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OSMOTIC DEHYDRATION OF MURASAKI-29: DETERMINATION OF THE PERFORMANCE RATIO AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM MODELLING

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Abstract

The Murasaki-29 sweet potato, characterized by its rich phenolic content and high sugar levels, is prone to spoilage due to its high moisture content. To address this, Osmotic Dehydration (OD) was investigated as a precursor to drying to economically extend the shelf life of the sweet potato by reducing moisture content while preserving nutritional quality. The effect of varying sugar concentration, temperature, and immersion time on the OD characteristics of Murasaki-29, as indicated by the performance ratio (Pr) was investigated while Adaptive Neuro-Fuzzy Inference System (ANFIS) modelling was employed to predict the OD process. Experimental results showed that while increased sugar concentration improved Pr, rising temperature negatively impacted Pr. The effect of increased time on OD characteristics was not consistent, with initial increment but later decrement. Among the tested ANFIS model configuration, the 2-trimf-ANFIS model achieved the highest accuracy with a correlation coefficient value (R) of 0.9904. The model's performance showed that ANFIS is a valuable tool in predicting OD processes. This study contributed to understanding the Murasaki-29 sweet potatoes OD processing, provided details into process characteristics and modelling, and suggested the need for optimization towards industrial utilization of the results.

Keywords: Murasaki-29 sweet potato; Performance ratio; Osmotic dehydration; ANFIS Modelling

Introduction

The Murasaki-29 sweet potato is a unique variety of sweet potato characterized by its dark purple skin and white flesh. It is resistant to southern root-knot nematode and soil rot, making it a robust choice for cultivation in various regions (Bonte *et al.*, 2008). Murasaki-29 sweet potatoes are visually appealing and nutritionally rich. It contains higher levels of sugar compared to regular orange-fleshed sweet potatoes, which contributes to the creamy texture and sweet flavour. Murasaki-29 is also noted for its high phenolic content, which has been linked to various health benefits, including antioxidant, anti-hyperglycemic, and anti-hypertensive properties (Chintha *et al.*, 2021). Murasaki-29 sweet potato can be used in a variety of dishes, from traditional baked sweet potatoes to more innovative recipes like sweet potato fries, soups, and desserts. The high sugar content in Murasaki-29 makes it suitable for use in sweet dishes and snacks. However, the high moisture content of Murasaki-29 enables deterioration and spoilage; therefore, postharvest operation or treatment of Murasaki-29 is essential. As a precursor to further utilization and processing such as drying, Osmotic Dehydration (OD) is a postharvest process that can effectively reduce the moisture content of sweet potatoes, thereby resulting in extended shelf life and suitability for various culinary applications.

OD is a widely utilized technique for preserving various agro-forestry produce. OD relies on the principles of osmosis and diffusion and the process involves immersing the produce into a hypertonic solution (Mari *et al.*, 2024). When agro-forestry produce are immersed in a hypertonic solution, such as a concentrated sugar or salt solution, water molecules move from the submerged produce (where the water concentration is higher) to the hypertonic solution (where the water concentration is lower) to achieve equilibrium. Simultaneously, solutes from the hypertonic solution, such as sugar or salt, also diffuse into the agro-forestry produce. This method not only reduces the moisture content but also enhances the flavour and nutritional value of the agro-forestry produce concerned (Bashir *et al.,* 2020). However, the rate of water loss and solute gain during OD depends on several factors, including the concentration and type of osmotic agent, temperature, immersion time, and the ratio of food to solution, amongst others (Yadav *et al.*, 2024).

OD offers several advantages over traditional drying methods (Mari *et al.*, 2024). Firstly, it helps in retaining the nutritional and sensory qualities of the food. Since the process does not occur at extremely high temperatures, there is minimal thermal degradation of heat-sensitive nutrients and bioactive compounds (Bashir *et al.*, 2020). Additionally, the infusion of solutes such as sugars and salts can enhance the flavour and texture of the dehydrated product. More also, OD reduces the energy requirements for subsequent drying processes (Yadav *et al.*, 2024). Through the removal of a significant amount of water by osmosis, the load on conventional drying methods, such as hot air drying or freeze-drying, is reduced, leading to energy savings (Mari *et al.*, 2024). This makes OD an energy-efficient and cost-effective method for food preservation.

The choice of osmotic agent and process parameters significantly influences the efficiency of OD process (Bashir *et al.,* 2020). Common osmotic agents include sucrose, glucose, and sodium chloride (NaCl). Each of the osmotic agents is effective, however a synergistic effect can be realised if they are combined to form a hypertonic solution. Temperature is another critical factor. Higher temperatures generally increase the rate of water loss and solute gain due to enhanced molecular mobility (Yadav *et al.,* 2024). However, excessively high temperatures can lead to undesirable changes in texture and colour. Therefore, prediction and thus optimization of OD characteristics are crucial for achieving the desired quality in dehydrated agro-forestry produces.

Models are essential for representation, understanding, prediction and optimization of the mass transfer dynamics during OD. The Peleg model is one of the empirical or semi-empirical models that is commonly used to describe the kinetics of water loss and solute gain in OD processes. This model considers the initial rate of mass transfer and the equilibrium state, providing a good fit for experimental data. In search for more accurate descriptive models, artificial intelligent (AI) models have shown potentials to precisely represent scientific findings (Okonkwo *et al.,* 2022). Commonly utilized AI models are Artificial Neural Networks (ANN), Fuzzy Logic (FL), Support Vector Machine (SVM), Adaptive Neuro Fuzzy inference System (ANFIS), Genetic Algorithm (GA) and multi gene genetic programming (MGGP), amongst others (Adeyi *et al.,* 2023).

A number of studies had been conducted on OD investigation and modelling of agro-forestry produces. For instance, Khanom *et al.,* (2014) investigated the influence of concentration of sugar on mass transfer of pineapple slices during OD process and found out that there were rapid rates of water loss, sugar gain, and weight reduction. Deshmukh *et al.,* (2021) studied OD of carrot strips with modelling effort; Azuara's and Peleg models were found to be best for representing moisture loss while Power law and Magee's model were found to be best fit for solid gain. The present author found that not much work had been done on the OD processing of Murasaki-29 and there is sparing report on modelling of Performance ratio of an OD process with Adaptive Neuro Fuzzy Inference System (ANFIS) AI method. Therefore, filling these gaps formed the focus of the present study.

Materials and Methods

The effect of OD process factors on the OD characteristics of Murasaki-29 Sweet Potato (MSP) tubers was determined experimentally. Fresh MSP tubers were sourced from a local market (Waso Market) in Ogbomoso, Oyo State, Nigeria. An Agricultural Extension Officer assisted in the identification of MSP amongst other varieties in the market. The MSP tubers were harvested 8 h prior to its purchase as informed by the seller. Thereafter, the purchased MSP tubers were taking to the laboratory for experimentation using a polythene bag.

In the laboratory, the MSP tubers were washed with drinkable water to remove dirt and air dried in the laboratory atmosphere at room temperature (28 – 30 ^{O}C).The tubers were manually peeled and tuber pulp was cut into cubes with dimensions of 3 x 3 x 3 cm^3. The initial moisture content of the MSP was 69.13%

w.bas determined by following the specifications of the Association of Official Analytical Chemists method (AOAC, 2005) using convective oven (SG-90526 - model, Stangas - company, Italy - country), at 105 ^{O}C for 24 h (Oranusi *et al.*, 2014).

In the experimentation, the effect of sugar concentration (40, 50 and 60%) in the osmotic solution, MSP pulp resident time (0 - 120 min, at 5 min interval) and temperature (30, 50 and 60 OC) were investigated in accordance with the work of Sutar and Prasad (2011). This resulted into fifty – four (54) experimental runs. Pre-weighed MSP cube samples were placed in a 500 ml capped glass bottles along with the osmotic solution (300 ml) for specific experimental conditions.

The mass exchange between the solution and the sample during OD process was assessed through Performance ratio (Pr) indicator as represented in Eqn. (1) – (3):

$$P_r = \frac{SG}{ML} \quad (1)$$

$$ML = \frac{M_i X_i - M_f X_f}{M_i} \text{ X } 100(\%) \quad (2)$$

$$SG = \frac{M_f(1-X_f) - M_i(1-X_i)}{M_i} \text{ X } 100(\%) \quad (3)$$

Where: ML is the moisture loss

SG is the solute gain

M_i is the sample’s initial weight,

X_i is the sample’s moisture content

M_f is the sample’s final weight after dehydration

X_f is the sample’s final moisture content after dehydration

Theory of ANFIS

ANFIS is a specialized Sugeno fuzzy inference system that integrates the capabilities of Artificial Neural Networks (ANN) and Fuzzy Logic (FL) to effectively model intricate relationships between input and output data (Ojediran *et al.*, 2021). The FL aspect of ANFIS handles the conversion of input data into membership functions. These functions are associated with specific rules, which are then related to the characteristics of the output data. Finally, these output characteristics are transformed into output membership functions, resulting in the final output

The shape and characteristics of the membership functions can be adjusted to enhance the system's accuracy (Okonkwo *et al.*, 2022). This adjustment is facilitated by the ANN component of ANFIS, which automatically fine-tunes the parameters of the FL membership functions to optimize performance. Typically, this tuning process employs algorithms like back-propagation or least squares approximation methods.

During the training phase, the system learns and formulates rules based on the input data to achieve precise approximations. Figure 1 illustrates the structure of a generalized ANFIS model featuring two input factors, labeled ‘a’ and ‘b’.

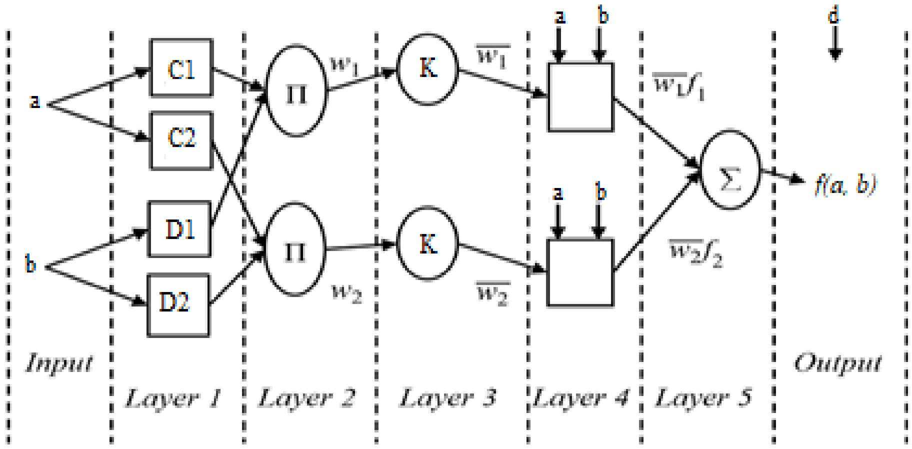


Figure 1 ANFIS Illustration (Adeyi *et al.* 2022)

Referring to the illustrated figure, the rules of a typical ANFIS structure are expressed in Equations (4) to (7) as follows:

Rule 1: If a is C_1 and b is D_1, then $f_1 = p_1a + q_1b + r_1$ (4)

Rule 2: If a is C_2 and b is D_2, then $f_2 = p_2a + q_2b + r_2$ (5)

Rule 3: If a is C_3 and b is D_3, then $f_3 = p_3a + q_3b + r_3$ (6)

Rule 4: If a is C_4 and b is D_4, then $f_4 = p_4a + q_4b + r_4$ (7)

The input layer consists of two inputs, 'a' and 'b'. Layer 1, denoted by Equation (8), contains the crisp inputs for the system being analyzed, where O^1represents the layer and i indicates the ANFIS node.

O_i^1= (input factors) (8)

In Layer 2, the provided crisp input data are transformed into a fuzzy space using designated membership functions (mf). This transformation process is known as fuzzification, which is why this layer is called the fuzzification layer. This layer comprises adaptive nodes, as represented by Equations (9) and (10), μA_i and μB_i depicts the input membership functions.

O_i^2= μA_i (input factor 1) for $i = 1, 2$ (9)

O_i^2= μB_i (input factors 2) for $i = 3, 4$ (10)

Layer 3 is known as the firing strength layer of the structure. In this layer, the product of the degrees to which the input factors align with the chosen membership functions is calculated, as shown in Equation (11).

$O_i^3 = wi = \mu A_i$ (input factor 1) × μB_i (input factor 2), …=1,2,3,4 (11)

Layer 4 is the normalization layer, where the relative firing strength of each rule is calculated by comparing it to the total firing strengths of all the rules. This layer consists of fixed nodes, as represented in Equation (12).

O_i^4 = w'= $wi/w1 + w2$, = 1, 2 (12)

Layer 5 is the defuzzification layer, represented by Equation (13). This layer contains the consequent parameters of the fuzzy rules, with its neurons closely connected to the normalization neurons.

$$O_i^5 = w_i' f_i = w'(p_i x + q_i y + r_i),\ i = 1, 2 \qquad (13)$$

Layer 6 provides the overall output for each input within the fuzzy space, calculated as the sum of the outputs from Layer 5. This is expressed in Equation (14).

$$O_i^6 = \text{overall output} = \sum_i w'_i f = \sum_i w_i f_i / \ \sum = 1, 2 \qquad (14)$$

The type and number of membership functions are crucial parameters that influence the performance of an ANFIS structure in modeling tasks. This study examined the optimal selection of these parameters by evaluating the impact of different membership function types (trimf, pimf, and gaussmf) and membership function numbers (2 and 3 mfs) on the accuracy of the ANFIS model for predicting and modeling the OD characteristics of MSP. The input factors considered include time (min), temperature (°C), and sugar concentration (%). The experimental data were divided into training (70%), checking (15%), and testing (15%) sets, following the methodology outlined by Okonkwo *et al.* (2022). The ANFIS model for predicting the OD characteristics was developed using MATLAB R2021 software.

Modelling Efficiency

The performance of the ANFIS model structures was evaluated using statistical metrics such as the correlation coefficient (R) and root mean square error (RMSE). A model is considered more accurate when it achieves a lower RMSE and a higher Rvalue, typically ranging from 0 to 1 (Adewale *et al.,* 2015). The mathematical expressions for these indicators are provided in Equations (15) and (16) (Adeyi *et al.,* 2018).

$$R = \frac{\left[\sum_{i=1}^{N}(Q_i - Q_m)(P_i - P_m)\right]^2}{\sum_{i=1}^{N}(Q_i - Q_m)^2 + (Q_i - Q_m)^2} \qquad (15)$$

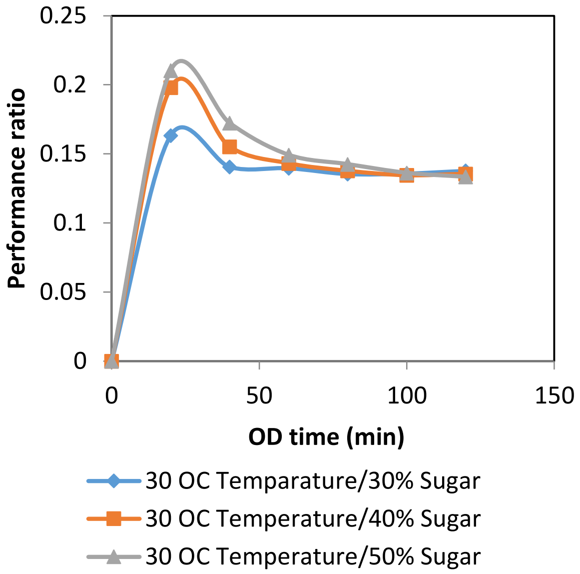
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - P_i)^2}{N}} \qquad (16)$$

Where: Q_i is the observed and P_i is the predicted value. Q_m and P_m represents the average values of the observed and predicted values. N represented the number of observations.

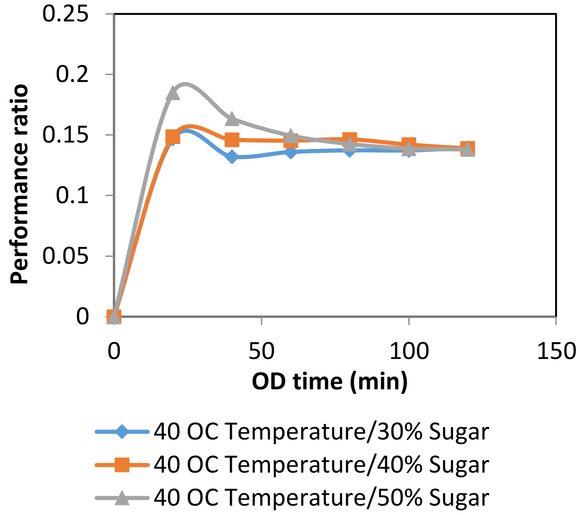
Results and Discussion

Effect of Temperature and Time on the Performance Ratio

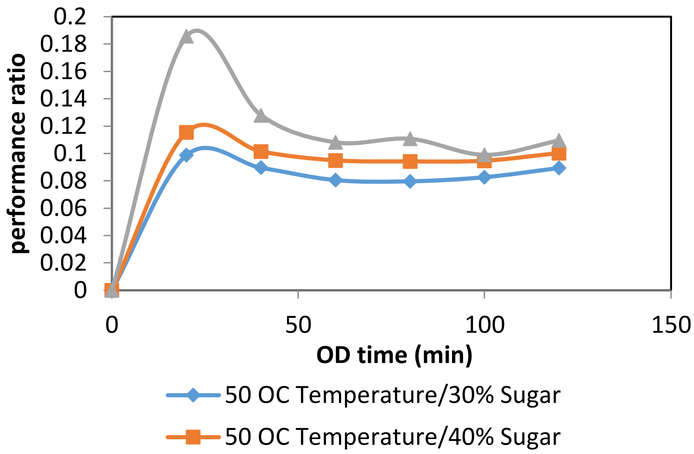
The effect of temperature and time on the OD performance ratio (Pr) of MSP is represented in Fig. 1 (a) – (c).



(a)



(b)



(c)

Figure 1: Effect of process condition on performance evaluation

Figures 1 (a) - (c) shows that the Performance ratio (Pr) in all observations, increased significantly between 0 - 20 min, until the peak was reached and sharp decrease in Pr noticed thereafter. The initial and most substantial increase in Pr during the first 20 minutes is attributed to the maximum potential difference that existed between MSP samples and the OD or hypertonic solution utilized, due to maximum moisture availability in the MSP samples and the maximum sugar availability in the OD or hypertonic solution (Mari *et al.*, 2024). This potential difference, which is typically greatest at the start of the process, leads to the highest mass transfer rate in terms of moisture loss from the sample and sugar intake into the sample. The potential difference is expected to reduce as the MSP samples reach saturation (that is, maximum moisture loss and maximum sugar gain). In addition, Pr decreased with increased temperature in all observations (Figure 1 (a) – (c)). This may be due to possible alterations in the microstructure of the MSP samples, potentially causing cell collapse that impedes the transfer of moisture and sugar. Pr also increased with increase in sugar quantity across all the observations. This is attributed to higher sugar concentrations creating greater osmotic pressure difference between the food material and the osmotic solution, which serves as the driving force for water removal (Wang and Feng, 2023). These results are in conformity with the findings of Pessoa *et al.,* (2020) in a study on OD of Cassava Cubes.

ANFIS modelling

The effect of ANFIS parameters (that is, membership function type and number) on the efficiency of ANFIS model prediction for the observed OD characteristics is depicted in Table 1.

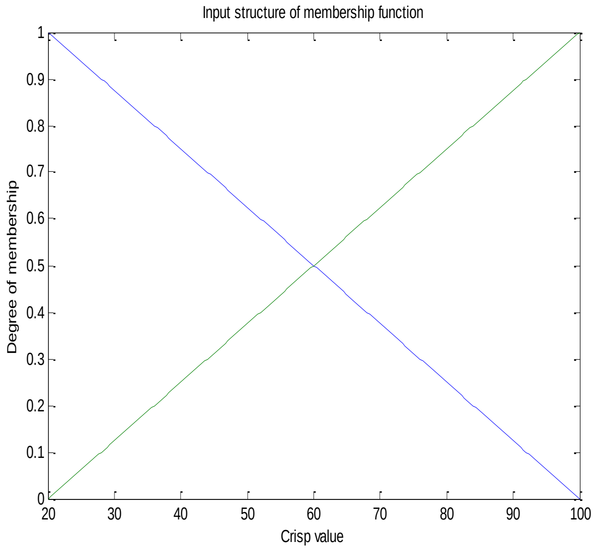
Table 1: Effect of ANFIS parameter on model quality

Mf Type	Mf Number	Epoch No.	R
trimf	2	100	0.9904
trimf	3	100	0.9684
pimf	2	100	0.8448
pimf	3	100	0.9684
gaussmf	2	100	0.9760
gaussmf	3	100	0.9740

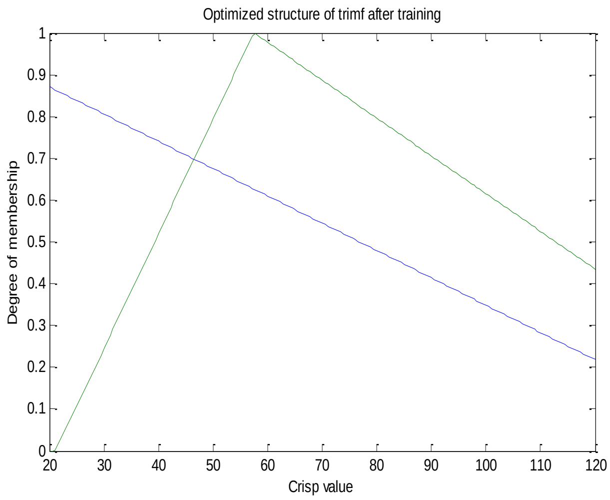
Table 1 shows that the 2-trimf ANFIS parameter achieved the highest coefficient of determination (R = 0.9904), indicating its effectiveness in modelling the observed MSP tuber's OD characteristics (Pr). The pimf membership function number (that is, 2 or 3) exhibited variable performances, with the least performance observed in Mf Number 2 (R = 0.8448). The two instances of the gaussmf membership function type (that is, 2 and 3 membership function number) displayed competitive performance metrics (that is, R = 0.9760 and R = 0.9740, respectively), suggesting they are effective alternatives of each other for modelling the data. This result implied that the choice of ANFIS parameter (that is, membership function type and membership function number) significantly influenced the effectiveness of ANFIS model, as indicated by the correlation coefficient (R) (Okonkwo *et al,* 2022).

Therefore, it is important to select appropriate membership functions number and type, and conduct multiple evaluations to optimize model performance in Adaptive neuro fuzzy inference systems (ANFIS). The same observation was reported by Ojediran *et al.*, (2021).

The characteristics of the best performing ANFIS parameter (that is, 2-trimf) in this study is represented in Fig. 2 (a) – (e).



(a)



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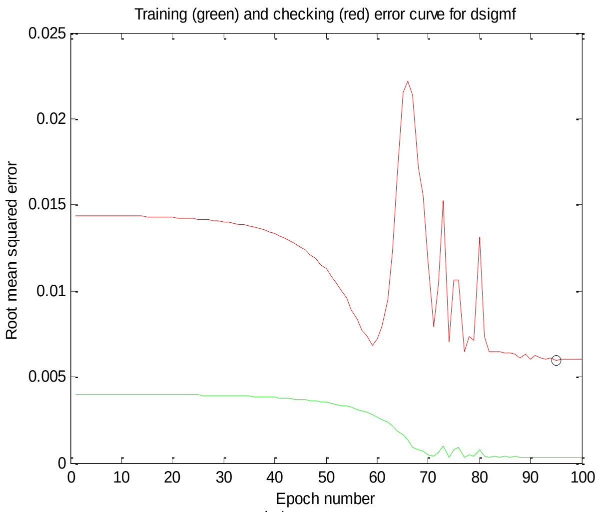
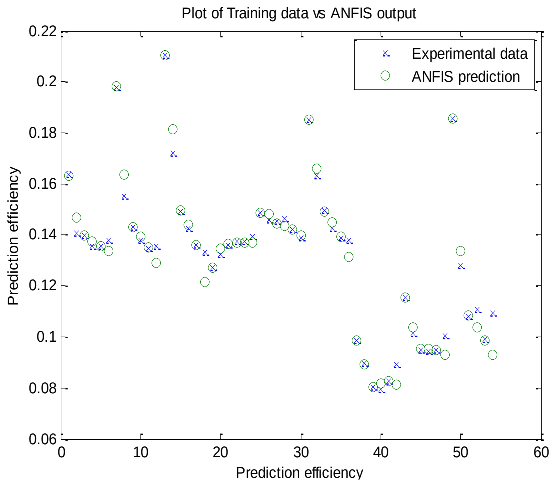


(c)



(d)

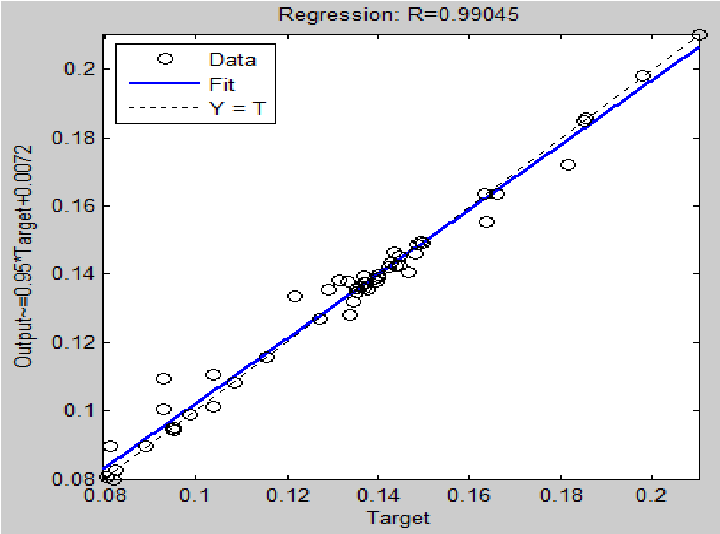


Figure 2: Characteristics of the best performing ANFIS parameter (2-trimf)

Figure 2 (a) shows the 2-trimf membership function parameter in an unrefined state while Figure 2 (b) shows its refined state after model establishment. This showed that ANFIS adjusted its parameters towards achieving best solution to the given problem. Usually, a membership function is a fundamental concept in fuzzy logic and fuzzy set theory that quantifies the degree to which a particular element belongs to a fuzzy set. Unlike traditional binary sets, where an element either belongs or does not belong to a set (0 or 1), fuzzy sets allow for varying degrees of membership ranging from 0 to 1 (Okonkwo *et al.*, 2022).

The training performance of the best performing membership function as represented in Figure 2 (c) showed that ANFIS 2-trimf parameter had a fluctuating error curve. A decreased error profile or trend showed desirable data pattern learning while an increased error profile or trend showed undesirable data overfitting or memorization (Ojediran *et al.*, 2022). In this case, ANFIS was able to overcome the memorization tendencies and settled into a comfortable learnt data pattern position at 95 epochs. The extended epoch number (that is, 95 out of 100) showed the complexity in the modelled data. Generally in computational analysis, quick convergence of solution is desirable to minimize computer memory utilization (Adeyi *et al.*, 2020), and thus faster result output leading to preservation of computing resources.

The scatter plot in Figure 2 (d) compares the experimental data with the ANFIS predictions (Amoo-Onidundu *et al.*, 2024). A close alignment of these points indicated that the ANFIS model effectively captures the underlying relationships in the data and provides accurate predictions (Oke *et al.*, 2017). The distribution of the points can help identify trends, patterns, or discrepancies between the predicted and actual performance. When green circles closely follow the trend of the blue crosses, it suggested that the ANFIS model performs well in predicting outcomes based on the available data. If there are significant deviations between the predicted and actual values (for instance, green circles that are far from corresponding blue crosses), it indicated limitations in the ANFIS model's ability to accurately predict with efficiency based on the input parameters (Adeyi *et al.*, 2022).

In Figure 2 (e), the fitted line represented the regression line that summarizes the relationship between the target values and the predicted outputs. The equation of the fitted line is presented as Output = 0.95 * Target + 0.0072, indicating that the model predictions are approximately 95% of the target values, with a slight positive offset (that is, 0.0072). The regression coefficient (that is, R = 0.99045), indicate a high degree of correlation between the predicted and actual values. This implied that the model explains approximately 99% of the variance in the target variable, reflecting strong predictive capability. The proximity of the data points to the fitted regression line indicates how closely the model predictions align with the actual observations. These results are useful for process design and control (Adeyi *et al.,* 2022).

Conclusion

This study investigated the effects of varying temperatures, time, and sugar concentration on the osmotic dehydration (OD) characteristics of Murasaki-29 sweet potatoes, using the performance ratio (Pr) as indicator. The results revealed that while sugar concentration increment increased Pr, higher temperatures negatively affect the Pr, possibly due to possible changes in the tuber's microstructure. The ANFIS modeling approach was highly effective, with the 2-trimf membership function achieving the highest correlation coefficient (R = 0.9904), suggesting its effectiveness in modeling and predicting the OD processes. The successful application of ANFIS in this study highlighted its potentials for use in decision-making and designing process controllers for industrial-scale food processing operations.

Declaration of Conflict of Interest

The author declares no conflict of interest on this article.

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