Fuzzy Logic Modeling of Yoghurt Incubation

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Abstract: Yoghurt production was modeled in this study based on different incubation temperatures, inoculum ratio of starter culture and incubation times. Experimental yoghurts were produced in two replicates and incubation final pH values of 343 yoghurt samples were determined. Resultant pH values were used in fuzzy logic modeling system. Fuzzy logic modelling was conducted in two sections: fuzzy rules were set and membership function was generated in the first section and defuzzification was conducted in the second section. Three different fuzzy sets (triangle membership function) were used for fuzzification of incubation temperature, inoculum ratio of culture and incubation time values. Since there were 7 membership functions of input parameters, 343 (7 x 7 x 7) rows of rule were generated. Mamdani method was used to tabulate fuzzy rules. Three trapezoidal sections of membership functions generated for defuzzification were used and membership function values were determined with the use of weighted average method. Incubation final pH values of 343 samples were assessed in modeling study and model outputs were compared with the expert decisions. Matlab (R2016b) software was used to assess model performance and model general performance was calculated as 90.27%. Automated yoghurt production lines should be designed in the future and put into service of food industry for present model to be used in industrial scale.
Keywords: yoghurt, fuzzy logic, artificial intelligence, automation

Bulanık Mantık ile Yoğurt İnkübasyonunun Modellenmesi

Öz: *Bu çalışmada farklı inkübasyon sıcaklıkları, starter kültür inokülasyon oranı ve inkübasyon süreleri baz alınarak yoğurt üretimi modellenmiştir. Deneme yoğurtları iki tekerrürlü olarak üretilmiş ve 343 yoğurt örneğinin inkübasyon sonundaki pH değerleri belirlenmiştir. Elde edilen pH değerleri bulanık mantık modelleme sisteminde kullanılmıştır. Bulanık mantık modellemesi iki bölümde gerçekleştirilmiştir: birinci bölümde bulanık kurallar belirlenmiş ve üyelik fonksiyonu oluşturulmuş, ikinci bölümde berraklaştırma yapılmıştır. İnkübasyon sıcaklığı, kültür inokülasyon oranı ve inkübasyon süresi değerlerinin bulanıklaştırılması için üç ayrı bulanık küme (üçgen üyelik fonksiyonu) kullanılmıştır. Girdi parametrelerinin 7 üyelik fonksiyonu olduğu için 343 (7 x 7 x 7) satırlık kural oluşturulmuştur. Bulanık kurallar tablosu için Mamdani yöntemi kullanılmıştır. Berraklaştırma için oluşturulan üyelik fonksiyonlarının üç yamuk alanı kullanılmış ve ağırlıklı ortalama yöntemi kullanılarak üyelik fonksiyonu değerleri belirlenmiştir.Modelleme çalışmasında 343 örneğin inkübasyon sonundaki pH'ları değerlendirilmiş ve model çıktıları uzman kararları ile karşılaştırılmıştır. Model performansını değerlendirmek için Matlab (R2016b) yazılımı kullanılmış ve model genel performansı %90.27 olarak hesaplanmıştır. Gelecekte otomatik yoğurt üretim hatlarının tasarlanarak gıda sektörünün hizmetine sunulması düşünülmektedir.*

Anahtar kelimeler: yoğurt, bulanık mantık, yapay zeka, otomasyon

INTRODUCTION

Fuzzy logic is commonly used to solve ambiguous problems and it is a branch of artificial intelligence. The primary target of artificial intelligence is to create computer programs able to think and decide like humans (Zadeh,1965; Awasthi et.al., 2011; Djekic et.al., 2018).

Food industry has long been controlled with traditional methods. However, automated control systems and intelligent machines have been initiated in food industry to facilitate various processes. On the other hand, varying nature of raw materials, high production capacities, time-dependent non-linear changes in system behaviors have made difficult the potential use of such advanced systems (Linko, 1998). In control of complex food processes, "fuzzy-logic" systems are employed to transfer experience-dependent information and uncertainties into computers since certain restrictions required by the computers were not available (Dirim, 2010).

Since fuzzy logic allows the use to decide in uncertainty cases, it is used in various industries including electronics industry, robotics, physiology, medicine, economy, biology, statistics, mathematics, food industry and etc. to set up decision-support systems, for data classification and modeling purposes (Halavati and Shouraki, 2005).

In food industry, fuzzy logic models have been used in cooking-pressing processes of cheeses (Guillaumea and Charnomordic, 2000), modeling microorganism growth and development, life-cycle modeling of *E. coli* and *Yersinia* in white cheese (Sofu and Ekinci, 2005), estimation of yoghurt storage durations (Sofu and Ekinci, 2007), determination of

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food frying durations (Rywotycki, 2003), classification of apples (Kavdır and Guyer, 2003; Shahin et.al., 2003), classification of tomatoes based on different quality criteria (Jahns et.al., 2001), classification of pizzas (Sun and Brosnan, 2003a; 2003b), kefir production (Akgül et.al., 2014), assessment of food security (Abiyeva et.al., 2016; Aliyeva et.al., 2017), pH control in food production (Chung et.al., 2010), potential use of essential oils in fruit juices as preservative (Başak, 2018), assessment of raw milk quality (Akıllı et.al., 2014) and identification of mastitis in raw milk (Cavero et.al., 2006; Kramer et.al., 2009b).

Yoghurt is appetizingly consumed almost in all countries (Niamsiri and Batt, 2009). It is produced from raw milk with the aid of lactic acid bacteria including *Lactobacillus delbrueckii* subsp*.* *bulgaricus* and *Streptococcus thermophilus* (Freitas, 2017).

Milk is pasteurized at 90–95 °C for 10–20 min to kill pathogenic and spoiling organisms. Following this heat treatment, milk is instantly cooled down to 42 °C, supplemented with starter culture (3%), left for incubation 42 °C for 4–6 h and finally cooled to stop fermentation (Özer, 2006; Tamime and Robinson, 1999).

The basic processes are similar in industrial yoghurt production. Besides milk composition, starter culture quantities, incubation temperature and time also influence taste-aroma and texture-consistency of yoghurts. Incubation temperature, time and starter culture levels may alter final pH of yoghurt (4.6) at which incubation was terminated (Özer, 2006; Tamime and Robinson, 1999).

Thermophilic starter culture is used in yoghurt production (Freitas, 2017). Thus, incubation temperature of yoghurt is 42-44 °C. Microorganism activity slows down and incubation prolongs at temperatures below 42 ºC. Moreover, microorganisms are not able to work out and acidity does not develop, in other words, yoghurt is not formed at temperatures over 44 ºC. Incubation time in yoghurt vary between 4-6 hours and the optimum is considered as 4 hours. Desired taste-aroma and pH are not achieved with incubation shorter than 4 hours. Besides, optimum pH of 4.6 is exceeded, acidity increases so quality criteria of yoghurt (taste-aroma) are negatively influenced at incubation longer than 4 hours. Desired pH and full-clotting are not achieved in shorter incubation. Similarly, starter culture levels significantly influence yoghurt formation, taste and aroma. At high inoculum ratios, acidity develops instantly, thus incubation is shortened and over acidification throughout the storage decrease the quality of yoghurt. Contrarily, at low inoculum levels, incubation prolongs and a weak gel will be formed.

In this study, fuzzy logic was used to model yoghurt production process with the use of final pH values of incubation influenced by incubation temperature, incubation time and inoculum ratio of culture.

MATERIAL AND METHODS

Yoghurt Production

Raw cow's milk obtained from Dairy Plant of Aydın Adnan Menderes University, Faculty of Agriculture. Yoghurt samples were produced in Aydın Adnan Menderes University Agricultural Biotechnology and Food Safety Application and Research Center (TARBIYOMER) Laboratories. Thermophilic yogurt culture (Yoflex Express 1.0 (Maysa, Istanbul) containing *Lactobacillus delbrueckii* subsp*.* *bulgaricus* and *Streptococcus thermophilus* bacteria was used. Skim milk powder was obtained from Akova Food Industry and Trade Cop. (Konya). The yoghurt production flow chart is presented in Figure 1.

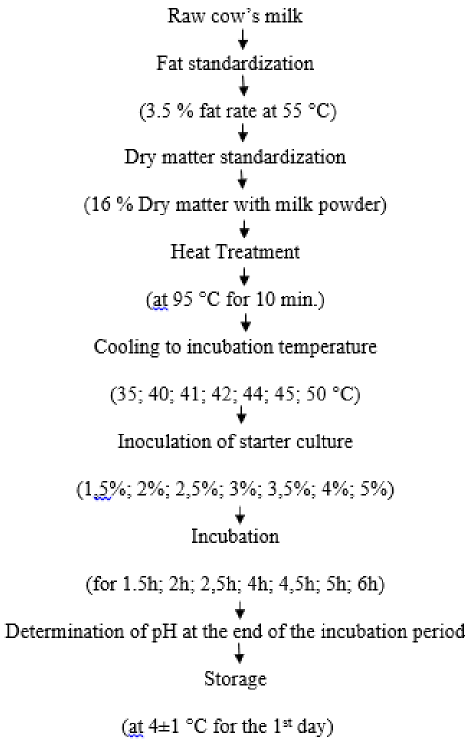


Figure 1. The production flow chart of yoghurt

The pH values of the samples at different incubation temperatures (35; 40; 41; 42; 44; 45; 50 °C), different starter culture addition rates (1,5%; 2%; 2,5%; 3%; 3,5%; 4%; 5%) and different incubation durations (1.5h; 2h; 2,5h; 4h; 4,5h; 5h; 6h) were measured with a combined electrode (Adwo, Romania) pH meter. Depending on the different incubation temperatures, starter culture addition rates and incubation time, yoghurts were produced in two replications. The average of the incubation pH results obtained from yoghurt produced with two repeats was obtained and the pH value of 343 yoghurt was obtained after incubation.

Fuzzy Logic Modeling

In membership function of a fuzzy set, each element of the universe of X is mapped to a value between 0 and 1 [0,1] as expressed below (Chen and Roger, 1994):

$$\mathrm{D} = \{(\mathrm{X}, \mu_\mathrm{D}(\mathrm{x})) | \mathrm{x} \epsilon \mathrm{X}\}$$

$$\mu_{D(x)}: \rightarrow [0,1] \qquad \textbf{(1)}$$

where;

X = Universal set,

D = Fuzzy subset in X,

$\mu_D(x)$ = Membership function of fuzzy set D.

Herein that function, 1 indicates 100% membership and 0 indicates 0% membership (not the member of that set).

As defined below, AND, OR and Complement are three primary operations of a fuzzy set;

$$\text{AND: } \mu_{C \cap D} = (\mu_C \wedge \mu_D) = \min(\mu_C, \mu_D) \qquad \textbf{(2)}$$

$$\text{OR: } \mu_{C \cup D} = (\mu_C \vee \mu_D) = \max(\mu_C, \mu_D) \qquad \textbf{(3)}$$

$$\text{Complement} = \overline{\mu_C} = 1 - \mu_D \qquad \textbf{(4)}$$

Present modeling works were conducted in two parts. Fuzzy rules and membership functions were set in the first part and defuzzification was performed in the second part (Figure 2).

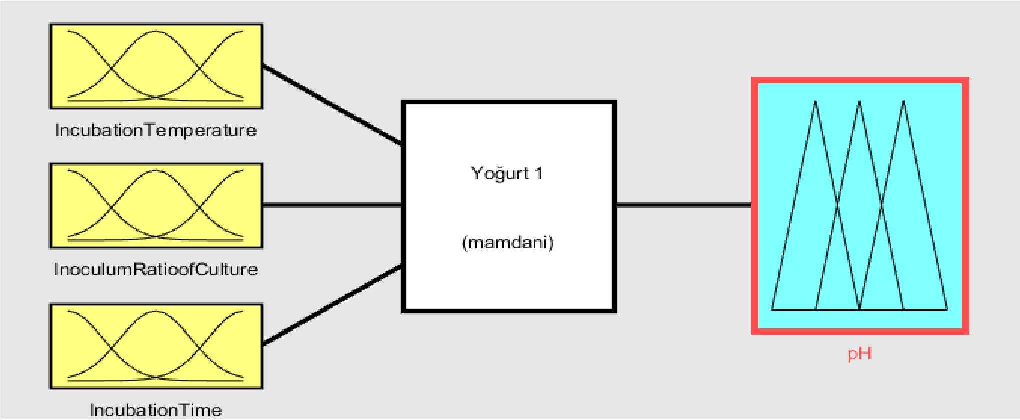
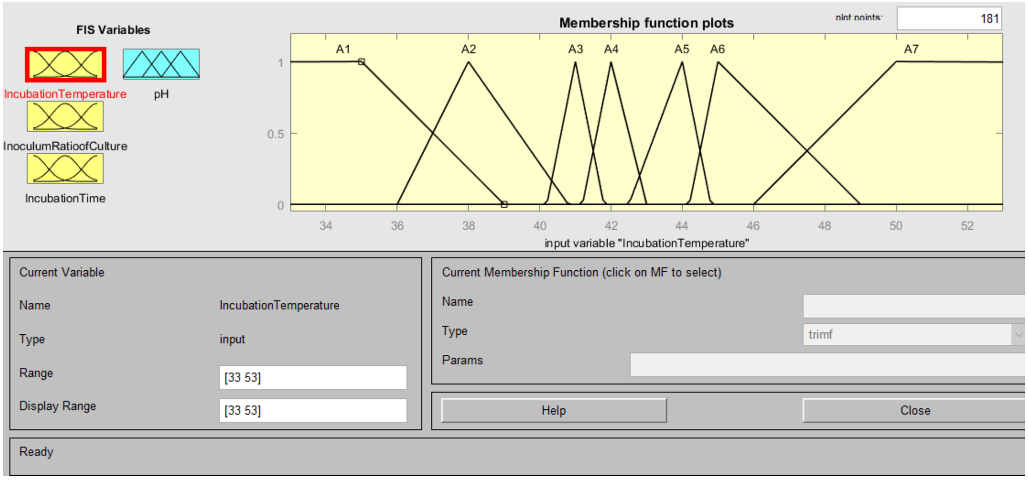


Figure 2. Modeling with fuzzy logic

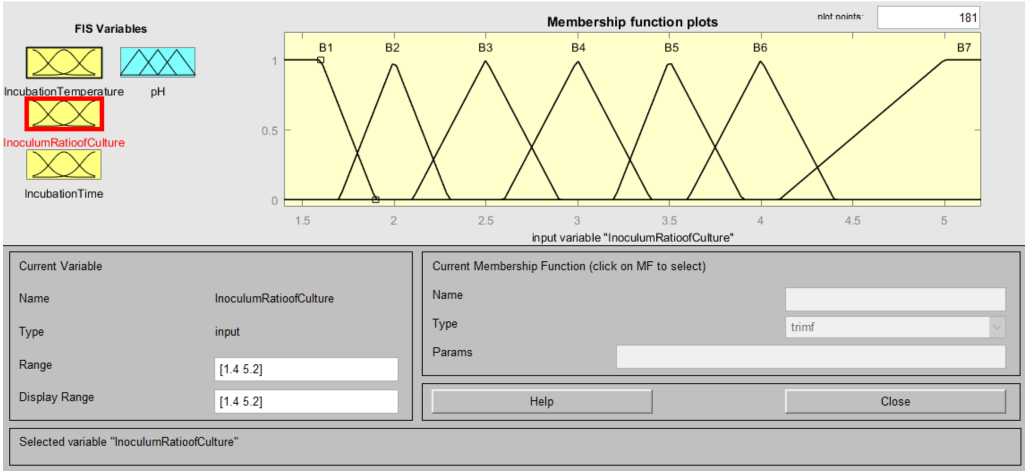
Determination of Membership Functions and Fuzzy Rules

The input parameters of fuzzy control (incubation temperature, incubation time, inoculum ratio of culture) were converted into fuzzy form with the use of triangular membership function (Figure 3, 4 and 5).



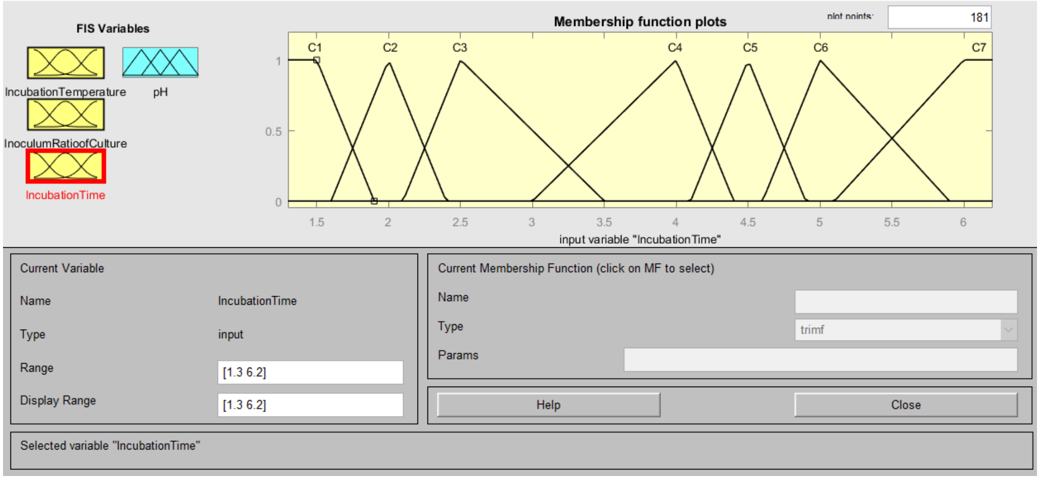
A1:Very Low, A2: Low, A3: Little Low, A4: Warm, A5: Normal, A6: Little High, A7: High,

Figure 3. Membership functions for incubation temperature



B1:Very Low, B2: Low, B3: Little Low, B4: Enough, B5: Normal, B6: Little High, B7: High,

Figure 4. Membership functions for the inoculum ratio of culture



C1: Not Enough, C2: Very Low, C3: Low, C4: Little Low, C5: Normal, C6: Little High, C7: High

Figure 5. Membership functions for the incubation time

In fuzzy modeling, a range should be set for incubation temperature, inoculum ratio of culture and incubation time For instance, the ranges for incubation temperature are presented in Equations 5, 6, 7, 8, 9, 10 and 11.

For a very low of incubation temperature (A1), the membership functions is

$\mu(A_1) = 1$, when incubation temperature input $x(1) \leq 35$

$$\mu(A_1) = \frac{(39 - x(1))}{4}, \text{when } 35 < x(1) \leq 39$$

$$\mu(A_1) = 0,\ x(1) > 39 \qquad \textbf{(5)}$$

For a low of incubation temperature (A2), the membership functions is

$\mu(A_2) = 0$, when incubation temperature input $x(1) \leq 36$ or $x(1) > 40.8$,

$$\mu(A_2) = \frac{(x(1) - 36)}{2}, \text{when } 36 < x(1) \leq 38$$

$$\mu(A_2) = \frac{(40.8 - x(1))}{2}, \text{when } 38 < x(1) \leq 40.8 \qquad \textbf{(6)}$$

For a little low of incubation temperature (A3), the membership functions is

$\mu(A_3) = 0$, when incubation temperature input $x(1) \leq 40.2$ or $x(1) > 41.8$,

$$\mu(A_3) = \frac{(x(1) - 40.2)}{0.8}, \text{when } 40.2 < x(1) \leq 41$$

$$\mu(A_3) = \frac{(41.8 - x(1))}{0.8}, \text{when } 41 < x(1) \leq 41.8 \qquad \textbf{(7)}$$

For a warm low of incubation temperature (A4), the membership functions is

$\mu(A_4) = 0$, when incubation temperature input $x(1) \le 41.2$ or $x(1) > 43$,

$$\mu(A_4) = \frac{(x(1) - 41.2)}{0.8}, \text{when } 41.2 < x(1) \le 42$$

$$\mu(A_4) = \frac{(43 - x(1))}{0.8}, \text{when } 43 < x(1) \le 42 \qquad (8)$$

For a normal of incubation temperature (A5), the membership functions is

$\mu(A_5) = 0$, when incubation temperature input $x(1) \le 42.5$ or $x(1) > 44.8$,

$$\mu(A_5) = \frac{(x(1) - 42.5)}{1.5}, \text{when } 44 < x(1) \le 42.5$$

$$\mu(A_5) = \frac{(44.8 - x(1))}{0.8}, \text{when } 44 < x(1) \le 44.8 \qquad (9)$$

For a little high of incubation temperature (A6), the membership functions is

$\mu(A_6) = 0$, when incubation temperature input $x(1) \le 44.2$ or $x(1) > 49$,

$$\mu(A_6) = \frac{(x(1) - 44.2)}{0.8}, \text{when } 44.2 < x(1) \le 45$$

$$\mu(A_6) = \frac{(49 - x(1))}{4}, \text{when } 45 < x(1) \le 49 \qquad (10)$$

For a high of incubation temperature (A7), the membership functions is

$\mu(A_7) = 0$, when $x(1) \le 46$

$$\mu(A_7) = \frac{(x(1) - 46)}{4}, \text{when } 46 < x(1) \le 50$$

$$\mu(A_7) = 1, x(1) > 50 \qquad (11)$$

Similarly, range values were also defined for inoculum ratio of culture and incubation time.

Following the definition of membership functions, a row of rules should be generated. Number of rows of rule is calculated by multiplying number of membership functions of input parameters. Since present input parameters have 7 membership functions, 7 x 7 x 7 = 343 rows of rule were obtained for these parameters. While generating fuzzy rules table (Table 1), M values were encoded in MATLAB 2016b software. Some of the rows of rules to be used in assessment of incubation final pH values are provided in Table 1.

Table 1. Fuzzy rules

	C1	C2	C3	C4	C5	C6	C7
A5+B1	M197	M198	M199	M200	M201	M202	M203
A5+B2	M204	M205	M206	M207	M208	M209	M210
A5+B3	M211	M212	M213	M214	M215	M216	M217
A5+B4	M218	M219	M220	M221	M222	M223	M224
A5+B5	M225	M226	M227	M228	M229	M230	M231
A5+B6	M232	M233	M234	M235	M236	M237	M238
A5+B7	M239	M240	M241	M242	M243	M244	M245

Where, A is membership functions for incubation temperature; A1:Very Low, A2: Low, A3: Little Low, A4: Warm, A5: Normal, A6: Little High, A7: High. B is membership functions for inoculum ratio of culture; B1:Very Low, B2: Low, B3: Little Low, B4: Enough, B5: Normal, B6: Little High, B7: High. C is membership functions for incubation time; C1: Not Enough, C2: Very Low, C3: Low, C4: Little Low, C5: Normal, C6: Little High, C7: High

In Table 1, light-grey rule cells indicate that yoghurt did not have consumable quality since the fermentation hasn't been completed. Dark-grey rule cells indicate that fermentation has been completed, but over acidification realized, thus yoghurts are acidic, sour. Three rows of rules used in identification of incubation final pH were defined below.

In case of normal incubation temperature (A5), very low inoculum ratio of culture (B1) and high incubation time (C7); yoghurt incubation final pH is assumed to be low (acidic) (rule M203 in Table 1).

In case of normal incubation temperature (A5), normal inoculum ratio of culture (B5) and little-low incubation time (C4); yoghurt incubation final pH is assumed to be normal (yoghurt formation pH) (rule M228 in Table 1).

In case of normal incubation temperature (A5), very low inoculum ratio of culture (B1) and not-enough incubation time (C1); yoghurt incubation final pH is assumed to be high (fermentation not realized) (rule M197 in Table 1).

When the operation in Equation was applied to rule sets, it will get the lowest value in membership functions of the row of rules. For instance, according to fuzzy AND (the minimum method) (Equation 2) operation used in IF THEN rule, the M228 in Table 1 will be defined as follows:

M228= (A5^B5^C4) = min (A5,B5,C4) **(12)**

The M values constituting the rules in Table 1 should be classified. Since 3 membership functions were used in assessment of yoghurt incubation final pH values (Table 2 or Figure 6), they can be separated into 3 classes (K_1, K_2 and K_3).

Table 2. Classification of yoghurt incubation final pH values

Yoghurt incubation final pH	Classification
K_1	Low

K_2	Normal
K_3	High

Where K is the final incubation pH output group that contains different class membership degrees. For instance, when the M values in Table 1 were classified, K1, K2 and K3 could be expressed as follows (Equation 13):

K1= (M214 M215 M216 M217 M221 M222 M223 M224 M227 M228 M231 M232 M233 M234 M239 M240 M243)

K2: (M203 M210 M229 M230 M235 M236 M237 M238 M241 M242 M244 M245)

K3: (M197 M198 M199 M200 M201 M202 M204 M205 M206 M207 M208 M209 M211 M212 M213 M218 M219 M220) **(13)**

These classes specified in Table 2 with the use of "M" values in Table 1 could be formed based on expert knowledge and experience.

When the OR (the maximum method) operation in Equation 3 was applied to membership functions of K-class, it gets the maximum value of membership functions in K-class. For instance, when this operation was applied to K2 (for M values in Table 1), K2 will be defined as follows:

$$\max k_2 = (M203 \vee M210 \vee M229 \vee M230 \vee M235 \vee M236 \vee M237 \vee M238 \vee M241 \vee M242 \vee M244 \vee M245)$$

$$= \max(M203, M210, M229, M230, M235, M236, M237, M238, M241, M242, M244, M245) \quad \textbf{(14)}$$

K-class membership functions will be required to find out "y" value in defuzzification process. The output vector "y" in Equation 15 indicates probabilities for incubation final pH before defuzzification (Lee 1990);

$$y = [\max(K1)\ \max(K2)\ \max(K3)] \quad \textbf{(15)}$$

Defuzzification

Three sections in membership function graph generated for defuzzification (Figure 6) will yield numerical values of yoghurt incubation final pH membership functions with the use of weighted average method.

For instance, in Equation 16 (Lee 1990), weighted average of trapezoidal section was calculated for low yoghurt incubation final pH membership function.

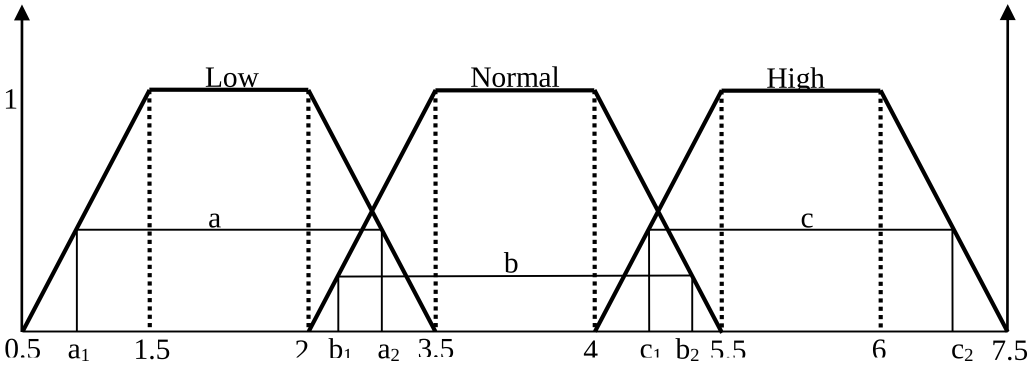


Figure 6. Determination of weighted average

$$\mathrm{sa} = \frac{(\mathrm{y}(1) \times (\mathrm{a} + 3))}{1.5} \quad \textbf{(16)}$$

where, $\mathrm{a} = \mathrm{a}_2 - \mathrm{a}_1$,

$\mathrm{a}_1 = \left(\left(0.5 \times \mathrm{y}(1)\right) + 0.5\right)$, and $\mathrm{a}_2 = \left(3.5 - \left(1.5 \times \mathrm{y}(1)\right)\right)$;

y(1) is the low yoghurt incubation final pH membership function, output from the output vector y (Equation 15); a, a_1 and a_2 are presented in Figure 6; sa is trapezoidal section. Membership degrees of sb and sc are calculated with the same approach in Equation 16 for medium and high yoghurt incubation final pH membership functions.

Weighted average of 3 sections in Figure 6 is expressed as "wa" yielding numerical values of yoghurt incubation final pH membership functions. The "wa" value was calculated with the use of Equation 17 (Kartalopoulos, 1996);

$$\mathrm{wa} = \frac{\mathrm{sa} \times (1.25) + \mathrm{sb} \times (2.25) + \mathrm{sc} \times (3.25)}{\mathrm{sa} + \mathrm{sb} + \mathrm{sc}} \quad \textbf{(17)}$$

In Equation 17, membership function values of fuzzy outputs of active rules (sa, sb and sc) are multiplied with their scale weights and then summed together. Resultant sum was divided by the sum of membership function values (sa, sb and sc) to get numerical control sign (Lee 1990). With the assessment of decided yoghurt incubation final pH values, system success will be identified.

RESULTS and DISCUSSION

In this study, incubation final pH values achieved in yoghurt production (based on incubation temperature, inoculum ratio of culture and incubation time) were assessed and decision-making process was modeled with the use of Fuzzy Logic. In Figure 6, incubation final pH membership classes were defined as: low 3≤pH≤4.15; normal 4.2≤pH≤4.6 and high pH≥4.65. General success of fuzzy logic model is provided in Table 3.

Table 3. General success of fuzzy logic model

Fuzzy Logic Prediction						
	Class	1	2	3	Total Predicted	%
Human Expert	1	54	6	3	63	85.7
	2	4	88	8	100	88.0
	3	-	11	169	180	93.9
Total Observed		58	105	180	311*/343	
%		93.1	83.8	93.9		90.27

*Accurately classified by fuzzy logic method

For success of modeling, pH of 343 yoghurts were assessed based on expert knowledge and experience and a decision was made. Of resultant decisions, 311 were considered as true and 32 were assessed as false. Thus, success of fuzzy modeling was calculated as 90.27%. Of these 32 false decisions, 29 belonged to close membership functions and 3 belonged to further membership functions.

Possible errors were attributed to expert knowledge and experience, membership functions (obliqueness and steepness of the triangles) and conjunctions of membership functions. Such errors may be minimized with the arrangements to be made on membership functions (obliqueness and steepness of the triangles) and conjunctions of membership functions, additional membership functions or removal of available functions.

While designating general success of the fuzzy modeling, acceptable erroneous decisions of neighboring (a lower or upper) memberships and the decision made by Fuzzy Logic could be accepted as true (Kavdır and Guyer, 2003). However, in case of yoghurt production, a lower or upper membership may alter the taste of final product, resultant product may not be served to markets since fermentation hasn't been completed, or the product may have a sour taste because of low pH. Such cases then generate problems in marketing of the product. Therefore, erroneous decisions of neighboring memberships were not taken into consideration in this study.

Akıllı et.al. (2014) developed a fuzzy logic-based decision support system for quality classification of raw milk samples. Total number of bacteria, somatic cell count and protein content of raw milk as the system inputs. Raw milk classification was the output of the designed system. To assess the system performance, fuzzy decisions were compared with the expert decisions and system performance was reported as 80%.

Harris (1998) used fuzzy logic method to assess composition and hygiene of raw milk samples. The researcher worked on two different data sets, generated 4 different quality classes and fuzzy quality assessments were compared with the standard techniques. As it was in present study, triangular and trapezoidal membership functions were used and quite efficient outcomes were achieved with fuzzy logic method.

Mehreban et.al. (2012) used fuzzy logic method to assess row milk quality in terms of microbiological and physiochemical traits. As it was again present study, triangular and trapezoidal membership functions, Mamdani inference method and center of gravity defuzzification methods were used. Researchers generated 5 quality classes and set 675 rules. System performance was assessed through expert classifications of raw milk samples and system performance was reported as 82.5%.

Sofu and Ekinci (2007) used artificial neural network models to estimate storage duration of yoghurt. Yoghurt samples were stored for 14 days and microbial contents and pH values were measured on the 1st, 7th and 14th day of storage. Resultant data were modeled with the artificial neural networks (ANN) and shelf life of yoghurt was estimated. With this modeling, quite a high correlation (R^2=0.9996) was achieved between the measured and estimated values.

Zaninelli et.al. (2016) used fuzzy modeling to estimate intramammary infections in milk goat. Animal health and milk quality could be monitored with electrical conductivity. Two pre-samples from 6 healthy Saanen goat were measured daily for 6 months and bacteriological tests and somatic cell counts were determined to assess animal health status. In fuzzy modeling, a sensitivity of 81% and a specificity of 69% were achieved. Resultant findings revealed that fuzzy logic was an interesting approach for milk goat since the model offered a greater accuracy than the other methods.

Sharma et.al. (2014) used soft computing–based intelligent models (connectionist and adaptive neuro-fuzzy inference system - ANFIS) to estimate moisture sorption isotherms of milk and pearl millet–based weaning feed, "fortified Nutrimix'' at 4 temperatures (15, 25, 35 and 45^{0}C) and over the water activity range of 0.11–0.97. A back-propagation algorithm with Bayesian regularization/Levenberg-Marquardt optimization mechanisms was employed to develop connectionist models. Resultant findings revealed that the soft computing models, especially ANFIS, yielded a greater performance than the conventional sorption models in estimation of isotherms.

Ma et.al. (2018) worked on raw milk monitoring and warning equipment and service platform to monitor raw milk temperature in storage tank and set a warning alarm in case of an exceptional case. Researchers used a data-based modelling approach to get, clean and use data to solve raw milk storage problems. BP neural network and Fuzzy Inference were used in raw milk monitoring and warning management system and prediction and warning was achieved in milk storage. Resultant findings revealed that designed model exhibited quite a high performance in prediction of raw milk storage temperature and reflecting variations in raw milk temperatures throughout the storage. Resultant platform and models offered a method to dairy operations for management of raw milk and prevention of temperature-induced spoilage in raw milk.

Djekic et.al. (2018) developed a model for sustainability of food transportation in a fuzzy ambient. Being aware of lack of evidence to assert that "local food" was more sustainable, two opposite milk distribution systems of Serbia between the local and cross and difficulties experienced in food transportation were assessed. Data mining was performed for 13 indicators and 4 types of data to calculate transportation sustainability index. The model was verified with the real data obtained for two types of dairy products of 4 dairy operations. Results revealed that transportation effect of foodstuffs should not be taken into consideration through sole interpretation of food miles. Present model calculated transportation sustainability index and identified the areas to be improved. It was concluded that fuzzy logic could efficiently be used to get a single transportation sustainability score.

As it was stated above, fuzzy logic applications have been used and still being searched by researchers in different disciplines ranging from the production and transportation of dairy products. With the recent developments in technology, further use of fuzzy logic in dairy industry is expected.

CONCLUSION

Yoghurt production was modeled with fuzzy logic in this study. Yoghurt incubation final pH values were decided based on incubation temperature, inoculum ratio of culture and incubation time. For this purpose, yoghurt pH values were measured at different incubation temperatures, inoculum ratio of culture and incubation times. Measured pH values were then used in modeling works.

Fuzzy logic modeling is somehow different in yoghurt from the other industrial products (except for foodstuffs). In other products, some of false decisions could be considered within the scope of acceptable error while assessing the performance of the system (an approach in which false decisions on pH for neighboring membership functions were accepted as true). On the other hand, false decisions were not taken into consideration in present model. Despite close memberships, they may influence taste, aroma and texture of yoghurt. With the present modeling of yoghurt production, decisions were made for 343 pH values. Of these decisions, 311 were accepted as true and 32 were accepted as false. Therefore, model performance was calculated as 90.27%.

Fuzzy logic yielded quite promising outcomes for further studies to be conducted in this area of research. For present software to be used in industrial scale, automated yoghurt production lines should be designed and put into service of food industry.

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