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Parameter estimation in Crystal Sugar production with MLR, ANN and ANFIS

Kristal Şeker üretiminde ÇDR, YSA ve ANFIS ile parametre tahmini

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Abstract

The sugar production process is a complex process in which many variables interact. The cost and time requirements of complex processes are reduced by computer-based modeling techniques and necessary actions can be taken regarding the obtained product quality. In this study for the crystallization stage, solution color which is one of the quality control criteria for sugar production, was predicted by multiple linear regression (MLR), artificial neural network (ANN) and adaptive neural fuzzy inference system (ANFIS). Production data (brix, purity, pol, pH, ash, color and vacuum temperature) obtained from Ankara Sugar Factory General Directorate. As a result of the sensitivity analysis ash, color and vacuum temperature was determined to be the most effective parameters on the estimated output and used as a model input variables. R and MSE values were used as model performance criteria. ANFIS showed better prediction performance than MLR and ANN, R= 0.99.

Keywords: Sugar production, Modeling, Artificial neural network, MLR, ANFIS.

Öz

Şeker üretim süreci, birçok değişkenin etkileşim içinde olduğu karmaşık bir süreçtir. Karmaşık süreçlerin maliyet ve zaman gereksinimleri, bilgisayar tabanlı modelleme teknikleri ile azaltılmakta ve elde edilen ürün kalitesi ile ilgili gerekli aksiyonlar zamanında alınabilmektedir. Bu çalışmada şeker üretimi için kalite kontrol kriterlerinden biri olan çözelti rengi, kristalizasyon aşaması için çoklu doğrusal regresyon (MLR), yapay sinir ağı (YSA) ve uyarlanabilir sinirsel bulanık çıkarım sistemi (ANFIS) ile tahmin edilmiştir. Üretim verileri (brix, saflık, pol, pH, kül, renk ve vakum sıcaklığı) Ankara Şeker Fabrikası Genel Müdürlüğü'nden alınmıştır. Duyarlılık analizi sonucunda kül, renk ve vakum sıcaklığının tahmin edilen çıktı üzerinde en etkili parametreler olduğu belirlenmiş ve model girdi değişkenleri olarak tanımlanmıştır. Model performans kriteri olarak R ve MSE değerleri kullanılmıştır. ANFIS, MLR ve ANN'den daha iyi tahmin performansı göstermiştir, R= 0.99.

Anahtar kelimeler: Şeker üretimi, Modelleme, yapay Sinir ağı, MLR, ANFIS.

1 Introduction

Turkey is an important sugar consumer with a population of approximately 83 million and it is estimated that Turkey's annual sugar consumption per capita is 30 kg. To meet this need, Turkey Şugar Factory (TÜRKSEKER) is a state corporation and is the largest sugar producer with 15 sugar factories [1].

Sugar production is generally made from sugar beet and sugar cane in the world and Turkey ranks 7th in sugar beet production. Obtaining sugar from sugar beet is a very complex process and a large number of production variables affect the quality of the product. The main purpose of the sugar factory is to have an efficient and profitable business by providing the required sugar quality and maximum sugar recovery [2]. It is difficult to predict product quality in the industrial production process. Traditional methods used in the modeling of complex production processes are not sufficient and forecast accuracy is not high [3].

In general, the proposed models can be divided into two groups as physical-based and data-based models. Data-driven techniques have ability to learn and to train from the data instead of creating and solving equations to make predictions with high accuracy [4].

One of these data-driven model is MLR. It is an analysis to reveal the relationship between a dependent variable and a series of independent variables associated with it. [5].

However, due to the MLR structure, the relationships between input and output are linear and are insufficient for modeling nonlinear processes with different known and unknown effects. ANN and ANFIS is very successful in modeling nonlinear and complex processes [6].

Artificial intelligence in modeling studies in the production processes has been a research area that has attracted a lot of attention recently. Historical data formed during industrial production are used in the prediction.

In the literature, quality control value estimation has never been made for sugar production stage. The solution color has an important role in the determination of produced sugar quality. The solution of a good sugar is colorless and clear. According to Turkish Food Codex Sugar Communication, sugar solution color should not be above 25 IU. Aim of this study is to estimate the solution color through modeling by MLR, ANN and ANFIS, using values of ash, color and vacuum temperature as input variables. The parameter estimation performed in this study was made for the crystallization step. For a large and complex process such as sugar production, parameter estimation with artificial intelligence is very important in terms of efficiency and cost.

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2 Material and method

2.1 Sugar production process

Sugar production process includes sugar production from beet, separation of unwanted substances in beet, washing, slicing, extraction, pressing, purification, evaporation, crystallization and packaging stage. The parameter estimation was made for the crystallization step [7].

The crystallization process is carried out in the refinery units of sugar factories at crystallization station as seen from Figure 1. For this purpose, cylindrical apparatus called vacuum boiler is used. Vacuum is created in the vacuum vessel and standard syrup is taken into the vacuum vessel. Steam is opened to the steam chamber and the firing process begins. The process of cooking crystal sugar in the refinery unit is the process of thickening the dark syrup until the dry matter content of the standard syrup, which is prepared after the addition of crystal white syrup, medium sugar and refined sugar, is 92-93%. During this process, the sugar crystallizes. Standard syrup entering the vacuum boilers in the crystallization unit is converted into crystal sugar as a product. Quality of sugar was measured by tests such as solution color, ash, polarization…etc [8].

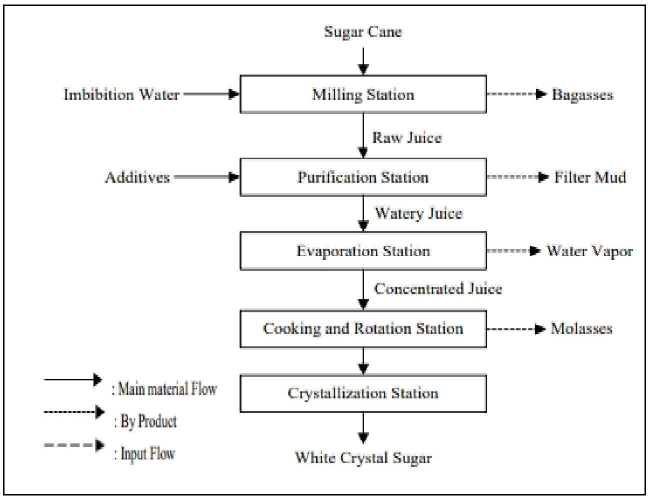

Figure 1. Sugar production process.

Sugar is tested in many ways to validate its quality. One of them is ICUMSA color measurement. The formation of color is the result of specific steps of the manufacturing processes. By measuring the color with the ICUMSA color chart, the consistency can be ensured and the value of product can be understand. The term color refers to a wide range of complex and molecular components that contribute to the overall appearance of sugar. Normally color measurement is measured by the sugar concentration and its UV absorbency. A number of difficulties arise in the actual evaluation of the color of a sugar solution from the absorbancy. There is often uncertainty concerning the actual color of a sugar solution because of complex reaction formations between sugar constituents and buffers. Also the pH of sucrose itself which has been neglected in the existing practice of color determination has an appreciable influence on color.

By solution color modeling, the degree of influence of the input components in the crystallization is determined. The effect of the changes in the variables on the product quality can be determined in advance and quick action can be taken.

2.2 MLR

Purpose of linear regression is to make predictions by revealing the relationship between a single dependent variable with more than one independent variable. MLR can be used when more than one change in the dependent variable associated with the multiple independent variables. The MLR model can be expressed in Eq. 1. as:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots . \beta_n X_n \tag{1}$$

y dependent parameter; $X_1 \dots X_n$ independent parameter; β_0, β_n unknown parameters [9].

2.3 ANN

In general, ANN can be defined as a system designed to model fetch performs function of the brain. It consists of connecting elements to each other by weights, each of which has its own memory. ANNs are computer programs that emulate biological neural networks [10].

As seen from Figure 2, $X_0 \dots X_n$ values are input values and weight values (W_0) are available for each input. After the input value and the weights (W_0) are multiplied ($W_n X_n$), all the product values are added together with the summation function to obtain the net input value of the system. After adding bias b to the net input value, it is transmitted to the activation function and an output value (Y) is obtained (Eq. 2) [11].

$$Y = f(\sum_i w_i x_i + b) \tag{2}$$

In ANN network architecture, the number of input variables is low or high it directly affects the precision of the result. The relationships in the existing data set are analyzed and the independent variables that have a great impact on the estimated value are selected as input variables [12]. Output is the value determined and estimated by the activation function. Summation function is the function used to calculate the total net input. Minimum, maximum or cumulative sum functions are used during calculation [13]. Transfer function is a mathematical function. It takes the net input value of the output of the summation function and converts it to an output. There are two types of activation functions, linear and nonlinear. While linear functions are more limited in capacity, nonlinear activation functions are used in the models to conclude nonlinear problems [14].

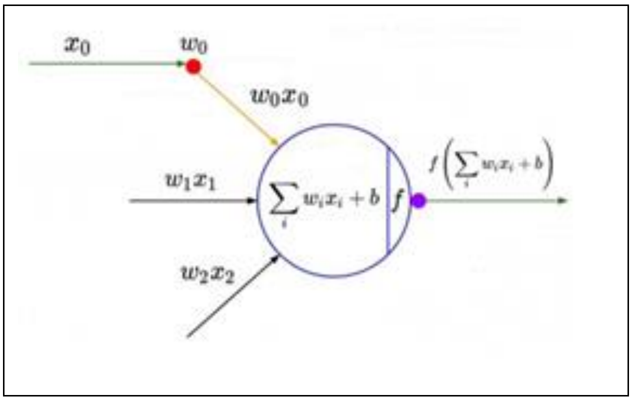

Figure 2. ANN working principles.

2.4 ANFIS

ANFIS is a hybrid artificial intelligence method that uses, parallel computation of artificial neural networks and learning ability of fuzzy logic. The starting point for creating a fuzzy system is the creation of the if-then rule. An effective tool for this purpose is a method that can transform data into necessary fuzzy rules. There are relationships between input and output variables based on learning ability by applying different training models with ANN [15]. ANFIS system based on the idea of combining learning ability of ANN and fuzzy logic advantages such as the ease of making human-like decisions and providing expert information [16].

The if-then rule equation proposed by the Takagi and Sugeno inference system for two input in the ANFIS system is:

$$Rule\ 1 = \text{If } x = A_1\ and\ y = B_1, then\ f_1 = p_1 x + q_1 y + r_1 \quad (3)$$

$$Rule\ 2: If\ x = A_2\ and\ y = B_2, then\ f_2 = p_2 x + q_2 y + r_2 \quad (4)$$

ANFIS consists of 5 layer feed forward artificial neural network structure. These layers are;

- 1st Layer: Cell count is equal to the number of input variable which creates an adaptive node,
- 2nd Layer: Nodes are fixed character. As many rules are created as the number of nodes. The node inputs are the membership function values of the variables, the node outputs are the weights of the rules,
- 3rd Layer: Node inputs are weights of rules and outputs are normalized weights degrees. The weights of the rules are normalized in this layer [17],
- 4rd Layer: In this layer, the each nodes contribution to the model output is calculated,
- 5th Layer: The overall output is calculated in this layer. Defuzzification process converted fuzzy value to exact value [18].

2.5 Data set

Data for the 2020-2021 campaign period was obtained from Turkish Sugar Factory (TÜRKSEKER) and used in the modeling studies. During sugar production, quality control tests are carried out for the intermediate and final product. In this context, brix, purity, polarization, pH, ash, color, vacuum temperature and solution color values were measured in the laboratory.

2.6 Data normalization

In ANN, training of the data presented to the ANN can be made more efficient by applying certain preprocessing steps to the network inputs and outputs. The normalization process is applied to the raw data. Training of artificial neural networks, raw can be very slow without applying normalization method to dataset. The min-max method normalizes the data linearly. Minimum is the lowest value that the data can take, while the maximum represents the highest value the data can take. Equation (5) is used to reduce a data to the range of 0 to 1 with the min-max method.

$$X_i = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})} \quad (5)$$

where Xi normalized data and X is input [19].

2.7 Model performance criteria

The estimation performance of the model can be measured and compared with some statistical methods. In this study, Mean Squared Error (MSE) (Eq. 6) and the correlation coefficient R (Eq.7) between observed and calculated values were used as performance criteria [20].

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_{observed -} Y_{predicted}\right)^2 \quad (6)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{observed -} Y_{predicted}\right)^2}{\sum_{i=1}^{n}\left(Y_{observed -} Y_{mean}\right)^2} \quad (7)$$

$Y_{predicted}$ is the data predicted by model, $Y_{observed}$ is the observed data, Y_{mean} is the arithmetic mean of the observed data and n is the number of observations.

3 Result and discussion

3.1 Sensitivity analysis

Sensitivity analysis impact on the model is to investigate the degree of effectiveness of the independent variables. Thus, It can be determined that which parameters are effective or not in the model. In artificial intelligence applications, as a result of the sensitivity analysis, the effect of all input parameters on the predicted value is determined and the number of inputs is decided [21]. In order to find the optimum number of input variables, sensitivity analysis was performed on all independent variables. The range, minimum, maximum, mean, standard deviation and variance values of the variables obtained by using the IBM SPSS program for sensitivity analysis was given in Table 1. Relationship between the output and the other independent variables are given in Table 2. The relationship between the variables was determined by the Pearson correlation coefficients. It was determined that brix, purity, polarization and pH values have negative effects on solution color, while ash, color and vacuum temperature have direct positive effects on solution color.

3.2 MLR Results

General equation from MLR analysis is:

$$Y = -24.74 + 0.393X_1, 0.007X_2 + 5.004X_3 \quad (8)$$

Where X_1 is vacuum temperature, X_2 is color and X_3 is ash. R2 value was found 0.37 as seen from Table 3.

Table 1. Sensitivity analysis of the variables.

	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Brix	10.35	62.55	72.90	67.34	1.83	3.364
Purity	2.34	94.14	96.48	95.43	0.49	0.244
Polarization	10.63	59.45	70.08	64.27	1.87	3.515
pH	1.10	8.0	9.10	8.58	0.248	0.062
Ash	0.85	1.09	1.94	1.35	0.16	0.026
Color	1381	995	2376	1494	326	10634
Vacuum Temperature	6	72	78	75	2.03	4.147
Solution Color	22	13.2	35.2	22.07	4.72	22.2

Table 2. Pearson correlation coefficient for variables.

Sol.	Brix	Purity	Polarization	pH	Ash	Color	Vacuum Temp.
Color	-.052	-.336	-.107	-.373	.461	.575	.079

Table 3. MLR model statistical values.

			Change Statistics	
R	R Square	Adjusted R Square	R Square Change	Sig. F Change
.608	.370	.342	.370	.000

Significance level is smaller than 0.05 and it indicate that model is significant. Collinearity values graphic shows that there is no linear connections between variables as seen from Figure 3.

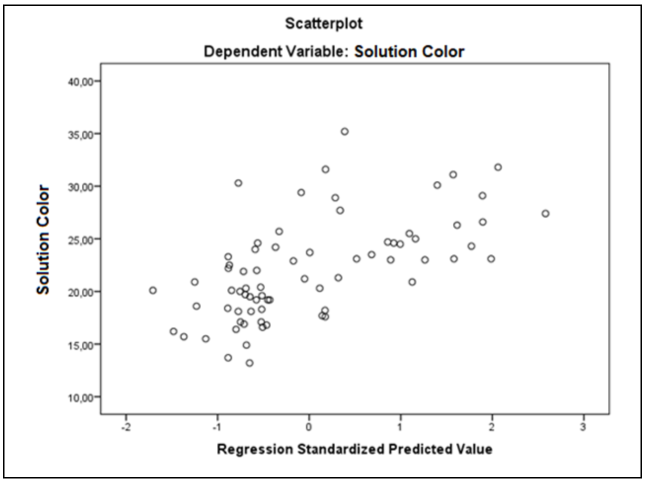

Figure 3. Collinearity values graphic.

3.3 ANN results

ANN studies were carried out with Matlab 2017a Neural Fitting Toolbox. Ash, color and vacuum temperature is input and solution color is output for the system as shown in Figure 4. The data set was divided into 70% training, 15% validation, and 15% testing. The feed forward ANN was used and when the number of neurons in the hidden layer was changed between 1-30, the best performing number was determined as 17 by trial and error.

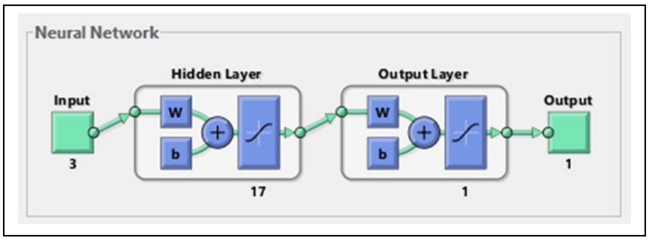

Figure 4. ANN structure

Performance criteria MSE is found 0.004 for training, 0.0045 for validation, 0.0039 for testing. R is found 0.82 for all system as seen from Figure 5.

3.4 ANFIS results

ANFIS studies were carried out in Matlab program through “anfisedit”. 70% of the data set was used for the training and 30% for testing. In the ANFIS model, 3 inputs and one output variable are defined as shown in the Figure 6. 18 fuzzy rules were created. The training process was carried out with the "Hybrid" algorithm. ANFIS has a wide variety of the shapes of membership functions; such as, Gaussian, trapezoidal, triangular, bell-shaped. Gaussmf was chosen because of their smoothness and concise notation.

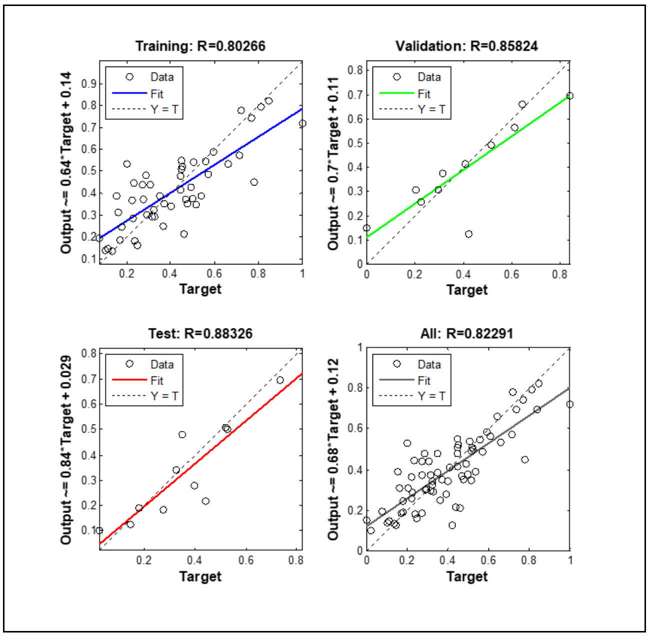

Figure 5. ANN network regression graphic.

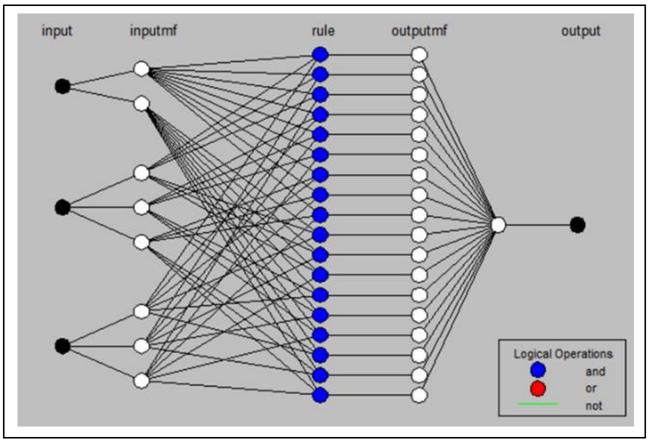

Figure 6. ANFIS structure.

ANFIS contains different membership functions gaussmf was chosen due to low error value. Epoch number was 100 and training error is 0.0038 as seen from Figure 7. R^2 was found 0.9986 as shown from Figure 8.

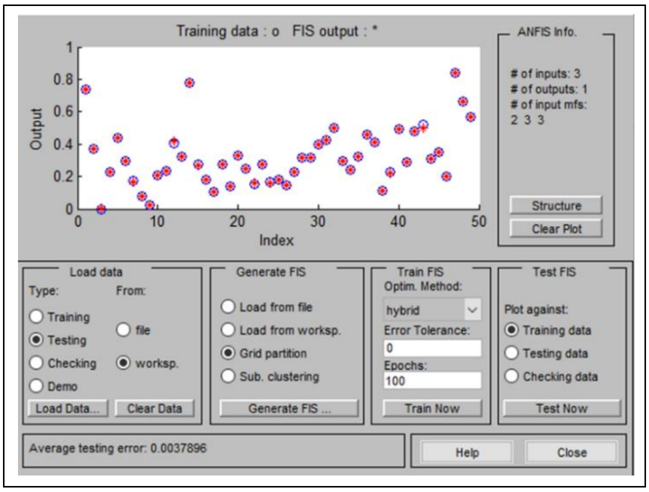

Figure 7. ANFIS training data output.

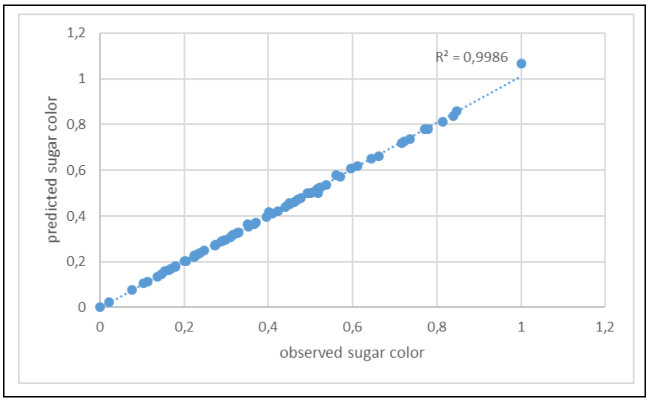

Figure 8. Comparison of measured and predicted output by ANFIS.

3.5 Comparing MLR, ANN and ANFIS

Main goal of the study is the prediction of solution color at crystallization stage of sugar production by MLR, ANN and ANFIS. The correlation coefficient (R) value of ANFIS was more significant than the ANN and MLR, which is found as 0.99, 0.82 and 0.6, respectively. In literature, Al-Mukhtar and Al-Yaseen used MLR, ANN and ANFIS for total dissolved solids (TDS) and electrical conductivity (EC) prediction in Abu-Ziriq marsh south of Iraq [22]. Larrea et al. used MLR, ANN and ANFIS for water level prediction for Salve Faccha Dam in the Andean Zone in Northern Ecuador [23]. Wong et al, used ANN, ANFIS and MLR for modeling of Cu (II) adsorption by using biochar derived from rambutan (Nephelium lappaceum) peel [24]. Rezaeianzadeh et al. used ANN and ANFIS for flood flow forecasting [25]. Caner and Akarslan used ANN and ANFIS for the prediction of specific energy factor in marble cutting process. Result of these studies showed that ANFIS showed better performance than ANN and MLR. In this study, similar results were obtained with the literature and ANFIS showed best performance with higher R and lower MSE value.

4 Conclusion

In this study, the output of crystallization step (solution color) prediction was examined by traditional and artificial intelligence techniques by using the measurements between the input and output streams for the crystallization step in the sugar production process. This prediction application is new for production stage in literature. Sugar production is a non-linear and dynamic process in which many parameters are effective during production. In prediction studies, the available data and the distribution of these data are very important in terms of the technique used. Artificial neural network method is better than other traditional methods. Artificial neural network can generalize the problem by learning the relations and solve problems within acceptable error limits. Traditional methods solve the problem step by step iteration while artificial intelligence reach the solution of problems quickly by working on time. ANFIS is a combination of ANN and fuzzy inference system (FIS) and has speed, fault tolerance, and adaptiveness. In this study ANFIS had a correlation between predicted and actual values, R=0.99 and ANN, R= 0.82. Ash, color and vacuum temperature is input, solution color is output for the system. The results suggest that the ANFIS seems to have produced a slightly better solution than that obtained using the ANN, and both are much better than the MLR. Observations were showed that the results from ANN are largely dependent on architecture of the network, which is very hard to select as it is a complex and time-consuming task. Another limitation that ANN has its inadequate ability to deal with fuzzy and nonlinear data, whereas ANFIS is largely free from both of those limitations. So the results suggest that the ANFIS method is superior to the ANN method in the prediction of solution color at crystallization stage of sugar production.

5 Author contribution statements

In the scope of this study, Fatma ERDEM contributed to the formation of the idea, collecting data, literature review, analysis and interpretation of results, writing the article.

6 Ethics committee approval and conflict of interest statement

There is no need to obtain permission from the ethics committee for the article prepared.

There is no conflict of interest with any person/institution in the article prepared.

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