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Fuzzy-Logic Modelling for Quality Prediction of Smoked Tilapia (*Oreochromis niloticus*) Fish

A. J. Adeyi[1], O. Adeyi[2], O. K. Ajayi [3, *], E. O. Oke[4, *]. A. D. Ogunsola[5], S. Oyelami[6]

[1,5]*Department of Mechanical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, NIGERIA*
[2,4]*Department of Chemical Engineering, Michael Okpara University of Agriculture, Umudike. Abia State, NIGERIA*
[3]*Department of Mechanical Engineering, ObafemiAwolowo University, Ile-Ife, Osun State, NIGERIA*
[6]*Department of Mechanical Engineering, Osun State University, Osogbo, Osun State, NIGERIA*

Abstract
Statistical modelling of hot smoke processing of pre-treated Tilapia (Oreochromis niloticus) fish was reportedly inaccurate, making it difficult to design, predict, and reproduce the finished product's quality; hence, accurate modelling of this process is a gap in study. This study filled this gap and extended the literature by investigating the accuracy of artificial intelligent based model for the same process. Fuzzy inference system (FIS) model was developed using the already presented dataset in the literature from where inaccurate statistical models were reportedly derived. The dataset is on the effect of smoke temperature (80, 90 and 100^{O}C) and smoke time (2.00, 2.50 and 3.00 h) on the gross energy value (GEV) (Kcal/g) and the overall acceptability (OA) properties of brined pre-solar dried and brined non-dried Tilapia (Oreochromis niloticus) fish. The efficiency of FIS membership function types (pimf, trimf and gbellmf) on the accuracy of the developed FIS model was also investigated. Coefficient of determination, root mean square error, individual percentage error and model accuracy were used to discern the model accuracy. Results showed that FIS had a modelling accuracy (R^2 value) between 0.9873 and 0.9999 as against 0.1072 and 0.5800 reported for the statistical model. The results suggested that FIS model outperformed the statistical model of Tilapia (Oreochromis niloticus) smoke processing and it is recommended for process/product design, control, and standardization.

Keywords: Fuzzy Inference System, Tilapia fish, Smoke drying, Membership function.

1.0 INTRODUCTION

Undoubtedly, fish farming is one of the fastest growing agricultural enterprises in Nigeria and by its contribution to the gross domestic product, which is considered huge, fishing and fish processing have significantly affected the nation's economy through employment generation, poverty alleviation, foreign exchange earnings and provision of raw materials for the animal feed industry [1]. Fish is a major source of protein and it is considered to be one of the most important diets in Nigeria [2]. It is also an important source of food and income to many people in the developing world [3]. Fish is highly nutritious and it is particularly valued for its protein, which is of higher quality compared to those of meat and egg [4].

Fish is a highly perishable harvest and its value starts to depreciate in few hours after harvesting, therefore, a means of fish preservation is desirable. Successful fish preservation will lead to postharvest loss reduction, conservation, improved market value and elimination of incessant catch. Fish smoking is an effective preservation method that is easily accessible. Fish smoke processing has always been in vogue since the existence of man; and it has also constituted an integral part of fish post-harvest processing industry in Nigeria. Apart from drying of fish through the applied hot smoke, the smoke components also improves the shelve stability and aroma/flavour of smoked fish product.

Drying process parameters are full of uncertainties due to complexity of transfer laws [5]. Smoking is a form of drying affected by factors including temperature, humidity, air velocity, and nature of fish, time of process, pre-treatments and others. These factors also affect the smoked fish quality [4]. The understanding of the associated mechanisms in smoke processing should be

*Corresponding author (**Tel:** +234 (0) 8035266603)
Email addresses: okajayi@oauife.edu.ng (O.K. Ajayi), adeyi.abiola@yahoo.com (A. J. Adeyi), adeyioladayo350@yahoo.com (O. Adeyi), okeolusola@mouau.edu.ng (O. E. Oke), adogunsola@lautech.edu.ng (A. D. Ogunsola) and seun.oyelami@uniosun.edu.ng (S. Oyelami)

detailed to enable desirable process and product design for nutritional qualities. Therefore, to design, understand, analyse and optimize the smoke processing conditions modelling is inevitable.

Several modelling strategies including physics modelling, empirical, semi-empirical, statistical and artificial intelligent modelling (AI) have been applied to represent drying related operations. However, AI models have increased flexibility, accuracy, reduced assumptions, online non-destructive measurement and tolerance of incomplete or noisy data [6]. AI methods include artificial neural networks (ANN), adaptive neuro fuzzy inference system (ANFIS), support vector machine (SVM), fuzzy inference system (FIS) or fuzzy logic (FL) and had been successfully applied in drying studies [7]. In the last decade, FL has proven its worth as a practical engineering problem-solving tool [8]. The FL is ideal for modelling and controlling of complex nonlinear systems because it systematically handles ambiguity [5]. FL modelling is robust, and apart from the fact that it has tolerance and can imbibe human-like reasoning, it can adequately model a complex system with multiple inputs and multiple outputs simultaneously [9]. FL is particularly suitable for process control if no model exists for the process or it is too complicated to handle or highly non-linear and sensitive in the operation region [10]. FL utilizes a knowledge-based control strategy that uses fuzzy linguistic variables into its rule set to model a ‘‘human-operator-like’’ control approach to cope with the uncertainty in process dynamics or the control environment. These rules can be obtained from the knowledge of the plant functions, engineering principles, statistical information, from observing the skilled human operators, achieved by means of interviews, questionnaires, and online recording of human-initiated control actions [7]. The FL specifies the input and output variables, applies the shape and number of membership functions to define the degrees of truth for each variable in the system [5, 11, 12]. The protocol of FL operation is represented in Fig. 1.

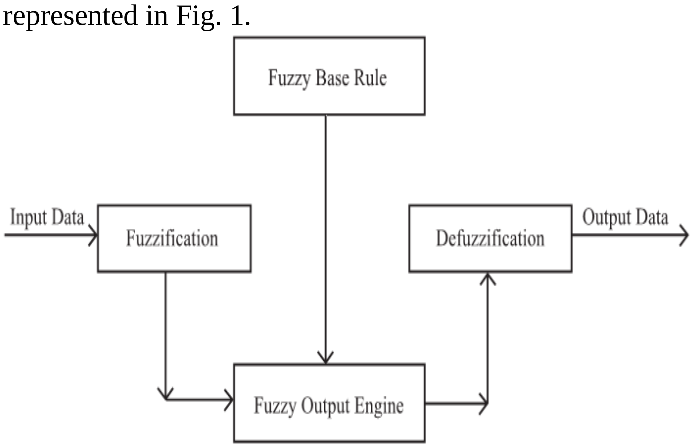

Figure 1: A typical flow diagram of FIS/FL process [11]

Amongst researches on note, Khodabakhsh*et al.* (2015) [11] modelled the drying kinetics of papaya fruit using FL table look-up scheme. Mamdani’s fuzzy inference system (FIS) with 56 independent rules was used to conduct fuzzy set operations. FL showed a high modelling capability. Sedat*et al.* (2004) [8] worked on FL model development for the prediction of cement compressive strength. FL and ANN prediction models for the 28-day compressive strength of cement mortar under standard curing conditions were created. Data collected from a cement plant were used in the model construction and testing. The input variables of alkali, Blaine, SO_3, and C_3S and the output variable of 28-day cement strength were fuzzified and triangular membership functions were employed for the fuzzy subsets.

The results showed that FIS model was accurate compared to ANN model.

Marcelo *et al.* (2015) [4] conducted FL modelling of soybean rust monocyclic process. The effects of temperature and leaf wetness on the monocyclic process of soybean rust in cultivars Conquista, Savana and Suprema, were modelled using FL and nonlinear regression models. The study concluded that FLS was better applied then non-linear regression models to estimate the potential disease spatial progress. In the work of Demeke and Alemu, (2015)[5] regarding model development for a smoking processing concerning the effect of pre-treatment, smoking temperature and smoking time on the gross energy value (GEV) (Kcal/g) and the overall acceptability (OA) properties of Tilapia (*Oreochromis niloticus*) fish, it was reported that all the built statistical models were insignificant and as such the model cannot be used to search the experimental space for the smoke process. Their submission is a gap in study which requires the search for a suitable model for a successful smoking operation of Tilapia (*Oreochromis niloticus*) fish.

Therefore, the aim of this study is to fill this lacuna. The objectives of the study are to investigate the suitability of FL/FIS model using the open sourced data of Demeke and Alemu, (2015)[5] and also investigate the performance of membership function type of the developed FL/FIS model.

2.0 METHODOLOGY

This section discusses the experimental data and FL/FIS model development used for the study.

The experimental data of Demeke and Alemu (2015) [3] was adopted in this study to develop the FL/FIS model. The procedure utilized to obtain the experimental data is represented in Fig. 2.

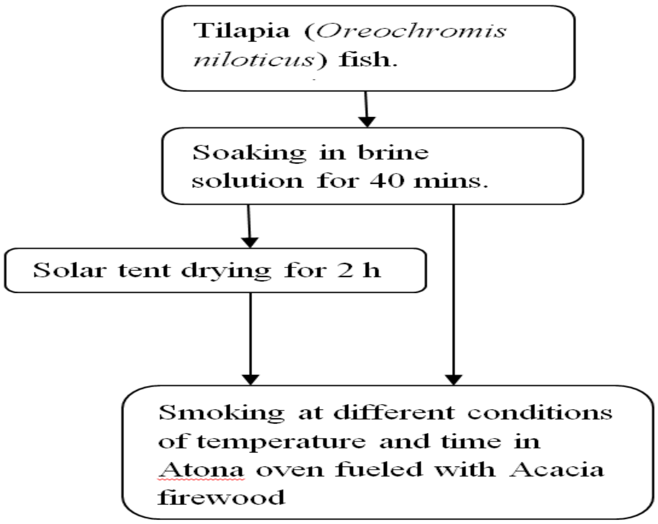

Figure 2: Experimental procedure

In this study, the type of pre-treatment, smoking temperature and smoking time were the input factors to the FL/FIS while gross energy value (Kcal/g) and overall acceptability were taken as the output factors. The optimum FL/FIS model was determined between three membership function types that include triangular membership function (trimf), gbell membership function (gbellmf) and pi membership function (pimf). Number of membership function for each input and output factor was chosen based on the number of experimental data point. The FL/FIS modelling was achieved in Matlab R2010a software. The prod and centroid methods were employed as the inference operator and defuzzification methods, respectively. The primary data assisted in FL/FIS rule formulation. Rules were formulated and are selectively combined based on Table 1 linguistic representations.

Table 1: FL/FIS linguistic rule table

Pre-treatment	Temperature (^{O}C)	Time (h)	Gross Energy Value (Kcal/g)	Overall Acceptability
No prior drying after brining	Low	short	Very low	low
Prior drying in sola dryer after brining	Average	Average	low	Relatively low
	High	Long	Relatively low	A bit low
			A bit low	A bit high
			A bit high	High
			High	
			Relatively high	
			Very high	
			Greatly high	

Performance criteria consisting of R^2, RMSE, individual percentage error and model accuracy as represented in Eqn. (1) – (4) were used to establish the effectiveness of the developed FL/FIS models.

Coefficient of determination (R^2)

$$R^2 = 1 - \sum_{i=1}^{N} \frac{(\text{Pred, i} - \text{Exp, i})^2}{(\text{Pred, i} - \text{AverageExp})^2} \tag{1}$$

Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\text{Exp, i} - \text{Pred, i})^2}{N}} \tag{2}$$

Individual Percentage Error (IPE)

$$IPE = \left(\frac{\text{Exp, i} - \text{Pred, i}}{\text{Exp, i}}\right) X\ 100\% \tag{3}$$

Model Accuracy (MA)

$$MA = \frac{1}{N}\sum_{i=1}^{N} [100 - ((\frac{\text{Exp, i} - \text{Pred, i}}{\text{Exp, i}})\text{X } 100\%)] \tag{4}$$

Where Pred,i is the ith predicted value, Exp,i is the ith experimental value and Averaged Exp is the average of all the experimental value. N represents the number of observations.

A model with the high (close to unity) R^2, percentage accuracy and low RMSE and percentage error signifies a good fit or performance [13].

3.0 RESULTS AND DISCUSSION

3.1 Optimal FL/FIS membership function

The developed FL/FIS model structure in this study is represented in Fig. 3.

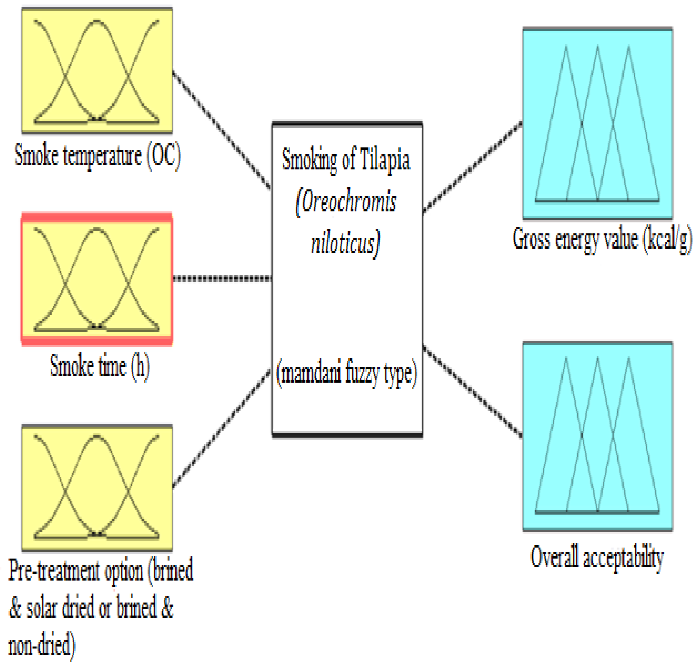

Figure 3: The Fuzzy Inference System used in this study

The model structure is a Mamdani fuzzy type with three input factors (smoke temperature, smoke time and pre-treatment option) and two output factors (gross energy value and overall acceptability). The middle rectangular structure is the expert system that functions by using set of input-output relational rules that were developed from the primary experimental data to predict or approximate the output from input and vice versa. The inner compositions of the input and output rectangular structure are the membership function that functions intrinsically with the set of rules during prediction. Due to the unique shape of each type of membership function, the accuracy of their prediction on specific data considered is significantly different. Therefore, there is need to search for accurate membership function for each data approximation or prediction effort using FL/FIS. Usually, this is achieved by trial-and-error measurement until the optimum membership function is established.

The effect of three selected membership function on accuracy of the FL/FIS model developed to study the effect of pre-treatment, smoke temperature and smoke time on the gross energy value and overall acceptability of Tilapia (*Oreochromis niloticus*) fish is represented in Table 2. The table showed the gbell membership function (gbellmf) had the least accuracy while pi membership function (pimf) has the highest accuracy by considering the coefficient of determination (R^2) and root mean square error (RMSE) values. A high value of R^2 and low value of RMSE signifies an accurate model performance. Therefore, the FL/FIS with pi membership function is reliable and it is the optimal FL/FIS model in this study.

The previously established statistical model by Demeke and Alemu [5] on the same experimental data used in this study had R^2 ranging between 0.1072 - 0.5800.

Table 2: Performance evaluation of the selected membership functions

Type of membership function	R^2 Value		RMSE Value	
	Gross Energy Value (Kcal/g)	Overall Acceptability	Gross Energy Value (Kcal/g)	Overall Acceptability
Triangular membership function	0.99537	0.99997	1.35213	0.04201
Gbell membership function	0.98739	0.99992	2.23189	0.06909
Pi membership function	0.99678	0.99998	1.12702	0.03495

Table 3: FL/FIS with pi membership function prediction capability for Gross energy value

Temp	Time	Experimental GEV (Kcal/g)	Predicted GEV (Kcal/g)	% Individual Error for GEV (Kcal/g)	Individual Accuracy for GEV (Kcal/g)
80	2	284.18	283.3687	0.2854	99.7145
80	2.5	280.37	278.9656	0.5009	99.4990
80	3	279.3	278.0511	0.4471	99.5528
90	2	262.64	264.3976	0.6692	99.3307

Temp	Time	Experimental GEV (Kcal/g)	Predicted GEV (Kcal/g)	% Individual Error for GEV (Kcal/g)	Individual Accuracy for GEV (Kcal/g)
90	2.5	277.38	276.5769	0.2895	99.7104
90	3	268.29	268.4067	0.0435	99.9564
100	2	259	259.7913	0.3055	99.6944
100	2.5	263.36	264.3976	0.3940	99.6059
100	3	283.13	281.9633	0.4120	99.5879
80	2	314.02	313.6097	0.1306	99.8693
80	2.5	315.06	316.1500	0.3459	99.6540
80	3	320.45	319.5584	0.2782	99.7217
90	2	291.79	292.7086	0.3148	99.6851
90	2.5	313.77	312.9128	0.2731	99.7268
90	3	308.96	307.1336	0.5911	99.4088
100	2	296.25	295.7529	0.1677	99.8322
100	2.5	301.63	300.1007	0.5069	99.4930
100	3	313.49	312.0033	0.4742	99.5257

Table 4: FL/FIS with pi membership function prediction capability for Overall Acceptability value

Temp	Time	Experiment OA	Predicted OA	% Individual Error for OA	Individual Accuracy for OA
80	2	7.9	7.8889	0.1400	99.8599
80	2.5	7.8	7.7551	0.5747	99.4252
80	3	7.4	7.4420	0.5688	99.4311
90	2	7.9	7.8889	0.1400	99.8599
90	2.5	7.7	7.6778	0.2874	99.7125
90	3	8	8.0221	0.2766	99.7233
100	2	8.2	8.1579	0.5133	99.4866
100	2.5	8	8.0221	0.2766	99.7233
100	3	8.2	8.1579	0.5133	99.4866
80	2	7.4	7.4467	0.6315	99.3684
80	2.5	7.4	7.4467	0.6315	99.3684
80	3	8	7.9584	0.5187	99.4812
90	2	8.1	8.0532	0.5769	99.4230
90	2.5	7.7	7.7276	0.3593	99.6406
90	3	8.1	8.0532	0.5769	99.4230
100	2	7.6	7.5861	0.1819	99.8180
100	2.5	7.7	7.7276	0.3593	99.6406
100	3	7.7	7.7276	0.3593	99.6406

This showed that FL/FIS models surpassed the statistical models. The prediction capability of the FL/FIS with pi membership function is represented in Table 3 and 4. The low individual prediction error and high individual accuracy confirms the capability of the FL/FIS with pi membership function. Khodabakhsh *et al.* (2015) [11] also reported the high values of R^2 (0.977-0.999) and low values of RMSE (0.013-0.065) when FL/FIS was utilized to model the drying kinetics of papaya fruit slices

3.2 *Effect of process factors on product quality measure based on FIS/FL (pimf) prediction*

The surface plots showing the effect of input factors (pre-treatment option, smoke temperature and smoke time) on the output factors (gross energy value (GEV) and overall acceptability (OA)) of brined and solar dried and brined non-dried Tilapia (*Oreochromis niloticus*) fish is depicted in Fig. 4 and 5.

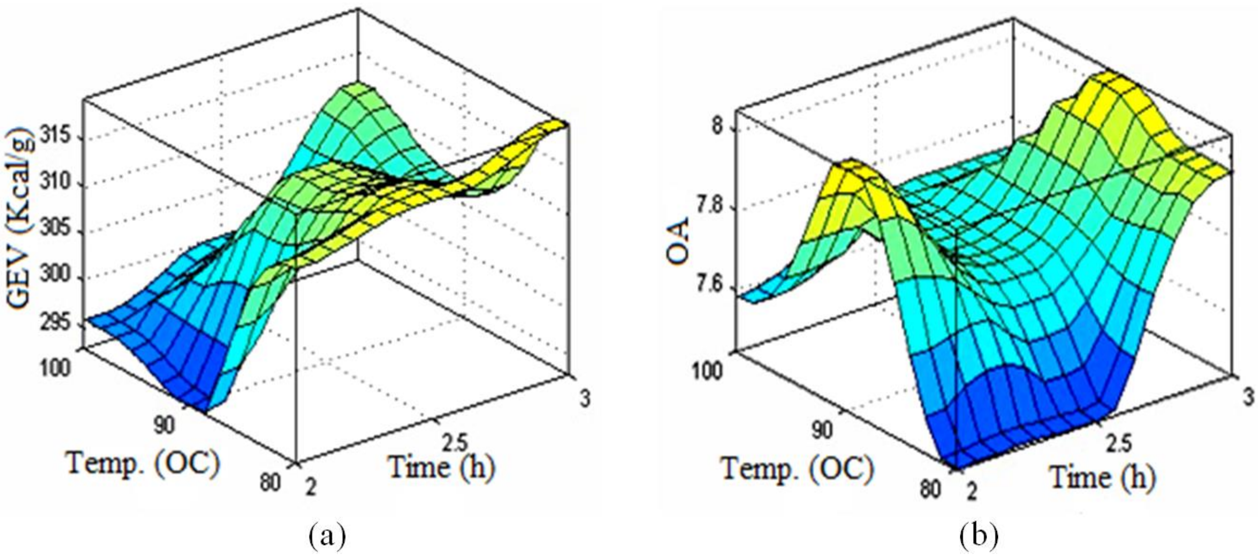

Fig. 4: Effect of smoking time and temperature on (a) gross energy value and (b) overall acceptability for brined and solar dried Tilapia (*Oreochromis niloticus*) fish pre-treatment option.

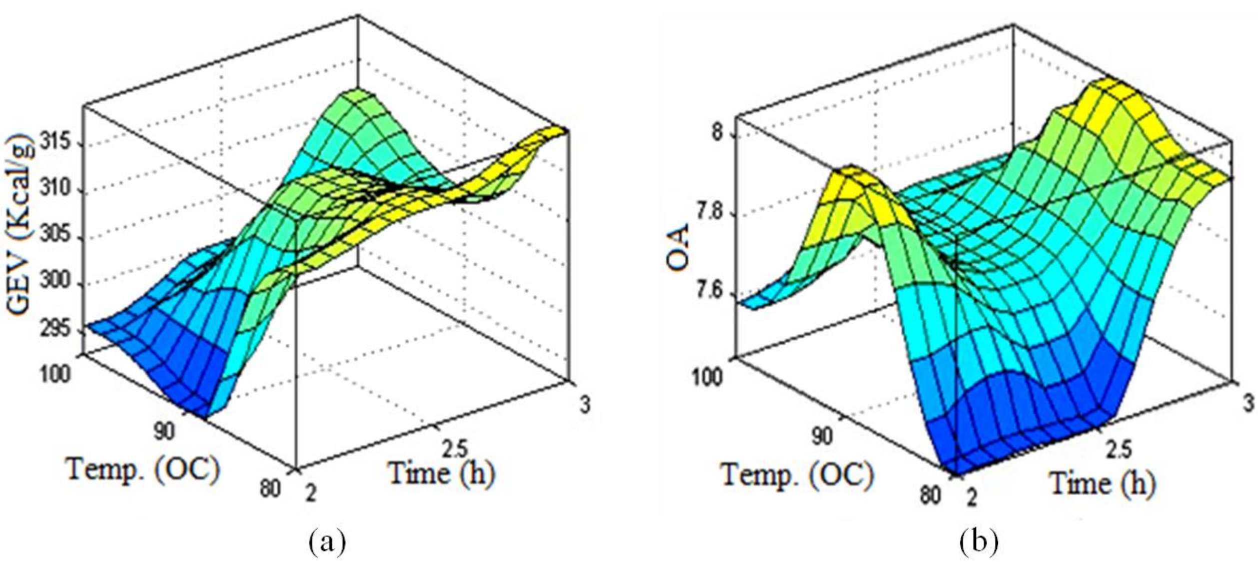

Figure 3 Effect of time and temperature on (a) gross energy value and (b) overall acceptability for no prior pre-treatment.

Fig. 4 (a) showed that GEV increased continuously with increased smoking time from 2 to 3 h. In addition to observations in Fig. 4 (a), GEV significantly decreased between 80 to 90^{O}C and slightly increased between 90 to 100^{O}C. Fig. 4 (b) showed that OA marginally increased from 2 to 2.5 h before a significant increase from 2.5 to 3 h. Also, Fig. 4 (b) showed that OA increased as smoking temperature increased between 80 to 90^{O}C before it decreased from 90^{O}C to 100^{O}C.

Fig. 5 (a) showed that GEV decreased with increased smoking temperature from 80 to 100^{O}C while it increased with increased smoking time from 2 to 3 h. Furthermore, Fig. 5 (b) showed that OA increased with increase in smoking temperature from 80 to 100^{O}C but decreased with increased time from 2 to 3 h. These results showed that increased in smoke temperature (90 to 100^{O}C) slightly benefited GEV for brined with solar dried Tilapia (*Oreochromis niloticus*) fish sample than brined non-dried Tilapia (*Oreochromis niloticus*) fish sample.

Increased in temperature significantly benefited the OA of brined non-dried Tilapia (*Oreochromis niloticus*) fish sample compared to brined with solar dried Tilapia (*Oreochromis niloticus*) fish samples. Increase smoking time significantly benefited the GEV of both pre-treatment sample options while it also benefited the OA of brined with solar dried pre-treated Tilapia (*Oreochromis niloticus*) fish sample between 2.5 to 3 h but was disadvantaged to the OA of brined non-dried Tilapia (*Oreochromis niloticus*) fish sample.

4.0 CONCLUSION

A fuzzy inference system or fuzzy logic (FIS/FL) model was designed for the modelling and prediction of gross energy value and overall acceptability brined with solar dried and brined no-dried Tilapia (*Oreochromis niloticus*) fish using the experimental data to build FIS/FL expert rules. The accuracy of the selected membership function type of the developed FIS/FL model was also investigated. The results showed that FIS/FL was successfully developed and FIS/FL with pi membership function performed best. The FIS/FL also outperformed the initially developed statistical model for the same experimental value. Its concluded that can be employed where statistical model may proved inadequate. Further studies that employed other artificial intelligent methods can be employed in smoking or drying operation for product or process control and standardization.

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