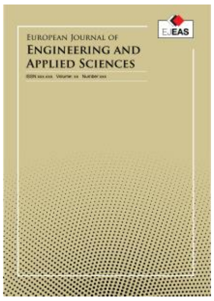
European Journal of
Engineering and Applied Sciences

ISSN: 2651-3412 (Print) & 2667-8454 (Online)
Journal homepage: http://dergipark.gov.tr/EJEAS
Published by Çorlu Faculty of Engineering, Tekirdağ Namık Kemal University

European J. Eng. App. Sci. 6(2), 50-55, 2023



Araştırma Makalesi

Comparison of Artificial Neural Networks and Fuzzy Logic Methods in the Hazelnut Shell Drying Process

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Geliş: 09.11.2023 *Kabul: 14.11.2023* *DOI: 10.55581/ejeas.1388492*

Abstract: Drying and storing food products have been widely used techniques for extending shelf life for many years. In recent times, there has been a focus on the drying of food residues, similar to the preservation of foods by drying. The process of drying a product involves reducing the moisture content within the product. However, the devices established to reduce moisture content are often costly and rely heavily on experience-based systems for determining the drying ratio. Therefore, in recent years, there has been significant interest in the mathematical modeling of drying processes and the creation of a model for system behavior using artificial intelligence methods. This study aims to model the drying process of hazelnut shells using artificial intelligence techniques, specifically artificial neural networks and fuzzy logic methods. The proximity of the models created to the experimental results of the drying ratio is examined.

Keywords: *ANFIS, Artifical Neural Network, Drying, Fuzzy Logic, Levenberg Marquardt, Prediction*

Fındık Kabuğu Kurutma Sürecinde Yapay Sinir Ağları ve Bulanık Mantık Yöntemlerinin Karşılaştırılması

Özet: Gıda ürünlerinin kurutularak saklanması kullanım ömrünü uzatması açısından uzun yıllardır kullanılan bir tekniktir. Gıdaların kurutularak saklanması gibi gıda artıklarının da kurutulması son yıllarda çalışmalara konu olmuştur. Ürün kurutma işlemi, ürün içerisindeki nem miktarının azaltılması anlamına gelmektedir. Nem miktarının azaltılması amacıyla kurulmuş olan düzenekler maliyetli ve daha çok kuruma oranının tespitinin tecrübeye dayandığı sistemlerdir. Bu sebeple son yıllarda kurutma süreçlerinin matematiksel olarak modellenmesi, yapay zeka yöntemleri ile sistem davranışının bir modelinin oluşturulması çalışmaları ilgi çekmiştir. Bu çalışmada fındık kabuğu kurutma işleminin yapay zeka tekniklerinden olan yapay sinir ağları ve bulanık mantık yöntemleri ile modellenmesi gerçekleştirilmesi hedeflenmiş ve oluşturulan modellerin kuruma oranının deneysel sonuçlarına yakınlığı incelenmiştir.

Anahtar kelimeler: *ANFIS, Bulanık Mantık, Kurutma, Levenberg Marquardt, Tahmin, Yapay Sinir Ağları*

1. Introduction

In today's world, many foods and food items cannot be stored for an extended period due to their high water content. Therefore, drying methods play a significant role in food preservation. Various techniques are employed to carry out the drying process.

Hazelnuts are a product that grows in the Blacksea region of Turkey. The drying of hazelnuts holds significant importance in the Blacksea region. Considering the climate conditions and soil structure of the region, there are challenges in open-air drying. Therefore, instead of relying on sunlight, drying machines are more commonly used. Drying systems, which include these drying machines, represent a more costly approach compared to open-air drying with sunlight. This cost includes both the setup and operation of the system.

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Consequently, utilizing artificial intelligence techniques based on past data to predict drying speed and efficiency has become an increasingly popular approach.

2. Literature Review

Hamed Akbarpour and colleagues (2016) obtained numerical and experimental results to demonstrate the impact of nonlinear models on predicting the pore size of nano-porous anodic alumina (NPAA). They employed ANFIS (Adaptive Neuro-Fuzzy Inference System) and MLR (Multiple Linear Regression) applications for this purpose. The results obtained from the models were compared between two empirical formulas to demonstrate the accuracy of the models and test data. The experimental results indicate that the models are sufficiently effective in predicting the pore size of NPAA membranes. ANFIS emerged as the superior model, with MLR performing better than other empirical formulas [1].

Saban Pusat and colleagues (2016) implemented a novel methodology to predict coal moisture content during the drying process. ANFIS was employed to predict coal moisture content at any given time during the drying process. Four different experiments were conducted with MSE and R^2 values during the testing phase. The experiments revealed that the ANFIS network achieved scientifically satisfactory results with acceptable deviations. By utilizing ANFIS, drying channels for cases not experimentally performed could be easily predicted. Moreover, the required number of experiments was reduced [2].

In 2018, Maryam Dolatabad and her team conducted a study to assess the concurrent removal efficiency of Basic Red 46 (BR46) and Cu (both dye and heavy metal) from aqueous solutions. They employed advanced feedforward Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models to predict the adsorption capacity of sawdust in the simultaneous removal of cationic dye and heavy metal ions. The reported results indicated that both ANN and ANFIS are promising predictive techniques, displaying satisfactory accuracy in predicting the simultaneous removal of dye and Cu (II) from aqueous solutions. The low values of the statistical parameters suggested superior performance for both models. The study achieved a robust regression analysis with an R^2 ranging from 0.98 to 0.99 for both dye and Cu removal [3].

Victor H. Quej and colleagues (2017) compared the performance of Support Vector Machine (SVM), ANFIS, ANN techniques to predict daily global solar radiation in Yucatán, Mexico. They used three statistical indicators (R^2, RMSE, and MAE) to evaluate model performance. The SVM technique with an RBF kernel demonstrated superiority over other approaches used for predicting global solar radiation in Yucatán, Mexico. This result suggests that SVM can be successfully employed to predict daily solar radiation in humid tropical environments in Mexico. While ANFIS and ANN techniques showed similar results, they did not perform as well as the SVM technique [4].

In 2018, Mohammad Kaveh and his team conducted a research study aiming to develop and apply an ANFIS and ANN model for predicting the drying properties of potatoes, garlic, and melons in a convective hot air dryer. The drying experiments were carried out at varying air temperatures of 40, 50, 60, and 70°C, coupled with air velocities of 0.5, 1, and 1.5 m/s. Various ANN and ANFIS models were used to determine the D effect and SEC performance. The results of this research showed that the ANFIS model exhibited high predictive capabilities for D effect, SEC, MR, and DR with R^2 values of 0.9900, 0.9917, 0.9774, and 0.9901, respectively. Therefore, the study concluded that the ANFIS model could be recommended as the best model [5].

Bahman Najafi and colleagues (2018) conducted small-scale biogas production using spent mushroom compost (SMC). From the biomass obtained through biogas production, they investigated factors influencing biogas production, including the C/N ratio, temperature, and retention time, as independent variables in biogas production and production modeling, using ANN and ANFIS methods. The study concluded that the ANFIS network accurately predicted output values in both thermophilic and mesophilic conditions [6].

Artur S. C. and colleagues (2018) compared the optimization of sugarcane delignification using Alkaline Hydrogen Peroxide (AHP) with ANN and ANFIS. Two variables were experimentally evaluated: temperature (25-45°C) and hydrogen peroxide concentration (1.5-7.5% (a/h)). The AHP pre-treatment proved successful in the delignification of sugarcane bagasse. Both ANN and ANFIS demonstrated good prediction efficiency with low RMSE values and R^2 values close to 1. The ANFIS model outperformed the ANN model in predicting xylose concentration [7].

3. Materials and Methods

In this study, drying process results for hazelnut products were obtained in the laboratory using a microwave setup. The obtained results, constituting 80% of the data, were used as training data for artificial intelligence methods, and the remaining 20% of experimental data was aimed at being predicted. A comparison of the two methods was conducted based on the predicted results.

The first artificial intelligence method used is the feedforward artificial neural network. Various models were created by using different transfer functions when forming ANN. The ANN model that provided results closest to the experimental data was compared with another method, ANFIS.

3.1. Artificial Neural Networks

The ability to derive, create, and discover new information through the learning process, which is a characteristic of the human brain, is a system that is mathematically represented. ANN learn through experiences, similar to humans, and utilize this learning in decision-making. Therefore, ANN has the capability of making good generalizations [8].

ANNs consist of neurons, and these neurons form a neural network by connecting to each other in various ways. They possess the capacity for learning, memory, and revealing relationships between data.

Recently, ANNs have become a popular and useful model in many disciplines for classification, clustering, pattern recognition, and prediction. ANNs, as a type of model for machine learning, have become relatively competitive in terms of utility compared to traditional regression and statistical models [9].

ANNs consist of layers (Figure 1). Neurons in each layer are connected to the neurons in the next layer. ANNs are examined in three main layers: the input layer, the hidden layer, and the output layer [10].

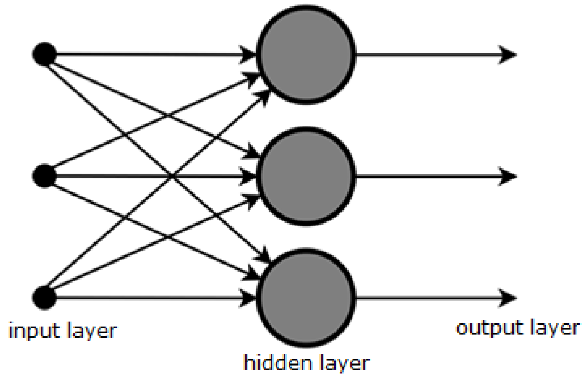

Figure 1. *Artificial Neural Networks General Architecture [10]*

3.2. ANFIS

ANFIS is a learning technique that transforms inputs into outputs through fuzzy logic and highly interconnected neural networks. It combines the advantages of both ANN and fuzzy logic under a single roof. ANFIS is a hybrid learning algorithm.

ANFIS provides an accelerated learning capacity and adaptable interpretive capabilities to model complex patterns and understand nonlinear relationships. It has been applied and refined in various fields, offering solutions to problems characterized by time and space complexity as well as widely occurring repetitive issues [11].

In fuzzy logic, there are various inference methods. Some of these inferences are specifically developed to operate directly within the framework of fuzzy logic. The two most commonly used methods are Mamdani inference and Sugeno inference.

In the Mamdani system, each input and output is a fuzzy value. Mamdani inference, with its more intuitive and easily understandable rule basis, is highly suitable for expert system applications, such as medical diagnosis, where rules are derived from human expert knowledge.

Sugeno fuzzy inference is a frequently preferred method in control problems. Unlike the Mamdani method, where fuzzy values are given as output, Sugeno provides the output in a functional form. Therefore, the Sugeno inference system is highly suitable for mathematical analysis.

3.2.1. Membership Functions

Membership functions are curves that define how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. It is a graphical representation of the magnitude of participation for each input. Rules use input membership values as weighting factors to determine their influence on fuzzy output sets. Once the functions are deduced, scaled, and combined, they are fuzzified into a clear output guiding the system.

The simplest membership functions are created using straight lines. Due to their simple formulas and computational efficiency, both triangular and trapezoidal shapes have been widely used [12].

3.3. Performance Measures

In this study, the performance measurements of predictions were utilized to determine how closely they approximated the experimental data. The methods used for performance measurements include the root mean square error, mean absolute percentage error, and R^2.

Root Mean Square Error (RMSE) (Eq. 1) provides the distance between predicted results and actual values as an absolute number. It is one of the most commonly used metrics to assess the quality of predictions. RMSE is the standard deviation of prediction errors (residuals). This value can range between 0 and infinity. A value close to zero indicates that the model is performing well.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{n} e_j^2}{n}} \tag{1}$$

Mean Absolute Percentage Error (MAPE) (Eq. 2) is one of the most commonly used measures of prediction accuracy due to its scale-independence and interpretability advantages. It is widely used because it is easy to interpret and explain. For example, a MAPE value of 10% means that the average difference between the predicted value and the actual value is 10%.

$$\mathrm{MAPE} = \frac{100}{n}\sum_{j}^{n}\frac{|e_j|}{|A_j|} \tag{2}$$

R-squared (R^2) (Eq. 3) is used to explain how well the independent variables in a linear regression model account for the variability in the dependent variable. The R^2 value always increases with the addition of independent variables, even if they are unnecessary, which can lead to the inclusion of irrelevant variables in the model.

$$r^2 = 1 - \left(\frac{\sum_{i=1}^{N}(o_i - t_i)^2}{\sum_{i}^{N}(t_i)^2}\right) \tag{3}$$

4. Experimental Results

In this study, a 9-feedforward artificial neural network model consisting of different transfer functions was trained, and predictions for the drying process of hazelnut products were made. Additionally, an ANFIS model was created, and a similar prediction process was carried out on the same dataset. 80% of the experimental data was used as training data.

Experimental data was obtained from a conveyor-belt microwave system established in the Laboratory of the Department of Mechanical Engineering at Tekirdağ Namık Kemal University [13].

The first step in the prediction process in artificial neural networks begins with the selection of input, output, and test data. Here, the input data consists of randomly selected 80% of the experimental data. The input data has four columns, including time, power, wet mass, and dry mass. The output data is the moisture content produced by the selected input data from the experimental data. Test data is determined as the remaining 20% of the experimental data not selected as input data.

After the data is selected, the process of creating an artificial neural network is carried out. First, the process of determining the number of neurons in the hidden layer is performed. In the experiments conducted in this study, models with 10, 20, and 30 neurons were tested. Three transfer functions were used in the experiments: hyperbolic tangent sigmoid, logistic sigmoid, and linear functions. By using these transfer functions separately in the experiments, a total of nine models were created. Additionally, the Levenberg-Marquardt algorithm was selected as the training function.

After the model is created, it needs to be trained with the training data. The process of training the network was carried out by selecting input and output data created by the training data. After the training process is completed, test data is input into the created artificial neural network to make predictions and generate predicted outputs. The regression graph of the model that gives the closest results to the experimental results from these 9 models is presented in Figure 2.

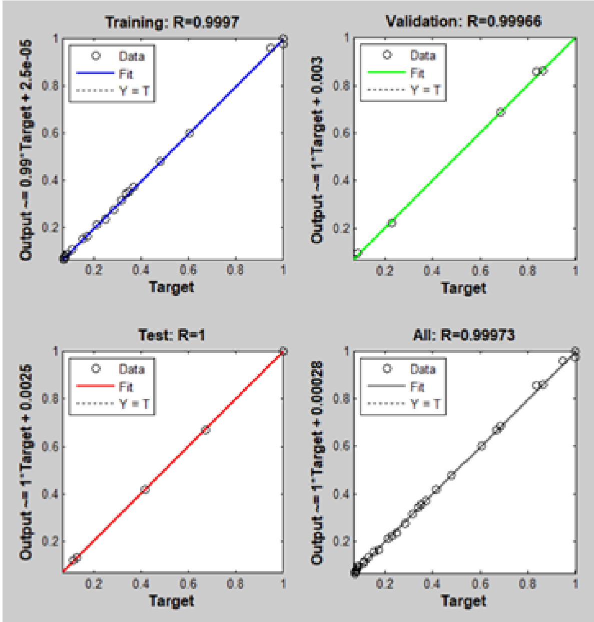

Figure 2. *Regression graph of the selected model.*

In ANNs, prediction processes were performed using the Feedforward Backpropagation Neural Network model. The results obtained with 3 different transfer function models and different numbers of neurons are specified in Table 1.

Table 1 ANN Model Results

Neuron	Transfer Function	Output Function										
	Logsig	Purelin	0,4382	0,1096	0,5520	0,0931	0,0838	0,0914	0,2720	0,1418	0,7307	0,0944
10	Tansig	Purelin	0,3941	0,1140	0,5142	0,1036	0,0675	0,0776	0,2462	0,1543	0,7323	0,0690
	Tansig	Logsig	0,5368	0,5368	0,5368	0,5368	0,5368	0,5368	0,5368	0,5368	0,7776	0,5368
	Logsig	Purelin	0,3837	0,1006	0,4927	0,0959	0,0515	0,0932	0,2665	0,1355	0,7287	0,0603
20	Tansig	Purelin	0,4004	0,1075	0,5085	0,0894	0,0877	0,0903	0,2692	0,1441	0,7191	0,0936
	Tansig	Logsig	0,5368	0,5368	0,5372	0,5368	0,5368	0,5368	0,5368	0,5368	0,7340	0,5368
	Logsig	Purelin	0,4325	0,1149	0,5610	0,0962	0,0217	0,0971	0,2577	0,1511	0,7110	0,0743
30	Tansig	Purelin	0,4677	0,0905	0,7174	0,0910	0,0727	0,0653	0,2602	0,1456	0,7150	0,0704
	Tansig	Logsig	0,5446	0,5368	0,5827	0,5368	0,5368	0,5368	0,5369	0,5368	0,6930	0,5368
	Exp. data		0,4181	0,1090	0,5348	0,0916	0,0775	0,0874	0,2564	0,1454	0,7237	0,0775

Based on the obtained results, the performance measurement of each model was conducted. Considering the measurements, it was determined that the most successful ANN model had 10 neurons in the hidden layer, a logistic sigmoid as the transfer function, and a linear transfer function for the output layer. The performance measurements for this model are provided in Table 2.

Table 2 Performance Measurement of the Best ANN Model

	Training data	Test data	All
RMSE	0,0074055	0,0065915	0,0099141
R^2	0,9997846	0,998788	0,9996615
MAPE	1,9275744	5,4020781	2,7750143

When creating the ANFIS model, which will be compared with this ANN model, the Sugeno inference method was selected, and the number of inputs was set to be the same as the ANN model. Figure 3 shows the ANFIS model, which has 4 inputs and a single output.

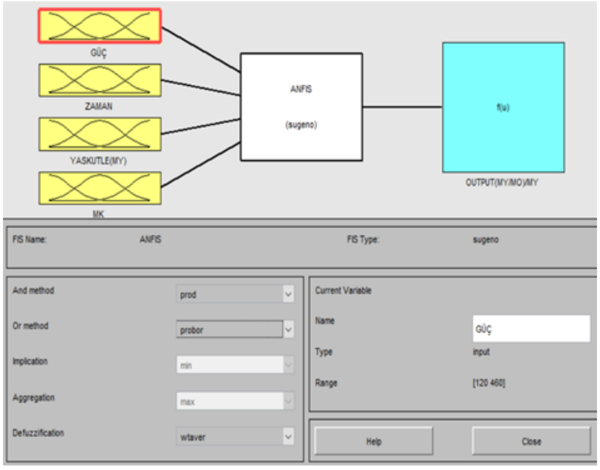

Figure 3. *ANFIS Sugeno Architecture*

After selecting the inference method, the process continues with the training of the model. For this training to take place, the training and test data must be added to the model first. After the training, the rules generated by the ANFIS model are obtained. These rules can be generated automatically or individually by writing them. Another important aspect for the ANFIS model is the membership functions. The membership functions for the created model are shown in Figure 4.

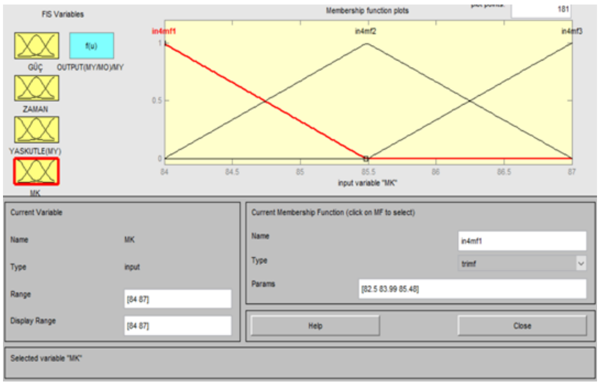

Figure 4. *Membership functions of the ANFIS model.*

The created model is ready to make predictions. The obtained output values are evaluated with the same performance measurement parameters as the ANN model. Table 3 shows the performance measurement of the ANFIS model.

Table 3 ANFIS Performance Measurement

	Training data	**Test data**	**All**
RMSE	0,0061833	0,0068424	0,0092224
R^2	0,9999998	0,9999933	0,99999903
MAPE	0,0746246	0,4662799	0,1701503

The predictions made with the ANFIS and ANN models are compared with the experimental data.

5. Conclusion

The experimental results of hazelnut Shell products previously dried with a microwave system in a laboratory environment were obtained, and the drying process of hazelnut Shell products with ANN and ANFIS was modeled. By providing a portion of the experimental data to the models as training data, the models were trained, and the aim was to predict the remaining part of the experimental data.

To achieve this goal, 9 ANN models with different transfer functions and neuron numbers were evaluated, and the most successful model was identified. The findings revealed that the Artificial Neural Network models achieved the best results with a 10-neuron Log-sigmoid and Purelin transfer function model.

Predictions for the test data were obtained for the ANFIS model created with the same data. In the examination, it was observed that the ANFIS model produced values closer to the experimental data.

In light of these models and data, predictions for drying without setting up an experimental design have become possible for hazelnut products.

Using similar data, different prediction methods and models can be employed in various fields, saving time and costs.

Author Contributions

Format analysis – Mert Levent (ML), Halil Nusret Buluş (HNB);

Experimental performance – ML, HNB;

Data collecting – Soner Çelen (SÇ), Aytaç Moralar (AM);

Literature review – ML, HNB;

Writing – HNB, ML;

Review and editing – HNB, SÇ, AM.

Declaration of Competing Interest

The authors declared no conflicts of interest with respect to the research to the research, authorship, and/or publication of this article.

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