INVESTIGAÇÃO COMPARATIVA DE TÉCNICAS DE MODELAGEM PARA PREDIÇÃO DO COEFICIENTE DE ATRITO ESTATICO DE ALGUMAS SEMENTES DE PLANTAS MEDICINAIS

COMPARATIVE INVESTIGATION OF MODELING TECHNIQUES FOR PREDICTION OF STATIC FRICTION COEFFICIENT OF SOME MEDICINAL PLANT SEEDS

بررسی مقایسه ای تکنیک های مدل سازی برای پیش بینی ضریب اصطکاک استاتیک برخی از دانه های گیاهان دارویی

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RESUMO

O coeficiente de atrito estático (CAE) de algumas sementes de plantas medicinais foi determinado como afetado pelo teor de umidade e superfície de contato. Os dados obtidos foram submetidos à análise de variância para investigar o efeito dos principais tratamentos no CAE. Regressão linear simples (RLS) e técnicas de modelagem inteligente (rede neural artificial (RNA) e sistema de inferência adaptativa neuro-difusa (ANFIS)) foram aplicadas para predição de CAE com base nas mudanças no teor de umidade, na superfície de contato e no tipo de semente. A capacidade de modelagem de três tipos de modelos foi comparada com base na comparação do coeficiente de determinação (R^2), do erro quadrático médio (RMSE) e do erro percentual absoluto médio (MAPE). Os resultados demonstraram que o teor de umidade, a superfície de contato e o tipo de semente afetaram significativamente o SFC ($P < 0,01$). O CAE aumentou conforme o teor de umidade aumentou. Os resultados de modelagem demonstraram que o melhor modelo ANFIS obtido com $R^2 = 0,982$, RMSE = 0,00138 e MAPE = 1,258% foi mais adequado que o melhor modelo de RNA e 25 modelos de RLS individuais para a predição de CAE.

Palavras-chave: regressão linear simples, rede neural artificial, sistema de inferência adaptativa neuro-fuzzy, avaliação de modelo, conteúdo de umidade.

ABSTRACT

The static friction coefficient (SFC) of some medicinal plant seeds was determined as affected by moisture content and contact surface. Obtained data were subjected to analysis of variance to investigate the effect of main treatments on SFC. Single linear regression (SLR) and intelligent modeling techniques (artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS)) were applied for SFC prediction based on changes in moisture content, the contact surface, and the seed type. The modeling capability of three model types was compared based on the comparison of the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE). The results demonstrated that moisture content, the contact surface, and seed type significantly affected SFC ($P < 0.01$). The SFC increased as moisture content increased. Modeling results demonstrated that the best ANFIS model with obtained $R^2=0.982$, RMSE=0.00138, and MAPE=1.258% was more suitable than the best ANN model and 25 individual SLR models for the SFC prediction.

Keywords: simple linear regression, artificial neural network, adaptive neuro-fuzzy inference system, model evaluation, moisture content.

چکیده

ضریب اصطکاک استاتیک (SFC) بعضی از دانه های گیاهان دارویی تحت تأثیر رطوبت و سطح تماس قرار گرفته است. داده های به دست آمده برای تجزیه و تحلیل واریانس مورد بررسی قرار گرفت تا تأثیر اصلی درمان بر روی SFC بررسی شود. پیش بینی SFC براساس تغییرات در میزان رطوبت، سطح تماس و نوع بذر مورد استفاده قرار گرفت.

(SLR) و تکنیک های مدل سازی هوشمند (شبکه عصبی مصنوعی) و سیستم استنتاج فازی سازگار (ANFIS) قابلیت مدل سازی سه مدل با مقایسه ضریب تعیین (R^2)، خطای متوسط مربعات خطا (RMSE) و میانگین خطای درصد مطلق (MAPE) مقایسه شد. نتایج نشان داد که رطوبت، سطح تماس و نوع دانه به طور معنی داری تحت تاثیر SFC قرار گرفت ($P < 0.01$). به SFC به دلیل افزایش رطوبت افزایش یافته است. نتایج مدل سازی نشان داد که بهترین مدل ANFIS با $R^2 = 0.982$ ، $RMSE = 0.00138$ و $MAPE = 1.258\%$ بهتر از بهترین مدل ANN و 25 مدل SLR شخصی برای پیش بینی SFC بود.

کلمات کلیدی: رگرسیون خطی ساده، شبکه عصبی مصنوعی، سیستم استنتاج فازی سازگار، ارزیابی مدل، رطوبت.

1. INTRODUCTION

SFC is one of the most important physical properties of agricultural products. It is frequently used in designing of handling, harvesting, separating, grading, storing, and processing equipment. Hence, it is essential to exactly determine the SFC of the product.

Mohsenin [1] stated that SFC depends not only on the type of product and contact surface but also the moisture content of the product. Consequently, in recent years, many works have been conducted to confirm this general idea for agricultural products [2-5].

The literature contains a considerable number of SLR equations obtained from the conventional statistical techniques for modeling SFC, based on moisture content variation. Some of them can be listed as Suthar and Das [6], Ozarslan [7], Dursun and Dursun [8], Kashaninejad et al. [9] and Avlara et al. [10]. The SLR models were fitted to SFC data for each type of product and contact surface in previous studies, resulting in several equations being proposed. It seems necessary to develop a comprehensive model for SFC prediction based on multiple variables (moisture content, the contact surface, and product type).

Development of a coupled soft computing model with artificial intelligence, such as ANN and ANFIS, can improve the predictive ability. In spite of older modeling techniques, including regression equations, artificial intelligence models can work with more than two variables to predict the target variable [11]. Furthermore, these models are capable of finding the nonlinear relationships between output and input parameters. An ANN is a data modeling environment based on the structure of the biological neural system. This modeling strategy is particularly useful where traditional approaches fail to work properly. Besides the ANN, ANFIS is a powerful tool to improve the efficiency of estimation for uncertain relationships based on the

concept of expert knowledge and training algorithm in a monitored framework.

Application of ANN modeling has been widely proposed to predict the agricultural engineering relationships by many researchers. The details of some recent attempts can be found in the literature [12-15]. There are many reports available in the literature showing the predictive ability of ANFIS in different agricultural studies [16-21]. The results of ANFIS modeling by the previous researchers demonstrated the good ability of the ANFIS model to predict the desired parameter on the basis of multiple variables.

Although researches on numerous agricultural products have added to the information about SFC over the years, there is a paucity of complete information on the SFC of medicinal plant seeds. Some partial attempts were done in case of fenugreek [22], coriander [23-24], castor [25], psyllium [26] and cardamom [27].

Due to the mentioned deficits in the previously published works, the present study focused on the following items:

- a) Investigation of frictional behavior of some commonly used medicinal plant seeds as affected by moisture content and contact surface type.
- b) To study the ability of SLR models to estimate the actual SFC in relation to moisture content.
- c) To assess the comprehensive intelligent models (ANN and ANFIS) in order to precisely predict SFC by taking into account moisture content, medicinal plant seed, and contact surface type.
- d) Conducting a comparative study between SLR and intelligent models to find the best-generalized model with the highest efficiency of SFC prediction.

2. STATEMENT OF THE PROBLEM

2. 1. Raw materials

Seeds of five medicinal plants, linseed (*Linum usitatissimum*), sand plantain (*Plantago afra*), fennel (*Foeniculum vulgare* Mill), caraway (*Bunium persicum* Boiss.) and chicory (*Cichorium intybus*), commonly grown and consumed in Fars region, were obtained from Agricultural Research Center, Medicinal and Aromatic Plants Unit, Fars province, Iran. Prior to the frictional tests, the seeds were cleaned by hand, removing the mixed material such as stone, dust, and broken seeds.

2. 2. Initial moisture content determination

The initial moisture content of cleaned seeds was determined by drying 10 g of samples in a convection oven at 105 ± 2 °C until a constant weight was gained [28]. In order to reduce error, all experiments were carried out in triplicate, and mean values were used. The initial moisture content of all seeds was found to be less than 2 % (d. b.).

2. 3. Sample preparation

In order to obtain samples with higher moisture content (8.8, 14.2, 19.7, 23.9 and 29.7% (d. b.)), samples were moistened with a certain additional quantity of distilled water calculated by the following equation (1) [29]:

$$W_w = W_t(M_f - M_i)/(100 - M_f) \quad (1)$$

The moistened samples were sealed in divided polyethylene bags and kept at 5 ± 0.5 °C in a refrigerator for ten days. This cooling time allowed water diffuse uniformly through the seeds [30]. Two hours before the experiments, the samples were kept at room temperature [31].

2. 4. Frictional experiments

For each contact surface, medicinal plant seed type and moisture content, the exact SFC was determined using the SFC measuring instrument. Before starting new trials, contact surface was cleaned by compressed air to remove any contamination remaining from previous trials. A frame, with negligible weight (dimensions: 20×20×10 mm), was used to

confine sample on the contact surface. There was no contact between the frame and the testable surface. All experiments were carried out in five replications.

2. 5. Statistical analysis

A total of 625 collected data were analyzed using SPSS 21 software. The effect of the contact surface, moisture content, and medicinal plant seed type on SFC were determined using the ANOVA method. The method was applied based on the factorial experiments in a completely randomized design with three treatment factors. The differences of means for three treatment factors were compared using TRT at 99% confidence level.

2. 6. Model development

2. 6. 1. SLR

The SLR model (equation 2) was fitted to the measured SFC, on the basis of moisture content for each contact surface and seed type, using MATLAB R2014b software. The model constants were then determined.

$$\text{SFC} = a(\text{MC}) + b \quad (2)$$

2. 6. 2. Intelligent models

2. 6 2. 1. ANN

The data Obtained from empirical tests were applied to train, validate, and test the commonly used technique of ANN, MLP network, for SFC prediction. The MLP network can be trained from mapping input data to output data through a hidden layer using error-back propagation algorithm. The aim of the training algorithm is to reduce the prediction error by optimization of weights and biases of the network [32].

In this study, moisture content (5 levels), the contact surface (5 types), and medicinal plant seeds (5 types) were selected as input variables. In the input layer simulation environment, numbers 1, 2, 3, 4, and 5 were used, respectively, for introducing linseed, sand plantain, fennel, caraway, and chicory for the SFC model. The same assumptions were also applied to introduce the contact surface types, glass, aluminum, plywood, galvanized steel, and rubber, to the input layer. The obtained SFC was chosen as the desired variable in the output

layer. All SFC data were divided into three data groups, training (70%), validation (15%) and test data (15%). To achieve the best structure for developing ANN model with the highest efficiency, the network parameters, such as the number of training cycle, the input and output transfer function and the number of neurons in the hidden layer, were optimized through several calibration tests. STATISTICA 10 software was used to simulate the ANN model.

2. 6. 2. 2. ANFIS

The ANFIS structure comprises five layers, respectively, fuzzification, fuzzy rule, normalization, defuzzification, and output layer. The ANFIS model can be trained like the ANN model. Combination of the least squares and back propagation method of error (Hybrid algorithm) are often used to train the ANFIS model. Relationships between the target parameter and input variables were extracted in the form of fuzzy rules in the ANFIS model.

Similar to the ANN model development, medicinal plant seed (5 types), moisture content (5 levels) and contact surface (5 types) were chosen as model input and the SFC were selected as model output. The ANFIS model was inspired by contact surface type of glass (=1), aluminum (=2), plywood (=3), galvanized steel (=4) and rubber (=5). The numbers were also applied for detection of linseed, sand plantain, fennel, caraway, and chicory, respectively. Collected data were shuffled and divided into three groups, based on 70%, 15% and 15% data for training, validating, and testing of each developed ANFIS model, respectively. The best topology of ANFIS model with the highest prediction ability of SFC was obtained by calibration of different input and output type of membership functions, defuzzification methods, the number of input membership functions and training cycle. In this study, the ANFIS toolbox of MATLAB R2014b was used to develop several ANFIS models.

2. 7. Performance analysis of developed models

The predictive ability of the developed SLR, ANN, and ANFIS models were evaluated using various statistical parameters such as the coefficient of determination (R^2), RMSE, and MAPE, based on the following equations:

$$R^2 = \frac{\sum_{i=1}^n (SFC_{exp,i} - SFC_{exp,ave})^2 - \sum_{i=1}^n (SFC_{exp,i} - SFC_{pre,i})^2}{\sum_{i=1}^n (SFC_{exp,i} - SFC_{exp,ave})^2} \quad (3)$$

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (SFC_{pre,i} - SFC_{exp,i})^2 \right]^{1/2} \quad (4)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \frac{|SFC_{exp,i} - SFC_{pre,i}|}{SFC_{exp,i}} \quad (5)$$

2. 8. Performance comparison of developed models

Not only the statistical indices of the developed models were compared, but the residual errors of models were also plotted to assess the goodness of fit of models to experimental data. The AAVRE was also calculated for models. The model with the highest value of R^2 and the least value of MAPE, RMSE, and AAVRE was selected as the best model to predict SFC.

3. RESULTS AND DISCUSSION

3. 1. Measured SFC

The result indicated that SFC of studied medicinal plant seeds were in a range between 0.298 and 0.945 for different contact surfaces and moisture content levels (8.8-29.7% (d. b.)). The maximum and minimum SFC for each seed are presented in table (1). For all experimental seeds, highest and lowest SFC were observed in the highest moisture content on rubber and lowest moisture content on glass, respectively. Similar to our results, the SFC range was reported by Tunde-Akintunde and Akintunde [33] for sesame seeds.

3. 2. Statistical analysis

Results of the ANOVA test for measured SFC are presented in table (2). According to the results, contact surface type, moisture content, and medicinal plant seed type indicated a significant effect on SFC ($P < 0.01$). It can be seen in Table (2) that interactions of the main treatments on SFC were also significant ($P < 0.01$). The significant effect of moisture content and contact surface type on SFC were similarly reported in earlier findings by Shafaei et al. [34] for some agricultural seeds.

TRT mean comparison results for two main treatments (contact surface and moisture content) on the measured SFC of medicinal plant

seed are presented in table (3). Different letters were used in the table (a, b, c, d, and e) to indicate significant differences at a confidence level of 99%. In one case, two of five contact surfaces had no significant effect on the corresponding SFC ($P>0.01$). Therefore, in the same condition, the SFC of the seeds showed the same trend on these contact surfaces.

3. 3. Effect of moisture content

The increasing trend in SFC with an increment of moisture content from 8.8 to 29.7% (d. b.) was observed for all five contact surfaces and medicinal plants seeds (figure 1). According to previous reports by the researchers, when the moisture content of seed increases, the surface of seed becomes cohesive, resulting in enhanced cohesive force between the surface of seed and contact surface and, thus, increased SFC [35-39].

3. 4. Effect of contact surface type

TRT results revealed that contact surface type significantly affected the SFC of experimental medicinal seeds (figure 2). For all studied seeds, the lowest SFC was found on the glass and then aluminum, plywood, galvanized steel and finally rubber contact surface, respectively. The SFC changed from lowest to highest value by about 74%. This might be owing to the variation of the contact surfaces quality. The maximum obtained SFC was measured on the rubber. It occurred as a result of the high adhesion between the seeds and the rubber. Our results were generally observed to be similar to the previous findings for neem nut [40], hazelnut [41], quinoa seed [42], round red lentil grain [43], seeds and kernels of *Jatropha curcas* L. [44] and flowers of lavender [45].

3. 5. Effect of medicinal plant seed type

As it can be seen in figure (3), the mean SFC of studied medicinal plant seeds ranged between 0.565 and 0.691. Different physical properties of the seeds resulted in variation of SFC in the same experimental conditions. The same letters in Figure (3) (a, b and c) indicate that there is no significant difference at a confidence level of 99% for corresponding medicinal plant seeds. Thus, in the same experimental conditions, these seeds can be used with considering the same frictional behavior. Similar to our results, previous studies have been demonstrated that SFC differed for three varieties of olive [46], watermelon seed

[47], sunflower seed and its kernel [48] and four varieties of wheat [49].

3. 6. Model evaluation

3. 6. 1. SLR

The coefficients (a and b) of SLR equations and their R^2 , RMSE and MAPE values were calculated by fitting the experimental data of SFC as a function of moisture content for each type of medicinal plant seed and contact surface (table 4). According to the results, although the relationship between SFC and moisture content for studied medicinal plant seeds on five contact surfaces was positively modeled by SLR, the SLR equations could not properly describe the SFC behavior thought the experimental conditions.

3. 6. 2. Intelligent models

3. 6. 2. 1. ANN

Table (5) presents descriptive results of properly trained ANN models offered by STATISTICA 10 software. From table (5), it is clear that the best trained ANN model was the model with the highest $R^2=0.706$, the lowest RMSE=0.07150, and MAPE=11.192. The value of AAVRE and standard deviation are 0.006608 and 0.05392, respectively. Although, there are a lot of published pieces of information previously cited about the successful application of the MLP network of ANN model for prediction of agricultural target based on multiple variables [50-53], it was found in present work that the MLP-ANN model with designed structure of three input neurons (moisture content, contact surface, and medicinal plant seed type), one hidden layer with eight neurons and one output neuron (SFC) did not suffice for SFC modeling.

In this study, it was found that there was no precise linear or nonlinear relationship between measured SFC and contact surface or medicinal plant seed type (section 3. 3. 2 and 3. 3. 3). Hence, the weakness of several trained ANN models to acceptably predict the SFC based on multiple variable changes in moisture content, the contact surface, and medicinal plant seed type might result in uncovering this imprecise relationship.

3. 6. 2. 2. ANFIS

Table (6) describes the five suitable topologies among the many developed ANFIS models with corresponding R^2 , RMSE, and MAPE values. According to the table (6), the best

SFC prediction was the one with $R^2=0.982$, $RMSE=0.00138$, and $MAPE=1.258\%$.

Evaluation of the results obtained from the best ANFIS model illustrated the goodness of the predictive ability of model existed in SFC estimation based on three input variables. The $AAVRE=0.02720$, via its standard deviation of 0.02612, was calculated for the best developed ANFIS model. Reviewing the earlier findings revealed that some agricultural studies have also been reasonably conducted using ANFIS models [54].

3. 7. Performance comparison of the developed models

Fitting the SLR model to obtained data revealed that the application of the SLR model provided 25 mathematical linear equations that could be used for each combination of the contact surface and medicinal plant seed type. Average statistical parameters, R^2 , $RMSE$, and $MAPE$, obtained from fitted SLR model were 0.914, 0.02889, and 5.233%, respectively. These values showed an almost imperfect fit of estimated and measured SFC.

In spite of SLR models which provided 25 mathematical linear equations, the intelligent models with multiple input variables were developed using the ANN or ANFIS simulator setup. The performance of the best developed ANFIS and ANN model is shown in figure (4). In comparison, the best ANFIS model, with $R^2=0.982$, $RMSE=0.00138$ and $MAPE=1.258\%$, was more accurate than the best ANN model, with $R^2=0.706$, $RMSE=0.07150$, and $MAPE=11.192\%$. Therefore, it can be stated that the ANFIS model was rated as better than the ANN model, followed by the SLR models, for SFC prediction.

4. Conclusions

The results obtained in this study can be summarized as:

- 1- Among the measured SFC of experimental medicinal plant seeds (linseed, sand plantain, fennel, chicory and caraway), the highest and lowest SFC (0.945 and 0.298) belonged to sand plantain with moisture content of 29.7% (d. b.) on rubber and chicory with moisture content of 8.8% (d. b.) on glass contact surface, respectively.
- 2- The ANOVA results demonstrated that the moisture content, medicinal plant seed,

and contact surface type significantly affected the SFC. The obtained information can be attended for designing post harvesting equipment such as cleaning, sorting, and packaging.

- 3- The SFC increased as moisture content increased for each type of medicinal plant seed and contact surface.
- 4- To excellently predict SFC with specific conditions, the best developed ANFIS model with obtained $R^2=0.982$, $RMSE=0.00138$, and $MAPE=1.258\%$ was proposed rather than the best trained ANN and 25 fitted SLR models. Suggested ANFIS model is useful in process control and providing accurate data within specified bounds.

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Nomenclature

a	coefficient of SLR model	M_i	initial moisture content of the sample (d. b. %)
b	coefficient of SLR model	$SFC_{pre,i}$	ith predicted SFC
MC	moisture content of the sample (d. b. %)	n	the number of data
M_f	final moisture content of the sample (d. b. %)	$SFC_{exp,ave}$	average of measured SFC
W_w	mass of added distilled water (g)	$SFC_{exp,i}$	ith measured SFC
W_t	initial mass of sample (g)		

Abbreviations

AAVRE: average of absolute values of residual errors; ANFIS: adaptive neuro-fuzzy inference system; ANN: artificial neural network; ANOVA: analysis of variance; MAPE: mean absolute percentage error; MLP: multi-layer perceptron; RMSE: root mean square error; SFC: static friction coefficient; SLR: simple linear regression; TRT: Tukey's range test.

Table 1. The SFC range for different medicinal plant seeds

Medicinal plant seed	Maximum $\pm$ standard deviation	Minimum $\pm$ standard deviation
linseed	0.861 $\pm$ 0.0071	0.402 $\pm$ 0.0084
sand plantain	0.945 $\pm$ 0.0062	0.386 $\pm$ 0.0159
fennel	0.898 $\pm$ 0.0191	0.339 $\pm$ 0.0168
chicory	0.735 $\pm$ 0.0041	0.298 $\pm$ 0.0044
caraway	0.916 $\pm$ 0.0104	0.344 $\pm$ 0.0155

Table 2. ANOVA results for measured SFC

Source of variation	Degree of freedom	Sum squares	Mean square	F value
Medicinal Plant Seed	4	1.161	0.290	1531.414**
Moisture Content (MC)	4	2.663	0.666	3511.816**
Contact Surface (CS)	4	8.043	2.011	10609.015**
MPS×MC	16	0.057	0.004	18.886**
MPS×CS	16	3.326	0.208	1096.766**
MC×CS	16	0.037	0.002	12.145**
MPS×MC×CS	64	0.139	0.002	11.486**
Error	500	0.095	0	
Total	624	15.521		

**Significant at less than 1% probability level

Table 3. TRT mean comparison results for the effect of main treatments on the measured SFC

Treatment	Medicinal plant seed				
	linseed	sand	fennel	chicory	caraway
moisture content					
8.8	0.556±0.023 ^a	0.566±0.029 ^a	0.586±0.030 ^a	0.496±0.029 ^a	0.557±0.034 ^a
14.2	0.611±0.021 ^b	0.623±0.029 ^b	0.657±0.026 ^b	0.535±0.027 ^b	0.619±0.037 ^b
19.7	0.661±0.022 ^c	0.662±0.030 ^c	0.688±0.028 ^c	0.564±0.027 ^c	0.664±0.040 ^c
23.9	0.715±0.019 ^d	0.706±0.026 ^d	0.739±0.025 ^d	0.603±0.027 ^d	0.717±0.035 ^d
29.7	0.755±0.018 ^e	0.759±0.022 ^e	0.784±0.021 ^e	0.630±0.027 ^e	0.766±0.031 ^e
contact surface					
glass	0.521±0.016 ^a	0.481±0.017 ^a	0.474±0.019 ^a	0.371±0.010 ^a	0.441±0.016 ^a
aluminum	0.603±0.016 ^b	0.673±0.013 ^b	0.637±0.015 ^b	0.437±0.007 ^b	0.467±0.018 ^b
plywood	0.626±0.017 ^c	0.686±0.011 ^b	0.716±0.015 ^c	0.658±0.011 ^c	0.813±0.015 ^c
galvanized steel	0.763±0.012 ^d	0.596±0.019 ^c	0.804±0.009 ^d	0.671±0.010 ^d	0.777±0.016 ^d
rubber	0.784±0.013 ^e	0.879±0.011 ^d	0.823±0.013 ^e	0.690±0.011 ^e	0.826±0.014 ^e

Table 4. The coefficients of the SLR model with statistical parameters of SFC modeling

Seed type	Contact surface	a	b	R ²	RMSE	MAPE (%)
linseed	glass	0.01047	0.319	0.916	0.03345	4.813
	aluminum	0.00107	0.396	0.926	0.06349	9.661
	plywood	0.01151	0.405	0.919	0.02970	3.938
	galvanized	0.00760	0.617	0.874	0.11008	6.910
	rubber	0.00854	0.619	0.968	0.01267	2.090
sand	glass	0.01093	0.270	0.898	0.02967	4.122
	aluminum	0.00841	0.511	0.901	0.04657	7.696
	plywood	0.00708	0.549	0.967	0.00860	4.643
	galvanized	0.01209	0.364	0.923	0.03634	7.035
	rubber	0.00697	0.745	0.962	0.01127	2.898
fennel	glass	0.01243	0.235	0.952	0.02247	3.264
	aluminum	0.00987	0.447	0.931	0.02172	4.407
	plywood	0.00994	0.525	0.883	0.03064	5.983
	galvanized	0.00581	0.692	0.872	0.01805	9.599
	rubber	0.00844	0.661	0.931	0.01853	3.619
chicory	glass	0.00646	0.247	0.885	0.01652	8.244
	aluminum	0.00489	0.596	0.898	0.01329	6.384
	plywood	0.00753	0.292	0.921	0.03856	4.506
	galvanized	0.00653	0.545	0.949	0.01229	2.275
	rubber	0.00706	0.522	0.875	0.01925	5.023
caraway	glass	0.01015	0.245	0.921	0.02394	3.538
	aluminum	0.01157	0.244	0.879	0.03440	5.135
	plywood	0.00897	0.641	0.870	0.02284	6.970
	galvanized	0.01030	0.578	0.881	0.03032	4.599
	rubber	0.00900	0.652	0.944	0.01767	3.480

Table 5. Five distinct structures of trained ANN models for SFC prediction

The number of neurons	The number of training cycles	Transfer function		R ²	RMSE	MAPE (%)
		Input	Output			
8	521	exponential	exponential	0.706	0.07150	11.192
5	642	tangent	sine	0.676	0.11759	13.135
4	185	tangent	logistic	0.664	0.12451	12.452
4	256	sine	tangent	0.574	0.21360	16.112
3	347	logistic	exponential	0.509	0.45386	16.324

Table 6. Information of selected ANFIS models to predict SFC

The number of training cycles	The number of input membership functions	Membership		Defuzzification method	R ²	RMSE	MAPE (%)
		Input	Output				
119	3,3,3	gaussian	linear	weighted sum	0.982	0.00138	1.258
75	3,4,3	Gbell	linear	weighted sum	0.976	0.00759	3.459
225	3,4,4	Gbell	constant	weighted sum	0.912	0.01556	7.340
184	3,4,4	gaussian	linear	weighted	0.894	0.04793	7.893
94	4,4,3	triangular	constant	weighted	0.881	0.07541	8.635

Figure 1. Effect of moisture content on the measured SFC of studied medicinal plant seeds for contact surface of ● the glass, ■ aluminum, ◆ plywood, ▲ galvanized steel, and × rubber

Figure 2. Results of TRT mean comparison for effect of contact surface type on the measured SFC of experimental medicinal plant seeds

Figure 3. Results of TRT mean comparison for effect of medicinal plant seed type on the measured SFC

Figure 4. Comparison between statistical parameters of evaluation of ANFIS and ANN ability in SFC prediction