0.676$). Also, ANFIS and MLP models showed close accuracy for AV. The MSE, NSME and MAE values of ANFIS were 0.0003, 0.317 and 0.0086, whereas they were 0.0003, 0.298 and 0.008 in the MLP model, respectively. The worst estimates were obtained from MLR ($R^2 = 0.59$). Moreover, the observed and predicted of IV values in the most appropriate models (ANFIS and MLP) are also similar, but ANFIS ($R^2 = 0.993$) showed a better result for the estimation of IV compared to MLP ($R^2 = 0.984$) and RBF ($R^2 = 0.939$) and MLR ($R^2 = 0.667$). As stated above, MLR was not appropriate models for prediction of oxidation parameters of soybean oil including curcumin. Whereas, ANFIS showed lower MSE, NSME and MAE compared to ANN (MLP and RBF) in prediction of soybean oil oxidation parameters. There are different research studies related to good performance of ANFIS in the literature. Yalcin et al. (2012) predicted the fatty acid composition of vegetable oils including hazelnut, soybean, sunflower, olive, canola, corn and cotton seed) based on rheological measurements using ANFIS and ANN models [28]. The results indicated that although, both models could satisfactory predict the fatty acid composition, ANFIS was more powerful than ANN. Samhouri et al. (2007) also used the ANFIS

Table 2 Errors in the prediction of oxidation parameters with different membership and transfer functions in ANFIS model

Membership function	Transfer	PV				AV				IV			
		MSE	NMSE	MAE	R^2	MSE	NMSE	MAE	R^2	MSE	NMSE	MAE	R^2
Bell	Linear tanhaxon	14.39	0.163	1.511	0.86	0.0003	0.32	0.008	0.72	21.58	0.33	2.87	0.82
Bell	Linear sigmoid axon	20.84	0.24	2.68	0.86	0.0003	0.28	0.008	0.72	2.59	0.04	1.188	0.96
Bell	Softmax axon	97.73	1.11	6.28	0.72	0.0007	0.627	0.01	0.69	12.8	0.2	3.09	0.98
Bell	Bias axon	15.34	0.17	2.13	0.9	0.0003	0.32	0.008	0.72	0.9	0.01	0.75	0.98
Bell	Linear axon	16.52	0.18	2.26	0.88	0.0003	0.31	0.008	0.72	0.87	0.01	0.73	0.98
Bell	Bell axon	11.64	0.13	1.88	0.92	0.0004	0.34	0.008	0.7	0.61	0.009	0.6	0.98
Gussian	Linear tanhaxon	18.55	0.21	2.44	0.88	0.0003	0.34	0.008	0.7	1.63	0.02	1.009	0.98
Gussian	Linear sigmoid axon	21.25	0.24	2.64	0.88	0.0003	0.3	0.008	0.72	4.03	0.06	1.22	0.94
Gussian	Softmax axon	97.85	1.11	6.29	0.72	0.0007	0.63	0.01	0.68	12.83	0.2	3.09	0.88
Gussian	Biasaxon	17.28	0.19	2.4	0.9	0.0003	0.34	0.008	0.7	0.72	0.01	0.67	0.98
Gussian	Linear axon	3.97	0.04	0.87	0.98	0.0003	0.3	0.008	0.72	0.47	0.007	0.53	0.993
Gussian	Axon	15.72	0.17	2.07	0.88	0.0003	0.3	0.008	0.7	0.99	0.01	0.83	0.98

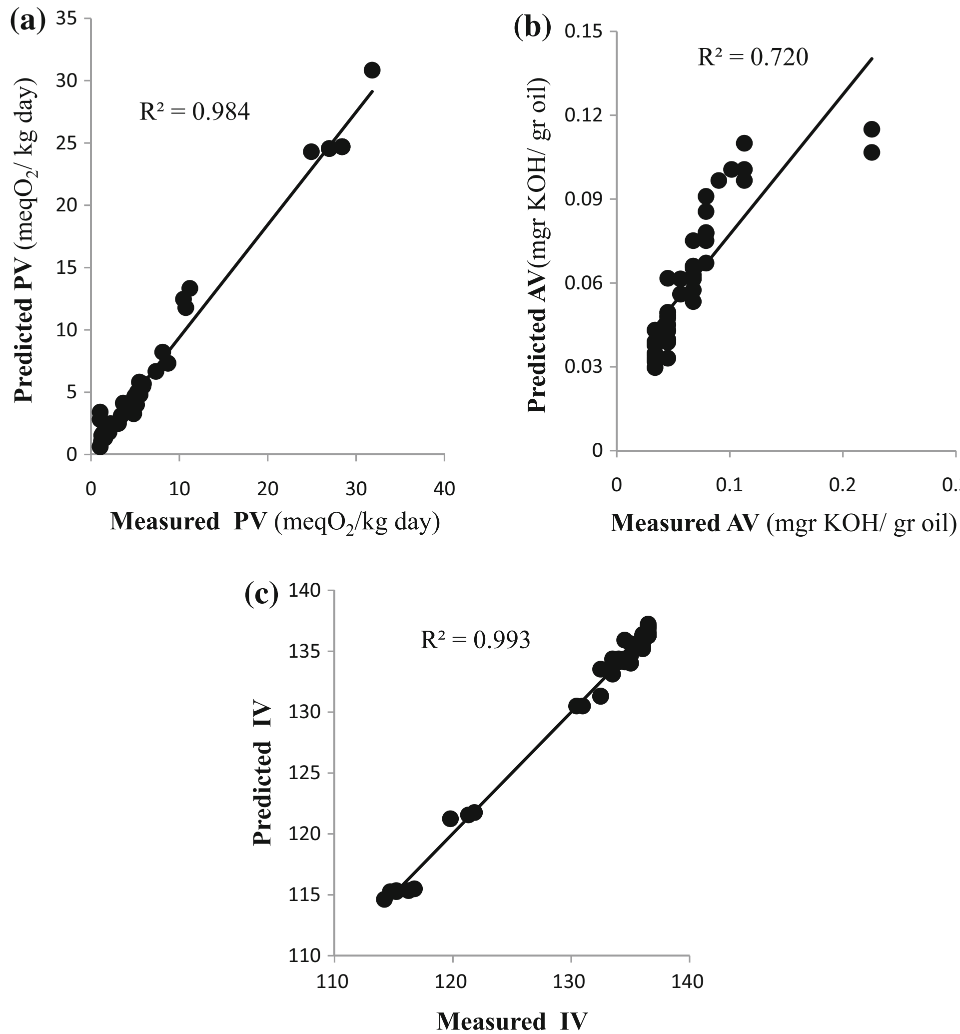

Fig. 2 Comparison between the measured and predicted data obtained by optimized ANFIS model for the prediction of **a** peroxide value (PV), **b** acid value (AV), **c** iodine value (IV) at both 25 and 55 °C

modeling technique for the color prediction of a model mayonnaise system with 98 % prediction accuracy [29]. Moreover, ANFIS used as more effective modeling technique for the estimation of PV, free fatty acid (FFA) and IV of hazelnut oil in presence of natural antioxidant compounds including gallic acid, ellagic acid, querecetin, β-carotene and retinol during storage in comparison with ANN [30]. Ekici et al. (2013) also predicted total anthocyanin content of grape skin, black carrot and red cabbage using ANFIS and ANN models. Comparison of the models showed that the ANFIS model performed better than the ANN model and the highest R^2 (0.9942) values was obtained for grape skin [31]. The antimicrobial effect of benzoic and cinnamic acids on Listeria monocytogens was compared with ANFIS, ANN and MLR. The results showed that the ANFIS model preformed better than two other models [32]. Other researches also stated that ANFIS is a technique that can be used efficiently to predict food properties and process [33, 34].

Changes of oxidative parameters of soybean oil samples including curcumin using optimized ANFIS model

Figure 3 presents three 3D plots of the surface of the optimized ANFIS model which indicated the changes of oxidative parameters (PV, AV and IV) of soybean oil including different concentrations of curcumin. Lipid hydroperoxides were identified as autoxidation products of oils which their content in fats and oil varies with condition of storage and concentrations of antioxidants added. The addition of curcumin into the soybean oil inhibited the formation of hydroperoxides. In general, the PVs were lower in preserved samples containing curcumin compared to control samples. And as the concentration of curcumin increased from 0.012 to 0.02 %, the PVs diminished (Fig. 3a). Moreover, the PVs of all samples increased with increasing the storage period, but the increase of the PV in the control sample was higher than other ones. So that, the

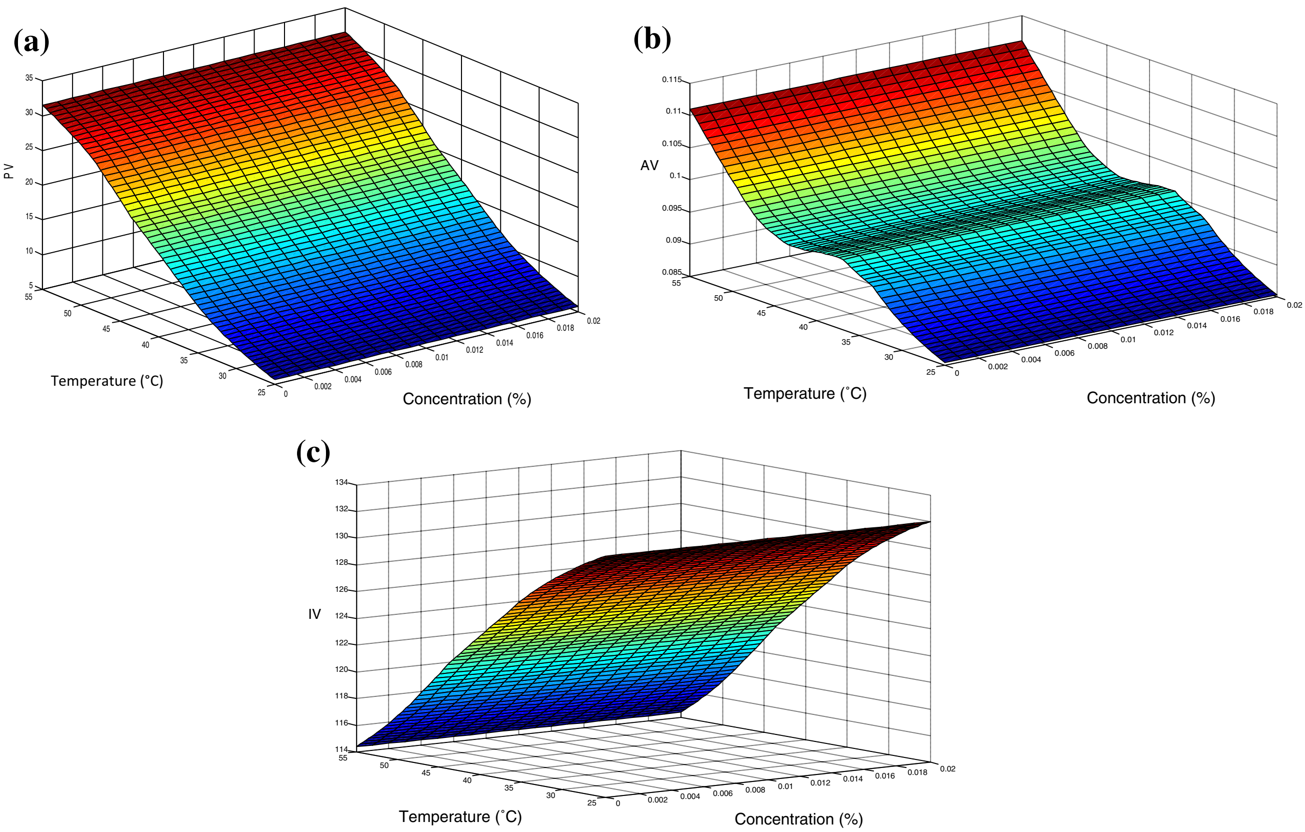

Fig. 3 3D surface plot for the estimated **a** PV, **b** AV, **c** IV with temperature and curcumin concentration changes for soybean oil samples using ANFIS

PV value of control samples at 55 °C, increased from 1.04 to 31.7 meq O_2/kg oil at the end of storage period. Whereas, the PV value of samples including 0.02 % curcumin reached 24.94 meq O_2/kg after 90 days of storage. As shown in Fig. 3a, the PVs of the samples increased by increasing the temperature. Because high temperature (55 °C) provided the necessary energy for hydroperoxide formation and also activation of hydroproxide to decompose into free radicals and secondary products. Whereas, at low temperature (25 °C) very stable hydroperoxides formed during hydrolytic deterioration of soybean oil triacylglycerols. So the PV of the blank samples as the temperature enhanced from 25 to 55 °C, changed from 4.75 to 31.7 meq O_2/kg oil after 90 days. Figure 4a–b also presents the trend of hyroperoxide formation based on measured data during the storage period (90 days) at 25 and 55 °C. as shown Fig. 4a, as the concentration of curcumin increased, the slope of PVs changes in the oxidation curve which shows the rate of hydroperoxide formation reduced. Moreover, comparison the Fig. 4a, b, clearly assert, the temperature had a significant role in oxidation rate of soybean oil samples.

Although hydroperoxides are more stable than radical species, leading to secondary oxidation products including aldehydes, ketones, alcohols, acids, and lactones. The secondary products are responsible for impaired taste and flavor of oils. As in known, the formation of FFA may be a measure of rancidity and an increased FFA level in the oil results in an increase in peroxide formation. As can be seen in Fig. 3b, it was found that temperature had a significant effect on the formation of FFA and increased the level of AV in the soybean oil samples including curcumin. As the temperature increased from 25 to 55 °C, the AV of control samples changed from 0.08 to 0.1 mgr KOH/gr oil at the end of storage period. Indeed, according to the Arrhenius equation, as the temperature increased, the energy of activation decreased [35]. As a consequence, the rate of FFA formation enhanced. Figure 4c–d also presents the AVs changes based on measured data during the storage period (90 days) at 25 and 55 °C. as can be seen in Fig. 4c–d, as the concentration of curcumin enhanced, the formation of FFA slightly decreased. So the best oxidative inhibition was shown in soybean oil samples including 0.02 % curcumin. IV is an indicator of a saturation level in oil and decreases with increasing saturation ratio in the chemical structure of triglycerides. The IV samples increased with increasing storage period because intense oxygen exposure caused oxidation in the oil as expected. In general, the best

Fig. 4 Effect of different concentrations of curcumin on the oxidation of soybean oil samples assessed by the peroxide value (**a**, **b**), acid value (**c**, **d**) and iodine value (**e**, **f**) at 25 and 55 °C, respectively

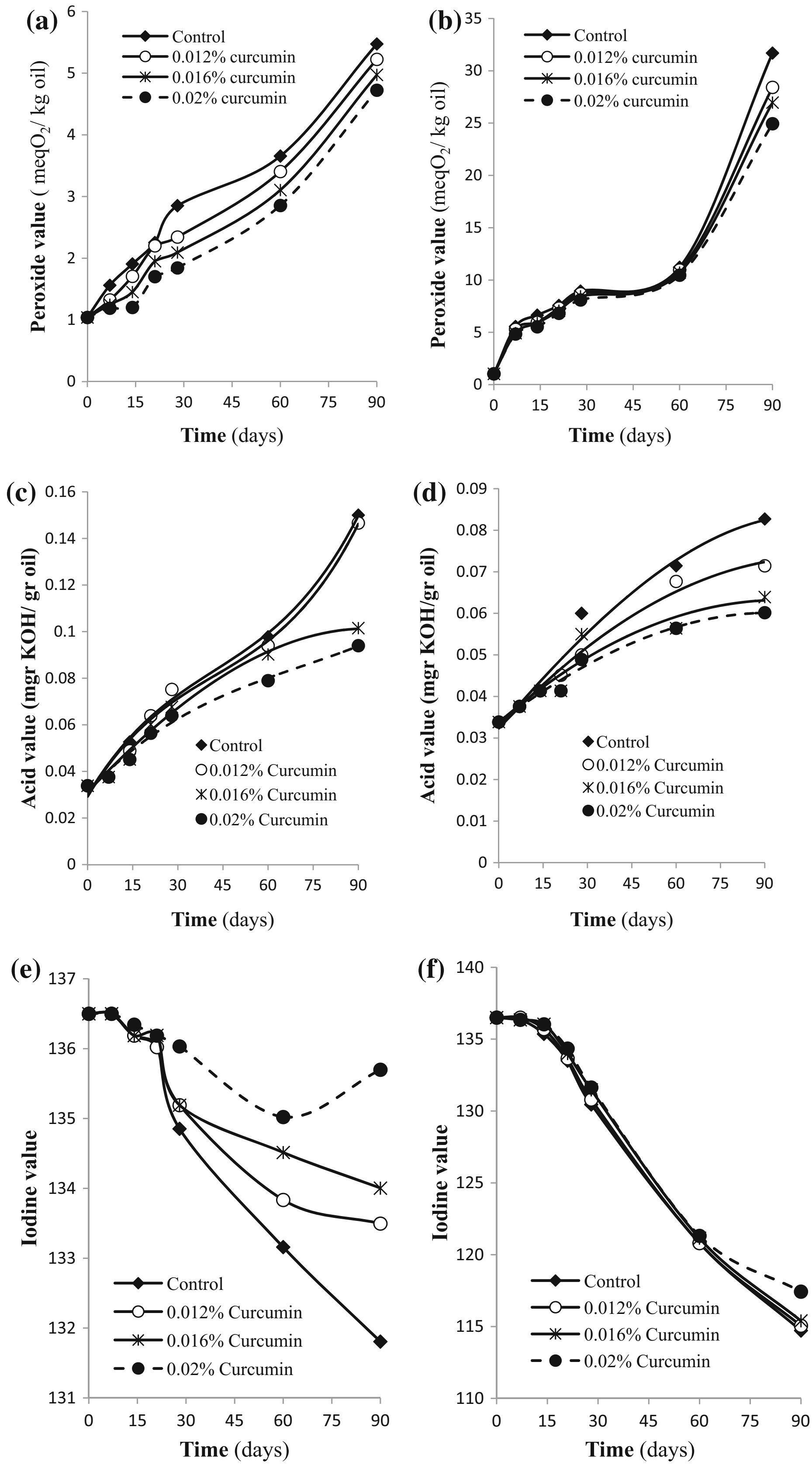

Table 3 Sensitivity analysis of output parameters on input parameters based on optimized model

Sensitivity	PV	AV	IV
Concentration	0.203653833	0.002014392	0.216018742
Temperature	1.824509512	0.003175329	1.772654351
Time	1.586724291	0.012349363	2.450645421

result of IV was observed in the sample containing 0.02 % curcumin. So that, the IV of control samples changed from 136.5 to 132.4 at 25 °C and 115.22 at 55 °C at the end of 90 days. It is clear that temperature had a dramatic effect on IV reduction. Figure 4e–f also presents the trend of IV reduction according to measured data during the storage period (90 days) at 25 and 55 °C. Indeed, measurement of unsaturation is somewhat more reliable in assessing the deterioration of edible oils than other analytical methods. As can be seen in Fig. 4e–f, during the storage, a decrease in unsaturation was observed in soybean oil samples. This decrease in unsaturation can be attributed to the destruction of double bonds by oxidation. So, curcumin as a natural antioxidant had a significant effect on inhibit the soybean oil oxidation. The evaluation of antioxidative properties of Curcuma longa (turmeric) leaf extract in palm olein at 180 °C showed 0.2 % of extract was more effective than 0.02 % BHT [36]. Moreover, Jayaprakasha et al. (2006) also reported 100 ppm of curcumin in a linoleic acid model system was found to be more effective than BHT followed by demethoxycurcumin and bisdemethoxycurcumin [37].

All results indicate that the predictive performance of ANFIS was the best among the constructed models. The sensitivity analysis of outputs including PV, AV and IV of ANFIS model also represented in Table 3. As is shown, the effect of temperature condition on all outputs was more significant than concentration of curcumin. Also, the effect of temperature on PV was the most. It means that among the oxidation parameters, PV is the most sensitive parameter then followed by IV and AV.

Conclusions

In this study, curcumin utilized as natural antioxidant to improve soybean oil shelf life. The results showed that curcumin added had an important inhibit or role on soybean oil oxidation compared to control samples. Also, the accuracy of ANFIS, ANN (MLP and RBF) and MLR models was compared to estimate the oxidation parameters including PV, AV and IV. A comparison of the models indicated that the ANFIS model performed better than the ANN and MLR models for estimating the PV, AV and IV. The MLR was found to be as sufficient as other models for estimation of the oxidation parameters of soybean oil samples. Whereas, the ANFIS models showed a significantly high degree of accuracy in the estimation of PV ($R^2 = 0.984$) and IV ($R^2 = 0.993$).

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