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Modelling and analysis of compressive strength properties of parboiled paddy and milled rice

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A b s t r a c t. The present investigation deals with analyzing the compressive strength properties of two varieties (Tarom and Fajr) of parboiled paddy and milled rice including: ultimate stress, modulus of elasticity, rupture force and rupture energy. Combined artificial neural network and genetic algorithm were also applied to model these properties. The parboiled samples were prepared with three soaking temperatures (25, 50 and 75°C) and three steaming times (10, 15 and 20 min). The samples were then dried to final moisture contents of 8, 10 and 12% (w.b.). In general, Tarom variety had higher compressive strength properties for paddy and milled rice than Fajr variety. With increase in steaming time from 10 to 20 min, all mentioned properties increased significantly, whereas these properties were decreased with increasing moisture content from 8 to 12% (w.b.). Coupled artificial neural network and genetic algorithm model with one hidden layer, three inputs (soaking temperature, steaming time and moisture content), was developed to predict the compressive strength properties as model outputs. Results indicated that this model could predict these properties with high correlation and low mean squared error.

K e y w o r d s: artificial neural network, genetic algorithm, paddy, milled rice

INTRODUCTION

Rice (*Oryza sativa* L.) is the principal food cereal in the world and it is the main food of over half of the world population (Razavi and Farahmandfar, 2008). The majority of Iranian rice (75%) is grown in Mazandaran and Guilan provinces (Zareiforoush *et al*., 2010). The production rate is still far from the country rice self-sufficiency. Increasing the grain severity and hence reducing the processing losses could be a possible way of compenzation for the increasing demand. The primary step in rice processing is dehusking of paddy, which results in brown rice. Polishing or removing of bran to yield white rice is the second step. Knowledge of the compressive strength properties of rice is important in the design of milling equipment to predict their cracking behaviour and to minimize the losses during handling, drying, cleaning and milling processes. For this reason, extensive studies have been done in this area, that would be reviewed here.

Shitanda *et al*. (2001) explored the physical and mechanical properties of paddy and rice. They showed that short-grain rice was harder than long-grain variety and had less broken grain. They noted that husking characteristics of rice are related to shape and size of rice. Cao *et al*. (2004) explored the effect of moisture content on some mechanical properties of brown rice. They showed that moisture content has a significant effect on mechanical properties *ie* compressive strength and tensile strength decreased with increasing moisture content. Corręa *et al*. (2007) explored mechanical behaviour of grains in rice processing. They showed that compressive force was significantly affected by processing. Zareiforoush *et al*. (2010) investigated the mechanical properties of two rice varieties. They recommended that lower rates of compressing load can minimize the percentage of cracked grains. Saif *et al*. (2004) showed that the parboiling process is suitable for enhancing ultimate tensile strength and modulus of elasticity of rice kernel. They reported that steaming time and drying temperature significantly affected tensile strength properties. Parnsakhorn and Noomhorm (2008) also noted that parboiling processes caused an increase in the hardness of rice. They showed that hardness increases with increase in soaking time and steaming time.

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The artificial neural network (ANN) method has recently been of interest to researches and engineers in various research areas and industries. ANN is increasingly being applied to process control and other areas, including the dynamic modelling of process operations, process prediction, optimizing, non-linear transformation, remote sensing technology and parameter estimation for the design of controllers (Yang *et al*., 2009). ANNs and rice producing have been coupled by many researchers. An ANN model was developed for paddy drying to predict energy consumption, final moisture content, kernel cracking, moisture removal rate, drying intensity and water mass removal rate (Zhang *et al.,* 2002). An ANN model was established to predict the flow rate of paddy rice grains through orifices on horizontal rotating cylindrical drum of a hand or tractor-drawn or self-propelled drum seeder (Kumar *et al.,* 2009). Yang *et al.* (2009) successfully used back propagation neural network (BP-ANN) and principal components analysis (PCA) to build a prediction model for the population occurrence of paddy stem borer. A three-layer BP-ANN model which could rapidly and objectively predict the grades of milled rice based on the surface lipid content was revealed by Chen and Huang (2010).

The so-called genetic algorithm (GA) has been introduced to offer advantages compared with traditional methods or system modelling and optimization problems. It is also used for an optimal value of a complex function by simulation of the biological evolutionary process based on crossover and mutation (Izadifar and Jahromi, 2007). The GA can be used to select the appropriate number of nodes in the hidden layer of ANNs. A simple GA-based model was applied to obtain the initial training parameters of a feed forward neural network for prediction of freezing and thawing times of foods (Goni *et al.,* 2008). Wongrat *et al.* (2011) combined GA and control vector parameterization to solve the synthesis of rice drying processes.

The review of literature indicates that the coupled ANN-GA is a hopeful approach to the modelling of compressive strength properties of parboiled paddy and milled rice. No publication was found on this subject in the literature. The objective of this work was to develop an ANN-GA model for the compressive strength properties (ultimate stress (MPa), modulus of elasticity (N mm^{-2}), rupture force (N) and rupture energy (mJ)) of parboiled paddy and milled rice as a function of soaking temperature, steaming time and moisture content. The paper presents the capability of GA to obtain the trained optimal topology of the neural network, too.

MATERIALS AND METHODS

Samples of paddy rice samples of Tarom and Fajr cultivars were provided by Haraz Technology Extension and Development Center (Mahmoodabad, Iran), those being two main long-grain rice varieties in the north of Iran. The initial moisture content of the samples was determined using the standard hot air oven method.

To prepare parboiled samples, the paddy grains were soaked in water at 25, 50 and 75°C for 48, 6 and 3 h, respectively. The paddy samples were then steamed for 10, 15 and 20 min at 100°C and atmospheric pressure. The moisture content of the paddy samples was about 40-45% (w.b.) at the end of steaming process. Parboiled paddy samples were left in shade until the moisture content reduced to 18% (w.b.). The samples were then dried in a standard hot air oven at 35-40°C, for 24-48 h, to achieve moisture content levels of 12, 10 and 8% (w.b.). Samples were coded and labelled according to their soaking temperature and steaming time. For example, the sample with initial soaking temperature of 75°C and steaming time of 20 min was given the label number of 75-20. Three sub-samples of both parboiled rice varieties, each of 500 g, were taken and dehusked at three mentioned moisture content levels, using a laboratory rubber roll type rice husker (ST 50, Yanmar, Japan). The whole brown rice kernels were subsequently milled to whiten the kernels, using a laboratory friction and abrasion vertical type whitener (VP-31, Yamamoto, Japan). Compressive strength properties, including ultimate stress (Y), modulus of elasticity (MOE), rupture force (F) and rupture energy (En) were measured. The experiments were also conducted at constant rate of 0.14 mm s^{-1} according to Shitanda *et al*. (2002). Compression experiments were performed at natural rest position of grain, using a digital stress-strain tester machine (H5KS-1929, UK). A computer was connected to the tester to record the compressive force and deformation of samples with time. The compressive test was stopped immediately at reaching the yield point which was specified by the cracking sound of grain. For each treatment ten grains were randomly selected and the average deformation curve was used for the analysis. The data extracted from experiments were analysed using SPSS (ver. 16) and Excel software for plotting the necessary charts. Analyzes of variance of means were conducted using Duncan multiple tests.

The feed-forward neural networks are the most popular architectures due to their structural flexibility and good representational capabilities (Salehi *et al.,* 2011). Any ANN model contains an input layer, an output layer and one or more hidden layers. The number of neurons in the input and output layers are equal to the number of system inputs and outputs, respectively. The ANN structure employed for modelling of mentioned properties had three input variables including soaking temperature, steaming time and moisture content level. The output variables of the ANNs were Y, MOE, F and En.

The number of hidden layers and their neurons is an important and crucial stage in the design of any ANN, which depends on the problem to be investigated. A network with very few hidden nodes would not be able to approximate a determined data set. However, a network with too many hidden nodes may over-fit the training set and would be unable to adapt to new input conditions. As others have done, the topology of the network was selected by trial and error. The other parameters of network also affect the network training process. These parameters are the mass of the connection between neurons and bias for each neuron in the hidden and output layers. These parameters are updated through a training procedure, with the aim of minimizing the difference between the network outputs and the target values. However, the response of a network strongly depends on the initial value of these parameters. Typically, the initial values of these parameters were selected randomly. Feed forward ANN with back-propagation training algorithm and the hyperbolic tangent sigmoid transfer function in the hidden and output layers were used. In order to obtain an ANN model having the best performance, Bayesian regularization (BR) algorithm was carried out during five hundred epochs.

Recently the GA method has been widely used for finding the best topology and initial parameters of ANN to obtain good training process (Goni *et al.,* 2008; Salehi *et al.,* 2011). Consequently, GA was employed for initializing of mass and bias. In this study, there were only 27 datasets available, due to the limit in experimental studies. Three datasets were randomly selected as testing sets. The remaining 24 datasets were used for training the ANN. In this regard a similar method has been reported by others such as Zhang *et al*. (2002). The remaining three datasets were used for testing purposes. The performance of ANN parameters was statistically measured by mean squared error (*MSE*) and regression coefficient (R^2).

The network having minimum *MSE* and maximum R^2 was selected as the best ANN model.

The genetic algorithm is a global search algorithm that simulates a natural evolution and is widely used for solving optimization and estimation problems. Selection, crossover and mutation are the base operations of GA. These operators act on the current population for producing the next population. The selection operator evaluates the population according to the best individuals. Individuals with high fitness values (representing better solutions to the problem) will have a higher probability of surviving and entering the pooling population, while low-valued individuals will have a high risk of being removed from the population. In this way individuals with the best genes or characteristics will have better chance of survival and mating. In this study the tournament method was used as the selection method. Crossover of two individuals (named as parents) were chosen randomly from pooling population and combined to produce two new individuals (named as children). In this work, uniform crossover with probability ($P_c = 0.8$) was applied. Mutation (random genetic changes) increases the ability of GA to escape from local optimum. The mutation makes small random changes with probability ($P_m = 0.005$) in the individuals (Shopova and Vaklieva-Bancheva, 2006). The individual with the best fitness value in the current population can be lost during the crossover and mutation procedures. To avoid this situation the individual with the best fitness value is stored as elite individual at the end of each generation. The elite individual is then directly added to the next generation.

For defining and initializing the ANN parameters in the GA space, the structure of ANN is determined and then the whole parameters (mass and bias) of network are coded by chromosomes. The developed algorithm, schematized in Fig. 1, was coded in Matlab software with the following procedure.

– Steps 1: defining the GA parameters (number of individual in population, initial population, maximum generations, P_m, P_c), ANN topology and preparing the experimental data in two sets (training and testing).
– Step 2: the ANN parameters set based on individual in the population, and then the ANN training and performance is evaluated for each individual as fitness value of each individual as a linear combination of the train and test mean square error (Goni *et al.,* 2008):

$$MSE_{Fitness} = \beta\, MSE_{Train} + (1-\beta) MSE_{Test}$$

where: β is weighing parameter with value selected as 0.3, in order to the effect of *MSE* for the test be greater than *MSE* for the training, this value was selected.

– Step 3: until the stopping criteria do not reach their maximum value, the operating algorithm is used for reproducing new generation. The elite individuals are also selected and directly added to the new generation.

In this research, the ANN had 3 neurons in the input layer and four neurons in the output layer. The soaking temperature, steaming time and moisture content were taken as the input parameters, where as the Y, MOE, F and En as output parameters for both varieties.

RESULTS AND DISCUSSION

The mean value and standard deviation of Y, MOE, F and En of parboiled paddy of Tarom and Fajr varieties in different soaking temperature, steaming time and moisture contents are given in Table 1, respectively. In general, the ultimate stress of both varieties decreased with increase in moisture content from 8 to 12% (w.b.). Cao *et al*. (2004) observed a similar trend for three brown rice varieties.

ANOVA results showed that the ultimate stress of both varieties was significantly affected ($p \leq 0.05$) by soaking temperature, where as 25 and 50°C soaking temperature had maximum and minimum ultimate stresses, respectively (Table 2). Results also show that ultimate stress of both paddies increased significantly ($p \leq 0.01$) with increase in steaming time. The highest and lowest values of ultimate stress of parboiled paddy of Tarom (5.14 and 3.28 MPa, respectively) and Fajr (4.96 and 3.23 MPa, respectively) were obtained for 25-20 and 50-10, respectively. According to Table 3 the ultimate stress of Tarom and Fajr paddy was

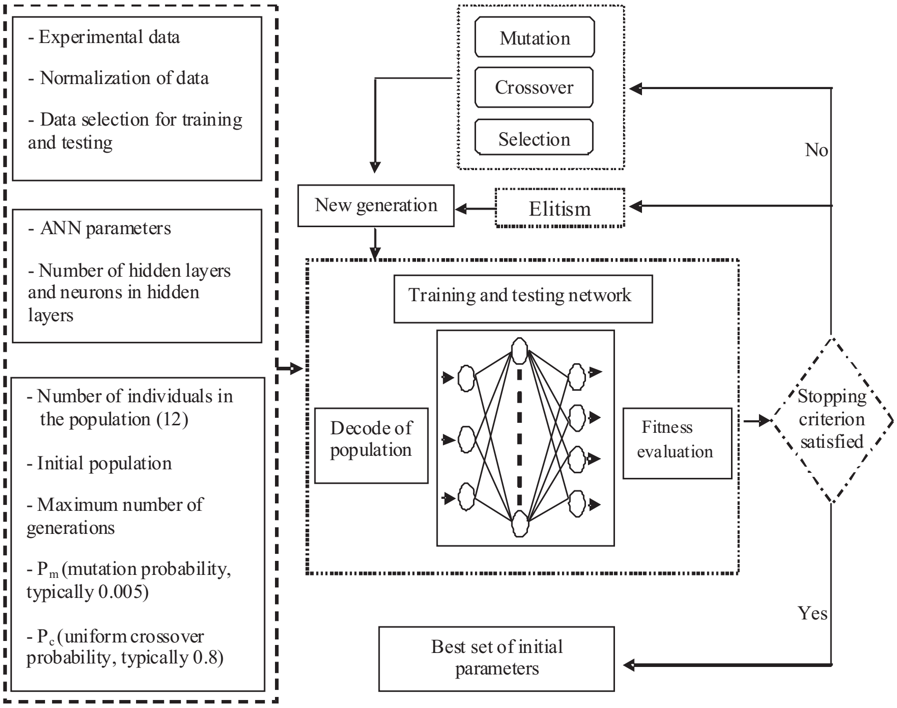

Fig. 1. Diagram of the developed combined GA-ANN.

significantly ($p \leq 0.01$) affected by variety; however Tarom variety had higher ultimate stress than Fajr. It may be related to differences in textural and strength properties of paddy husk and bran. According to Table 1, the modulus of elasticity of both parboiled paddies decreased with increase in moisture content from 8 to 12% (w.b.). The results were similar to those reported by Zhang *et al.* (2005) and Ekinci *et al.* (2010). In general, soaking temperatures of 25 and 50°C represent the highest and lowest values, respectively, for modulus of elasticity of Tarom and Fajr paddy varieties, and it was significantly affected by soaking temperature ($p \leq 0.01$). Modulus of elasticity increased significantly ($p \leq 0.01$) with increase in steaming time for each soaking temperature. ANOVA results (Table 2) showed that the modulus of elasticity of both paddies was significantly affected by variety ($p \leq 0.01$), while Tarom variety had higher modulus of elasticity than Fajr. The lowest and highest values of modulus of elasticity of parboiled Tarom paddy (36.54 and 54.1 N mm^{-2}, respectively) and Fajr paddy (35.17 and 52.62 N mm^{-2}, respectively) were obtained for 50-10 and 25-20, respectively (Table 1).

According to these Tables, rupture force of both paddies decreased with increase in moisture content from 8 to 12% (w.b.). In this regard similar results have been reported by others such as Zhang *et al.* (2005), Ekinci *et al.* (2010) and Singh *et al.* (2010). Rupture force of Tarom and Fajr varieties was significantly affected ($p \leq 0.05$) by soaking temperature, where the highest and lowest values were related to 25 and 50°C, respectively. Rupture force of both varieties increased significantly ($p \leq 0.01$) with increase in steaming time from 10 to 20 min, which agrees with the results of Saif *et al.* (2004). However, Tarom variety had higher rupture force than Fajr. The lowest and highest values of Tarom at 266.1 and 279.5 N, and Fajr paddy at 265.3 and 278.1 N, respectively, were obtained.

Rupture energy of Tarom and Fajr parboiled paddy was affected significantly ($p \leq 0.01$) by moisture content. Rupture energy decreased with increase in moisture content from 8 to 12% (w.b.). Similar trends have been observed elsewhere (Zhang *et al.,* 2005; Ekinci *et al.,* 2010), while some researchers reported that rupture energy increased with increase in moisture content (Altuntas and Yıldız, 2007; Singh *et al.,* 2010). According to Table 1, the highest and lowest values of rupture energy of parboiled paddy for Tarom (42.7 and 28.5 mJ, respectively), and for Fajr (39.8 and 26.9 mJ, respectively) were obtained for 25-20 and 50-10, respectively. It is seen that rupture energy was significantly affected ($p \leq 0.01$) by soaking temperature *ie* 25 and 50°C had the highest and the lowest rupture energy values, respectively. Increase in steaming time from 10 to 20 min caused a meaningful increase ($p \leq 0.01$) in the rupture energy of parboiled paddy. Figure 2 shows the results of ANN optimization by GA as *MSE* versus the number of neurons in hidden layer for Tarom and Fajr paddy varieties. The optimal ANN-GA model had the lowest *MSE* value across all the networks. These graphs illustrate that for Tarom paddy the optimal network has *MSE* of 0.027 for train, 0.069 for fitness and 0.087 for test with 9 neurons in hidden layer. The corresponding values for Fajr paddy are 0.014 for train, 0.061for fitness and 0.081 for test with 11

T a b l e 1. Compressive strength properties of parboiled Tarom and Fajr paddy with different soaking temperature, steaming time and moisture content

Para-meters	Moisture content (%)	Soaking temperature 25			50			75		
		Steaming time								
		10	15	20	10	15	20	10	15	20
		Tarom paddy								
Y(MPa)	8	3.97±0.39a	4.16±0.16a	5.14±0.14a	3.73±0.20a	4.00±0.19a	4.69±0.16a	3.85±0.12a	4.17±0.11a	4.98±0.16a
	10	3.58±0.46b	3.95±0.18b	4.56±0.19b	3.39±0.25b	3.80±0.20a	4.35±0.17b	3.50±0.31b	3.87±0.09b	4.53±0.16b
	12	3.35±0.47b	3.81±0.20b	4.27±0.24c	3.28±0.36b	3.67±0.24b	4.11±0.11b	3.33±0.18b	3.78±0.19c	4.19±0.15c
MOE ($N\ mm^{-2}$)	8	46.53±0.45a	48.75±0.15a	54.10±0.33a	42.17±0.27a	44.53±0.27a	50.62±0.37a	46.09±0.54a	48.66±0.30a	52.14±0.61a
	10	45.27±0.20b	46.07±0.47b	49.11±0.37b	40.01±0.14a	42.40±0.47b	45.14±0.22b	43.11±0.20b	44.87±0.26b	47.77±0.31b
	12	40.62±0.26c	42.21±0.51c	46.66±0.33c	36.54±0.33b	38.46±0.27c	40.39±0.47c	38.83±0.27c	41.12±0.31c	44.03±0.41c
F (N)	8	274.6±0.29a	276.6±0.25a	279.5±0.22a	273.1±0.12a	274.8±0.24a	276.8±0.20a	273.7±0.19a	275.8±0.28a	277.9±0.16a
	10	271.0±0.20b	273.2±0.18b	276.3±0.28b	268.3±0.18b	269.9±0.18b	273.5±0.16a	270.9±0.12b	272.9±0.09b	275.9±0.09b
	12	269.7±0.28c	271.8±0.28c	272.4±0.22c	266.1±0.14c	268.6±0.22b	269.9±0.22b	267.5±0.23c	269.9±0.12c	271.7±0.12c
En (mJ)	8	37.60±0.28a	39.10±0.16a	42.70±0.18a	35.30±0.14a	37.30±0.14a	40.20±0.13a	37.00±0.81a	38.90±0.09a	41.10±0.15a
	10	34.30±0.10b	36.70±0.20b	40.11±0.14b	30.20±0.14b	33.70±0.19b	36.10±0.11b	33.10±0.14b	35.70±0.11b	38.60±0.12b
	12	31.80±0.10c	34.41±0.20c	37.90±0.18c	28.50±0.14c	31.60±0.17c	34.90±0.12b	30.90±0.10c	33.30±0.15b	36.10±0.13c
		Fajr paddy								
Y(MPa)	8	3.90±0.19a	4.10±0.18a	4.96±0.09a	3.70±0.10a	4.00±0.17a	4.66±0.11a	3.83±0.11a	4.13±0.09a	4.88±0.06a
	10	3.60±0.21b	3.88±0.17b	4.70±0.14b	3.28±0.16b	3.69±0.08b	4.25±0.08b	3.35±0.11b	3.71±0.09b	4.44±0.11b
	12	3.28±0.13c	3.75±0.13b	4.21±0.09c	3.23±0.13b	3.59±0.11b	3.95±0.08c	3.30±0.12b	3.68±0.07b	4.17±0.09b
MOE ($N\ mm^{-2}$)	8	46.11±0.15a	48.09±0.12a	52.62±0.32a	41.67±0.21a	43.31±0.32a	48.93±0.16a	45.22±0.25a	46.55±0.21a	49.88±0.15a
	10	44.13±0.15b	45.78±0.22b	48.32±0.28b	38.54±0.16b	39.98±0.42b	43.73±0.20b	42.71±0.23b	44.17±0.06b	45.61±0.23b
	12	39.17±0.48c	41.39±0.16c	44.14±0.09c	35.17±0.08c	36.89±0.34c	39.01±0.07c	37.93±0.21c	39.86±0.14c	42.39±0.15c
F (N)	8	272.5±0.23a	274.9±0.15a	278.1±0.08a	271.8±0.16a	273.3±0.24a	275.3±0.24a	272.1±0.09a	273.8±0.21a	275.5±0.24a
	10	270.6±0.21b	272.8±0.17b	275.3±0.20b	267.7±0.18b	270.0±0.18b	273.1±0.12b	269.8±0.12b	271.4±0.19b	273.4±0.22b
	12	269.1±0.14b	271.6±0.21b	272.1±0.14c	265.3±0.19c	267.7±0.18c	270.9±0.12c	268.3±0.16b	268.1±0.10c	270.8±0.19c
En (mJ)	8	34.10±0.14a	37.50±0.15a	39.80±0.14a	31.60±0.14a	34.70±0.37a	36.40±0.16a	33.20±0.15a	35.90±0.14a	37.80±0.14a
	10	31.20±0.09b	34.70±0.26b	36.20±0.11b	28.30±0.16b	31.60±0.12b	33.70±0.12b	29.70±0.21b	32.10±0.09b	35.70±0.22b
	12	29.50±0.08c	31.30±0.12c	34.60±0.17c	26.90±0.10c	29.70±0.16c	30.10±0.08c	27.20±0.15c	29.20±0.12c	32.10±0.10c

neurons in hidden layer. Table 3 shows the *MSE* for training and testing data and correlation coefficient (R^2) value for the predicted data of optimal GA-ANN model. As it shown, the high value of R^2 (0.910-0.991) and low value of *MSE* (0.017-0.720), for both varieties, confirmed that the ANN-GA model can adequately describe the relationship between Y, MOE, F, En of the paddies and the parboiling process parameters.

The mean value and standard deviation of ultimate stress, modulus of elasticity, rupture force and rupture energy of parboiled milled rice for Tarom and Fajr varieties in different soaking temperatures, steaming times and moisture contents are given in Table 4, respectively. According to the results, ultimate stress of milled rice decreased significantly with increase in moisture content from 8 to 12% (w.b.). The highest and lowest values of ultimate stress were obtained at 25 and 50°C, respectively. For both varieties increase in steaming time from 10 to 20 min caused an increase of the ultimate stress of milled rice. Comparing data in Table 1 with those of Tables 2 and 3 it can be concluded that ultimate stress of paddy was higher than that of milled rice. It may be because of removing husk and bran in milling process caused this property to decrease. In general, milled rice of parboiled Tarom variety had higher ultimate stress than Fajr *ie* the highest and lowest values of ultimate stress for Tarom were 2.59 and 1.98 MPa, and for Fajr were 2.5 and 1.98 MPa, respectively.

Modulus of elasticity of parboiled milled rice of Tarom and Fajr varieties meaningfully ($p \leq 0.01$) decreased with increase in moisture content from 8 to 12% (w.b). Similar results were obtained by Zhang *et al.* (2005) and Ekinci *et al.* (2010). Modulus of elasticity was significantly ($p \leq 0.01$) affected by soaking temperature (Table 5). Increase in steaming time caused an increase of the modulus of elasticity of milled rice of parboiled paddy. The lowest and highest values of modulus of elasticity for milled rice of parboiled Tarom (44.71 and 59.73 N mm^{-2}, respectively) and Fajr (41.17 and 57.89 N mm^{-2}, respectively) were observed for 15-10 and 25-20, respectively. Rupture force of milled rice decreased significantly ($p \leq 0.01$) with increase in moisture content from 8 to 12% (w.b.). The highest and lowest values of rupture force obtained for Tarom milled rice were 200.5 and 185.5 N, respectively, and for Fajr milled rice – 198.8 and 185.1 N, respectively.

According to Table 7, soaking temperature of parboiled milled rice has a significant ($p \leq 0.01$) effect on rupture force, the highest and lowest values of this property being observed at 25 and 50°C, respectively. Rupture force of milled rice increased meaningfully ($p \leq 0.01$) with increase in steaming time from 10 to 20 min. However, Tarom variety had higher rupture force than Fajr, and this property was

T a b l e 2. ANOVA indicating the effect of independent variables on compressive strength properties of parboiled paddy

Source	DOF	"F" value			
		Y	MOE	F	En
V	1	89.42**	242.73**	4.63*	3284.67**
S_t	2	125.9**	1380.04**	12.52**	3193.55**
S_T	2	60.53*	1026.24**	3.65*	1011.57**
Mc	2	39.98*	257.52**	6.58**	3685.3**
$S_t \times V$	2	40.13*	70.85**	0.89ns	195.85**
$S_T \times V$	2	14.19*	19.74*	1.59*	210.98**
$S_T \times S_t$	4	3.63**	65.57**	0.83ns	85.83*
$S_t \times M_c$	4	14.08*	328.02**	0.33ns	63.64*
$M_c \times V$	2	0.12ns	7.54*	2.01*	50.96*
$S_T \times M_c$	4	3.09*	19.74*	1.43ns	94.41**
$S_T \times S_t \times V$	4	10.12*	27.25**	0.75ns	94.02**
$S_t \times M_c \times V$	4	0.50ns	9.31*	3.02*	113.59**
$S_T \times S_t \times M_c$	8	0.56ns	65.06*	0.30ns	44.15*
$S_T \times M_c \times V$	4	1.42ns	31.07**	1.16ns	78.75*
$S_T \times S_t \times M_c \times V$	8	0.25ns	11.44*	1.17ns	26.89ns
Error	486				
Total	539				

V– variety, S_t – steaming time, S_T – soaking temperature, M_c – moisture content, significant at: *$p \leq 0.05$, **$p \leq 0.01$, ns – not significant. Other explanations as in Table 1.

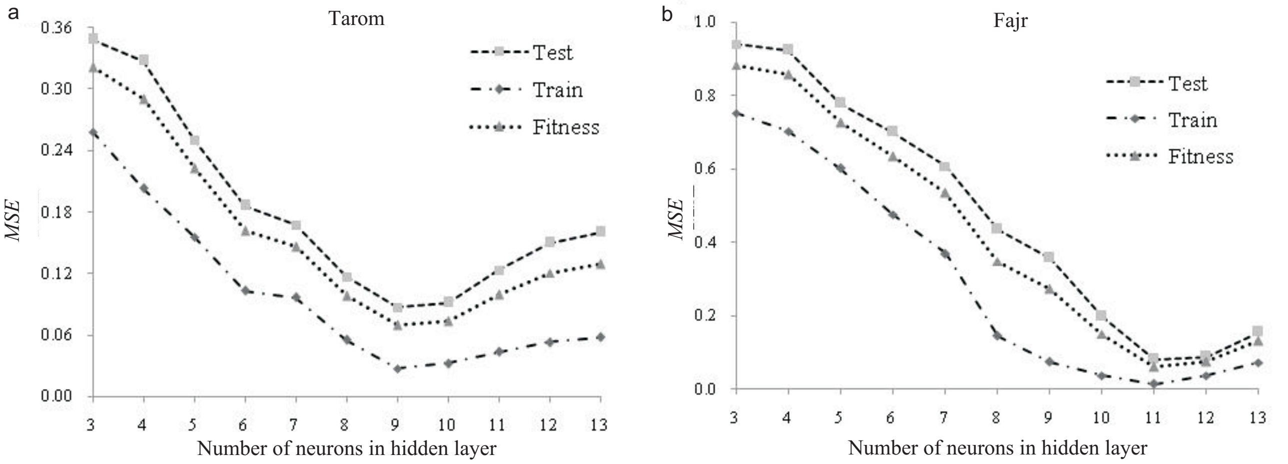

Fig. 2. Estimation of training, fitness and test of GA-ANN model as *MSE* versus number of neurons in hidden layer for: a – Tarom and b – Fajr paddy varieties.

T a b l e 3. Correlation coefficient and mean square error for performance of ANN-GA model for parboiled Tarom and Fajr paddy varieties

Compressive strength properties	*MSE* of				R^2	
	training data		testing data			
	Tarom	Fajr	Tarom	Fajr	Tarom	Fajr
Y	0.122	0.048	0.132	0.056	0.923	0.915
MOE	0.017	0.151	0.041	0.720	0.975	0.910
F	0.073	0.055	0.095	0.166	0.984	0.929
En	0.090	0.122	0.160	0.547	0.991	0.990

Explanations as in Table 1.

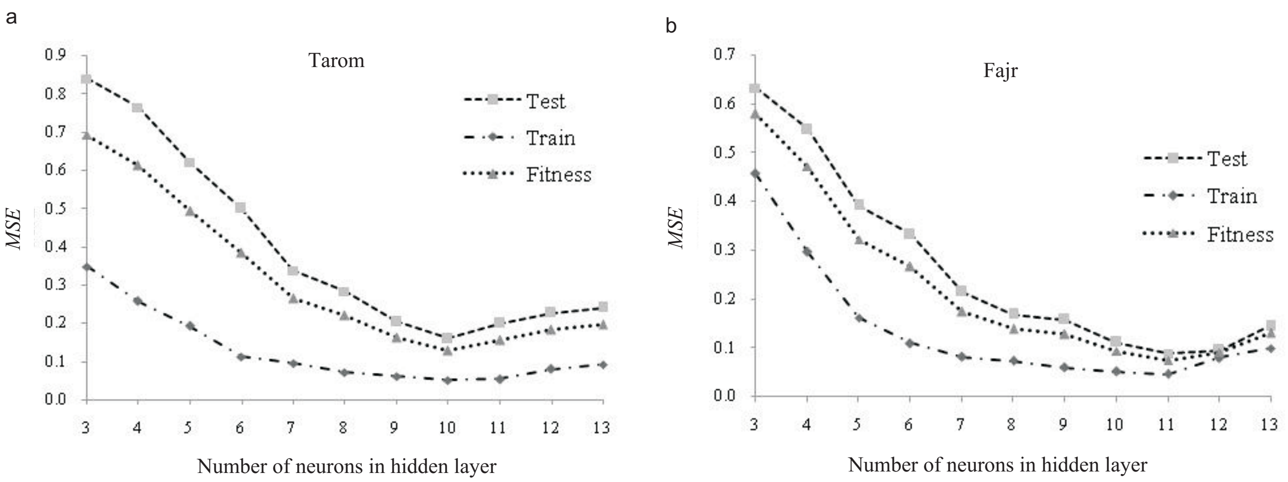

Fig. 3. Estimation of training, fitness and test of GA-ANN model as *MSE* versus number of neurons in hidden layer for: a – Tarom and b – Fajr milled rice varieties.

T a b l e 4. Compressive strength properties of parboiled Tarom and Fajr rices with different soaking temperature, steaming time, and moisture content

Para-meters	Moisture content (%)	Soaking temperature								
		25			50			75		
		Steaming time								
		10	15	20	10	15	20	10	15	20
		Tarom								
Y(MPa)	8	2.30±0.10a	2.47±0.08a	2.59±0.11a	2.25±0.10a	2.35±0.05a	2.40±0.08a	2.30±0.06a	2.39±0.06a	2.44±0.04a
	10	2.25±0.09a	2.40±0.08b	2.49±0.09b	2.12±0.12b	2.30±0.08b	2.37±0.09a	2.09±0.11b	2.33±0.05a	2.39±0.02b
	12	2.00±0.16b	2.33±0.06c	2.31±0.07c	1.98±0.31c	2.25±0.08c	2.28±0.08b	2.00±0.19b	b2.28±0.07b	2.30±0.08b
MOE ($N\ mm^{-2}$)	8	54.04±0.10a	56.72±0.25a	59.73±0.12a	50.02±0.32a	52.81±0.16a	55.01±0.07a	53.70±0.17a	55.35±0.12a	57.79±0.18a
	10	51.80±0.11b	53.08±0.07b	57.41±0.53b	47.14±0.12b	50.40±0.15b	53.95±0.12b	49.60±0.23b	52.60±0.26b	56.47±0.11b
	12	49.67±0.06c	50.90±0.08c	53.81±0.13c	44.71±0.13c	45.50±0.17c	50.98±0.12c	46.35±0.29c	48.03±0.11c	52.71±0.08c
F (N)	8	194.3±0.13a	197.5±0.25a	200.5±0.23a	192.1±0.13a	195.3±0.17a	197.6±0.24a	193.7±0.16a	196.1±0.18a	198.9±0.14a
	10	190.1±0.10b	194.3±0.19b	197.1±0.14b	189.7±0.18b	192.2±0.18b	194.5±0.19b	190.0±0.36b	193.1±0.19b	195.5±0.45b
	12	189.7±0.20c	191.6±0.23c	194.2±0.24c	185.5±0.18c	190.0±0.12c	192.7±0.22c	187.1±0.16c	190.1±0.76c	191.3±0.13c
En (mJ)	8	23.40±0.08a	25.10±0.09a	27.20±0.13a	20.20±0.12a	22.70±0.15a	24.90±0.08a	22.10±0.14a	24.30±0.11a	26.30±0.15a
	10	21.70±0.18b	23.20±0.15b	24.30±0.12b	18.70±0.18b	20.90±0.12b	22.50±0.09b	20.30±0.12b	21.90±0.11b	23.90±0.12b
	12	19.50±0.11c	20.90±0.12c	21.20±0.13c	17.80±0.19b	18.90±0.12c	20.80±0.13c	18.70±0.10c	19.30±0.12c	22.10±0.08c
		Fajr								
Y(MPa)	8	2.28±0.08a	2.39±0.04a	2.50±0.03a	2.23±0.05a	2.30±0.04a	2.38±0.04a	2.27±0.03a	2.35±0.05a	2.48±0.03a
	10	2.22±0.03b	2.35±0.03b	2.45±0.03b	2.14±0.04b	2.24±0.05b	2.31±0.04b	2.17±0.02b	2.29±0.03b	2.40±0.04b
	12	2.11±0.06c	2.28±0.03c	2.37±0.03c	1.98±0.08c	2.00±0.06c	2.23±0.05c	1.98±0.06c	2.22±0.03c	2.27±0.04c
MOE ($N\ mm^{-2}$)	8	52.71±0.21a	54.12±0.10a	57.89±0.21a	49.07±0.11a	51.50±0.23a	54.39±0.27a	51.33±0.20a	53.04±0.09a	56.66±0.31a
	10	49.07±0.11b	52.81±0.14b	55.35±0.12b	45.28±0.10b	48.95±0.17b	51.12±0.10b	47.20±0.16b	50.87±0.14b	53.31±0.17b
	12	48.62±0.16c	49.30±0.22c	51.66±0.17c	41.17±0.14c	44.20±0.18c	48.43±0.18c	43.80±0.16c	47.11±0.11c	49.97±0.22c
F (N)	8	191.3±0.13a	195.3±0.25a	198.8±0.18a	192.0±0.23a	194.1±0.17a	196.3±0.18a	190.7±0.22a	194.4±0.23a	197.3±0.15a
	10	188.2±0.13b	193.1±0.19b	196.1±0.14b	188.3±0.19b	191.8±0.16b	193.1±0.18b	187.6±0.16b	192.7±0.18b	195.2±0.20b
	12	186.6±0.23c	190.2±0.13c	193.2±0.15c	185.1±0.08c	189.1±0.16c	191.2±0.12c	185.1±0.10c	190.0±0.46c	192.7±0.17c
En (mJ)	8	22.10±0.08a	24.30±0.13a	26.90±0.11a	18.30±0.10a	20.30±0.08a	23.10±0.09a	21.20±0.12a	22.90±0.12a	24.80±0.13a
	10	20.30±0.11b	23.00±0.65b	24.10±0.10b	16.50±0.10b	18.70±0.10b	21.00±0.29b	19.80±0.11b	21.00±0.31b	23.20±0.08b
	12	18.70±0.14c	19.90±0.09c	20.70±0.10c	13.90±0.09c	15.90±0.09c	19.50±0.08c	17.80±0.14c	19.30±0.11c	20.00±0.48c

Explanations as in Table 1.

T a b l e 5. ANOVA indicating the effect of independent variables on compressive strength properties of parboiled milled rice

Source	DOF	"F" value			
		Y	MOE	F	En
V	1	14.52*	78.81**	317.15**	309.23**
S_t	2	351.99**	263.08**	256.97**	808.54**
S_T	2	68.23**	157.65**	174.68**	538.48**
Mc	2	240.72**	346.01**	179.51**	113.96**
S_t×V	2	10.94*	1.815^{NS}	129.66**	49.67**
S_T×V	2	2.63^{NS}	0.37^{NS}	109.61**	446.02**
S_T×S_t	4	1.88^{NS}	5.96*	77.23**	122.19**
S_t×M_c	4	7.38*	2.90*	33.09*	124.92**
M_c×V	2	0.56^{NS}	0.56^{NS}	63.03**	16.92*
S_T×M_c	4	0.68^{NS}	1.96^{NS}	12.90*	47.26**
S_T×S_t×V	4	0.81^{NS}	4.45*	95.50**	37.24**
S_t×M_c×V	4	1.88^{NS}	1.11^{NS}	10.53*	9.63*
S_T×S_t×M_c	8	2.25*	2.19*	73.04**	34.26**
S_T×M_c×V	4	4.02*	1.39^{NS}	33.51**	24.48*
S_T×S_t×M_c×V	8	1.41^{NS}	1.21^{NS}	9.57*	21.17*
Error	486				
Total	539				

Explanation as in Table 2.

T a b l e 6. Correlation coefficients and mean square error for performance of ANN-GA model for parboiled Tarom and Fajr milled rice varieties

Compressive strength properties	*MSE* of				R^2	
	training data		testing data			
	Tarom	Fajr	Tarom	Fajr	Tarom	Fajr
Y	0.011	0.155	0.371	0.659	0.962	0.900
MOE	0.093	0.034	0.135	0.083	0.978	0.905
F	0.048	0.024	0.051	0.068	0.988	0.987
En	0.059	0.015	0.088	0.096	0.927	0.955

Explanations as in Table 1.

affected significantly by variety. Comparing the data obtained for paddies and milled rice samples, it can be observed that paddy had higher rupture force than milled rice, which could have been an effect of the increased resistance of paddy husk and bran against compressive force, which has already been reported by Corręa *et al.* (2007). ANOVA results (Table 5) showed that moisture content had a significant effect on rupture energy *ie* this property decreased with increase in moisture content from 8 to 12% (w.b.). The lowest and highest values of rupture energy for Tarom milled rice were obtained as 7.8, 27.7 mJ and for Fajr as 13.9, 26.9 mJ, respectively. Rupture energy of milled rice was meaningfully ($p \leq 0.01$) affected by soaking temperature and the highest and lowest values were observed for 25 and 50°C, respectively. Rupture energy of milled rice increased significantly ($p \leq 0.01$) with increase in steaming time from 10 to 20 min. However, milled rice of Tarom variety had higher rupture energy than that of Fajr. Figure 3 shows the results of ANN optimization by GA as *MSE* versus number of neurons in hidden layer for Tarom and Fajr milled rice varieties. As shown, the value of *MSE* decreased with increase in the number of neurons in hidden layer until it became the lowest value of *MSE* at 10 for Tarom and 11 neurons for Fajr milled rice. It is also seen that the optimal network has *MSE* values of 0.051 for train, 0.126 for fitness and 0.159 for test of Tarom milled rice. The corresponding values for Fajr are 0.044 for train, 0.74 for fitness and 0.087 for test, respectively. The *MSE* for training and testing data and R^2 value of Tarom and Fajr milled rice for optimal GA-ANN model are presented in Table 6. Comparison of the predicted results with experimental data shows very small *MSE* (0.011-0.659) and high R^2 (0.9-0.988), indicating good agreement between compressive strength properties and parboiling process. In this regard some researchers reported high R^2 and low *MSE* for modelling and predicting of products, such as Sablani and Rahman (2003) for predicting thermal conductivity of food, Gulati *et al.* (2010) for modelling and optimization of soybean hydration for facilitating soybean processing, Fathi *et al.* (2011) for an intelligent modelling system to predict the physicochemical properties of dried kiwifruit. As a result, the developed model can be used efficiently for the modelling of compressive strength properties of parboiled paddy and milled rice.

CONCLUSIONS

1. Compressive strength values of parboiled paddy and milled rice were significantly affected by varieties, Tarom had higher values than Fajr for paddy and milled rice.

2. Removing husk and bran in milling process caused the ultimate stress, rupture force and rupture energy of milled rice to decrease.

3. All mentioned properties increased significantly with increase in steaming time from 10 to 20 min.

4. The best GA-ANN model observed had 9 and 11 neurons in hidden layer for Tarom and Fajr paddy, respectively.

5. The developed model can be used efficiently to predict compressive strength properties of parboiled paddy and milled rice.

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