Fuzzy Logic Based Decision Making for Customer Loyalty Analysis and Relationship Management

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***Abstract*—This paper presents customer loyalty analysis and relationship management by incorporating fuzzy logic approach. We employ a case study of Jane and Juliet supermarket located in Uyo, Akwa Ibom State in Nigeria, where data are collected. We employed Knowledge-based system approach in gathering all the knowledge for the knowledge-base. We explore object oriented design tool in the development of our system. The system is developed using NETBEANS IDE, JAVA, MYSQL, MATLAB etc. The results obtained in this approach can allow companies to improve the customer equity, to launch loyalty programs, to automate mass customization, to maximize the customers' value and, this way, the companies' profit**.

Keywords-component; Fuzzy Inference, Customer Relationship, Loyalty analysis, Knowledge-base, Object-Oriented design.

I. INTRODUCTION

In today's world of marketing, some organizations are faced with the numerous problems such as, (i) not satisfying their customers with their sales and services (ii) not keeping track of their customers and customer loyalty and thus lose some of their loyal customers (iii) unable to focus their entire organization around their customers (iv) decrease in company's marketing and sales practices (v) unable to achieve greater profit because there is no reliable and efficient customer loyalty analysis and relationship management information system in most organizations. Customer relationship management (CRM) comprises a set of processes and enabling technologies supporting a business strategy to build long term, profitable relationships with specific customers [1]. It is a fact that a successful company not only put customers first, but put customers at the center of the organization because the changes in customer behavior determines unpredictable profitability and may be the cause for inefficient marketing planning. Customer data and information technology (IT) tools form the foundation upon which any successful CRM strategy is built [2]. The need for greater profitability requires an organization to proactively pursue its relationships with customers [3]. Although CRM has become widely recognized as an important business approach, there is no universally accepted definition of CRM [4].

Organizational success is, in part, dependent on its ability not only to assemble relevant data on the perception and the requirements of their customers but also to be committed to position customer satisfaction in the heart of their corporate objectives so that the organization can identify opportunities, discover and analyze problem areas and implement strategic adaptations [5][6]. Therefore, it is essential to build refined strategies for customers based on their value [7]. There are many potential benefits provided by CRM and some of them include; (1) Increased customer retention and loyalty, (2) higher customer profitability, (3) value creation for the customer, (4) customization of products and services, (5) lower process (6) higher quality products and services [8].

Reference [9] examines customer relationship management, or CRM, from the perspective of strategy formulation and implementation. In today's competitive era, customer relationship management can be adopted as a core business strategy in order to help organizations manage customer interactions more effectively, [10]. Reference [11] defines a standard product loyalty status, or *SPLS*, using customers' purchasing records to evaluate each customer's loyalty to a certain product. Reference [12] explores the role of CRM in enhancing organizational growth in reference to the banking industry (HDFC bank) by trend analysis method. Reference [13] carries out empirical study in Assessment of Customer Relationship Management for Global Shipping

Carrier-based Logistics Service Providers in Taiwan. Reference [14] discuss and demonstrate the concept of CRM and data mining. Reference [15] proposes a new procedure, joining quantitative value of RFM attributes and K-means algorithm into rough set theory (RS theory); to extract meaning rules and it can effectively improve these drawbacks. Reference [16] performs analysis of CRM programs practiced by passengers' airline industry of India and its impact on customer satisfaction and loyalty. Reference [17] demonstrates the effect of customer loyalty on the customer lifetime value. Reference [18] applies and compares the analytic hierarchy process (AHP) to evaluate the organizations readiness in E-CRM implementation.

Fuzzy logic is a powerful technique for solving a wide range of industrial control and information processing applications [19]. Fuzzy logic controller has its origin with the E. H. Mamdani [20] researches, based on theories proposed by L. Zadeh [21]. It has emerged as a tool to deal with decisions in which the phenomena are uncertain, imprecise, partial truth or qualitative decision-making problems to achieve robustness, tractability, and low cost, but it cannot automatically acquire the rules it uses to make those decisions [22]. Reference [23] proposes a fuzzy classification model for online customers. Reference [24] implements a data mining solution to customer segmentation for decayable products. Reference [25] proposes a fuzzy logic model for estimation of the intention to purchase based on the available information sources and the expert knowledge. Reference [26] design a fuzzy Classification Query Language which allows marketers to improve customer equity, launch loyalty programs, automate mass customization, and refine marketing campaigns. Reference [27] develops fuzzy evaluation and classification model to get the situation of the company, show the benefit of high CS and propose a solution of increase CS in CRM. Reference [28] proposes a hierarchical fuzzy classification of online customers which combines a relational databases and fuzzy logic. Reference [29] propose concepts, methods and models to conceive the important criteria affecting the customers' satisfaction in banking systems based on Delphi method. Classifying these criteria based on Kano Model. Reference [30] designs a fuzzy model for selection of customers who should be targeted for deposit subscription schemes. Selection criteria are formulated on the basis of customer's loan balance, customer's age and annual income.

This paper aims at developing a fuzzy based decision support framework for customer loyalty and relationship management. The components of the model include; (1) a prototype of computer aided system for customer loyalty analysis and relationship management system that helps supermarket to identify the level of loyalty of their customers, (2) a database model to store important information about customers. (3) a knowledge base model for obtaining important information that will be used in developing a decision support system. (4) a fuzzy logic decision support system for customer loyalty analysis and relationship management that aids companies in making important decisions to improve their services to customers and thus maximize profit. In order to achieve our objective, a study of a knowledge based system for customer loyalty and relationship management is carried out. We employ a case study of Jane and Juliet supermarket located in Uyo, Akwa Ibom State in Nigeria, where data are collected. We explore object oriented design tool and knowledge base design technique in the development of our system. The Mamdani's Max-Min technique is employed to infer data from the rules developed. This resulted in the establishment of some degrees of influence of input variables on the output. The system is developed using NETBEANS IDE, JAVA, MYSQL, MATLAB etc. The proposed system will serve as a tool for managers explore in order to build and maintain loyal and valued customer relationships and thus increase profitability in their organizations.

In section 2, we present the research objective while in Section 3 the research methodology is presented. Section 4 presents the model experiment while in Section 5 results of findings are discussed. Finally in Section 6, conclusion and some recommendations are made.

II. Research Objective

The objective of this paper is to develop a fuzzy- based decision support framework and apply the model for customer loyalty and relationship management to improve sales accuracy, reliability, robustness and profit generated by an industry.

III. Research Methodology

Figure 1 shows the architecture of fuzzy logic model for customer loyalty analysis and relationship management. The architecture of fuzzy logic model for customer loyalty analysis and relationship management is made of knowledge based which comprises database model and fuzzy logic model and the user interface. The knowledge base design of fuzzy logic model for customer loyalty analysis and relationship management is made up of both static and dynamic information about the decision variables and about the different factors that influence customer and marketing companies' decision for customer loyalty and relationship management for profit optimization. Fuzzy variables are defined by fuzzy sets, which in turn are defined by membership functions. Figure 2 shows data-base model for customer loyalty analysis and relationship management. The database proposed in this paper is made of the five main classes (objects and their associated attributes), Customer, Product, Transaction, Behavior and Stock. The structure of fuzzy logic model for customer loyalty analysis and relationship management is shown in Figure 3.

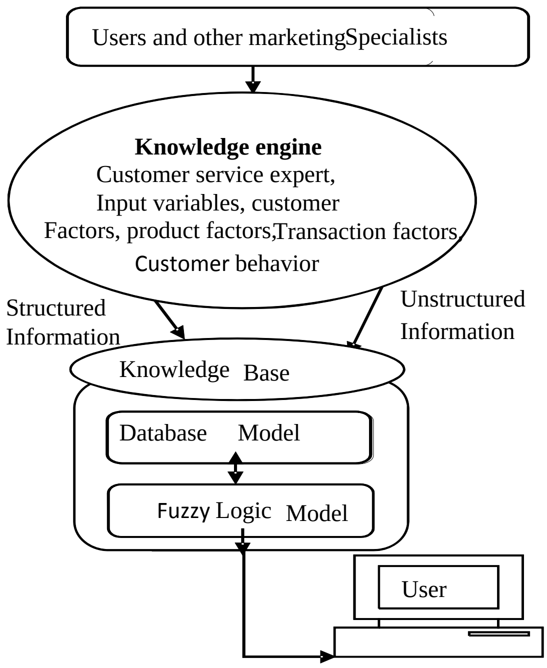

Fig 1: Database model for customer loyalty analysis and relationship management

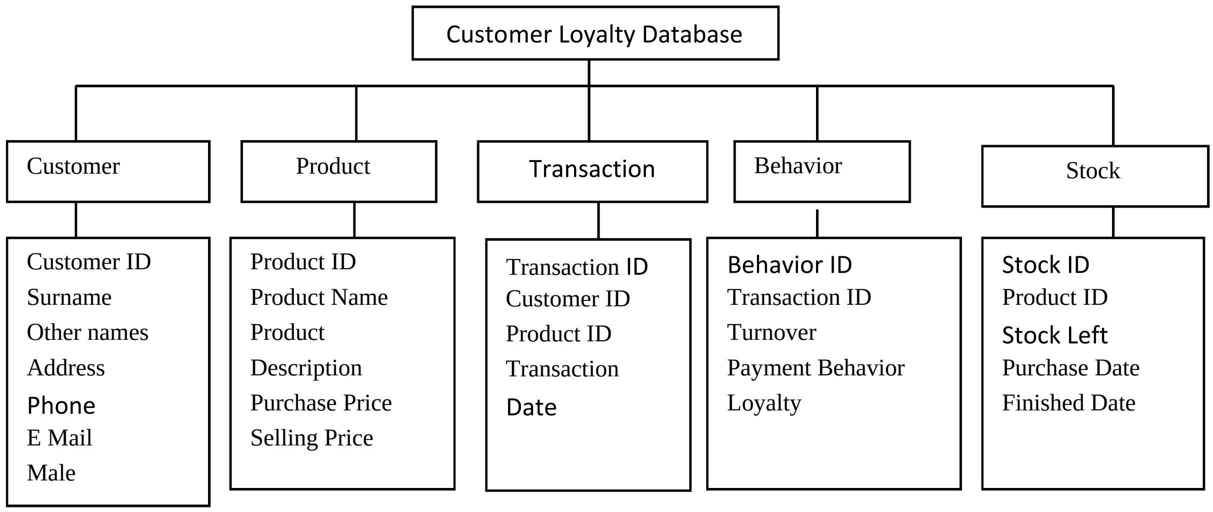

Fig 2: Database model for customer loyalty analysis and relationship management

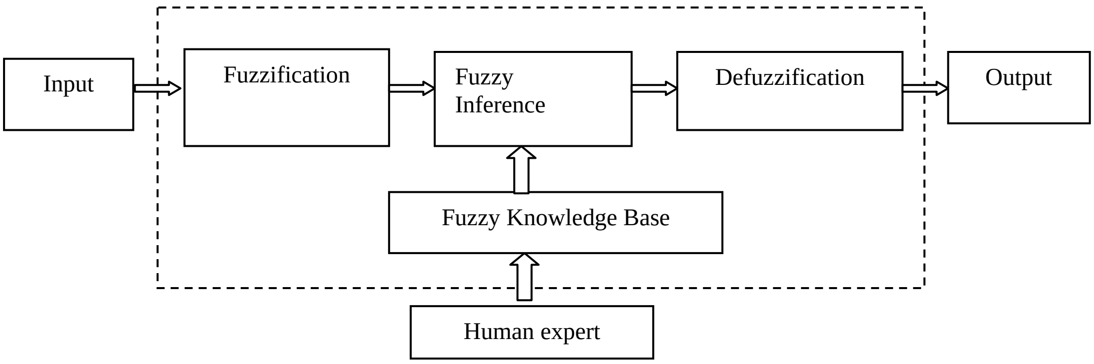

Fig. 3: Fuzzy Logic Model for Customer Relationship management

The main building units of a fuzzy logic design of customer loyalty analysis and management system involve the following: (i) Fuzzification unit (ii)

Fuzzy Inference unit (iii) Fuzzy Knowledge-base unit (iv) Defuzzification unit.

Fuzzification of data is carried out on the transformed data by selecting input parameters into the horizontal axis and projecting vertically to the upper boundary of membership function to determine the degree of membership. This is then used to map the output value specified in the individual rules to an intermediate output measuring fuzzy sets. Parameters used in fuzzy logic model are; Turnover, Payment behavior, Proximity, Specialty and Loyalty. These parameters constitute the fuzzy logic input variables used to generate the fuzzy logic model. The fuzzy linguistics variable defined on each parameter are; {High Turnover, Medium Turnover, Low Turnover}, {Attractive payment Behavior, Less payment Behavior, More Attractive payment Behavior}, {True loyalty, latent loyalty, pseudo loyalty, no loyalty}, producing a scalar value and a linguistic expression from domain. In this paper, the universe of discourse for the input variables and output variable are chosen to be [0, 100], [0, 100], [0, 100], [0, 100] and [0, 100] respectively. These data sets are employed in the design of the rule base for the fuzzy logic model.

We employ triangular membership function method in this paper because of its simplicity, precision in determining the value of the input parameters, common, good enough in most cases and cheap to implement by hardware or software The linguistic expression for input and output variables with their corresponding membership functions are evaluated. Triangular curves depend on three parameters a_1, a_2, and $a_3$and are given by equation (1); a_2 defines the triangular peak location, while a_1 and a_3 define the triangular end points. Linguistic expressions for the input variables (Turnover, Payment behaviour, Proximity and Specialty) are evaluated into their membership functions as shown in (2) – (5).The linguistic expression for Loyalty (output variables) is evaluated and presented in (6). The linguistic variable for each membership functions is further fuzzified; a case of turnover is represented mathematically in (7) – (9). Each linguistic value of fuzzy output membership function is further evaluated and assigned a label emphasizing the degree of the value assigned as indicated in (10) – (12).

$$\mu(x) = \begin{cases} 0 & \text{if } x < a_1 \\ x - a_1/a_2 - a_1 & \text{if } a_1 <= x < a_2 \\ a_3 - x/\ a_3 - a_2 & \text{if } a_2 <= x < a_3 \\ 0 & \text{if } x > a_3 \end{cases} \quad (1)$$

$$TO(x) = \begin{cases} \text{If } 25 <= x < 50 & \text{“Low Turnover”} \\ \text{If } 50 <= x < 75 & \text{“Medium Turnover”} \\ \text{If } 75 <= x <= 100 & \text{“High Turnover”} \end{cases} \quad (2)$$

$$PB(x) = \begin{cases} \text{If } 25 <= x < 50 & \text{“Less Attractive”} \\ \text{If } 50 <= x < 75 & \text{“Attractive”} \\ \text{If } 75 <= x <= 100 & \text{“More Attractive”} \end{cases} \quad (3)$$

$$PR(x) \begin{cases} \text{If } 25 <= x < 50 & \text{“Close”} \\ \text{If } 50 <= x < 75 & \text{“Closer”} \\ \text{If } 75 <= x <= 100 & \text{“Closest”} \end{cases} \quad (4)$$

$$SP(x) = \begin{cases} \text{If } 25 <= x < 50 & \text{“Low”} \\ \text{If } 50 <= x < 75 & \text{“Medium”} \\ \text{If } 75 <= x <= 100 & \text{“High”} \end{cases} \quad (5)$$

$$LO(x) \begin{cases} \text{If } 25 < x < 50 & \text{“Pseudo Loyalty”} \\ \text{If } 50 <= x < 75 & \text{“Latent Loyalty”} \\ \text{If } 75 <= x <= 100 & \text{“True Loyalty”} \end{cases} \quad (6)$$

$$\mu_{Low\text{-}To}(x) = \begin{cases} 00 & \text{if } x<0 \\ (x - 0)/25 & \text{if } 0<= x <25 \\ (50- x)/25 & \text{if } 25<= x <= 50 \\ 0 & \text{if } x >50 \end{cases} \quad (7)$$

$$\mu_{Med\text{-}To}(x) = \begin{cases} 0 & \text{if } x< 25 \\ (x -25)/25 & \text{if } 25 <= x < 50 \\ (75-x)/25 & \text{if } 50 <= x <= 75 \\ 0 & \text{if } x >75 \end{cases} \quad (8)$$

$$\mu_{High\text{-}To}(x) = \begin{cases} 0 & \text{if } x< 50 \\ (x -50)/25 & \text{if } 50 <= x < 75 \\ (100-x)/25 & \text{if } 75 <= x <= 100 \\ 0 & \text{if } x >100 \end{cases} \quad (9)$$

Linguistic values are assigned to the linguistic variables, Turnover, Payment behavior, Proximity and Specialty of loyalty analysis. A case of Turnover is shown in Equation (2). In Equations (7) to (9), each linguistic value is assigned a label emphasizing the degree of the value assigned. For example, Equation (2) evaluates the degree of high of the Turnover, if the value of Turnover is for instance, 50, the degree of influence for medium evaluates to 0.5 (50%) severity, whereas, 75 evaluates to 0.75 (75%) for high Turnover. MatLab 2007 is employed in this paper for the membership function plots, the graphical formats which show the fuzzy membership curves for the Turnover, Payment Behavior, Proximity, Specialty and Loyalty and presented in Figures (4 – 8) respectively with overlap parameters of 0.5 based on the defined ranges. Triangular membership functions are used to describe the variables. The degree of membership for a “Turnover” of 65 for instance, projects up to the middle of the overlapping part of the "medium" and "high" function so the result is "medium" membership = 0.40 and "high" membership = 0.60, while low is zero. Only rules associated with "medium" and "high" turnover will actually apply to the output response.

We obtain our rule base from derivation based on the supermarket’s records, expert experience, control engineering knowledge and the experience of a manager who is working at Jane and Juliet supermarket for over 5 years. The expert also assisted in defining the fuzzy rules and the fuzzy set. There are 4 inputs in the knowledge base namely; turnover, payment behavior, proximity and specialty, with 3 fuzzy sets each as antecedent parameters and 3 fuzzy sets each as consequent parameters. From the expert knowledge, these are used to generate 81 rules for the rule base defined for the decision-making unit. Parts of the rules are presented in Table 1.

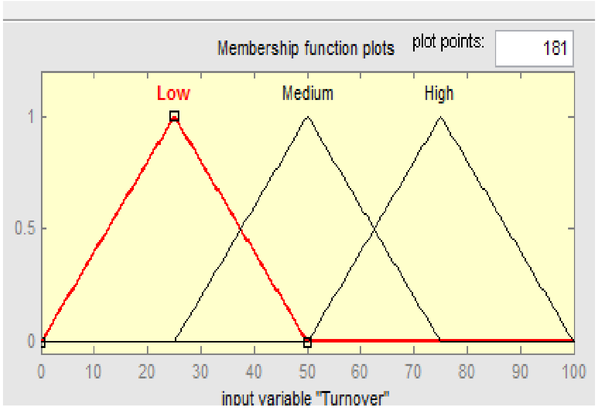

Fig. 4: Membership Function Plot for Turnover

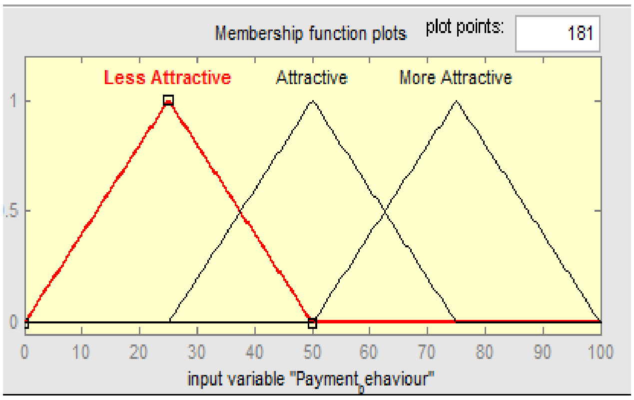

Fig.5: Membership Function Plot for Payment Behaviour

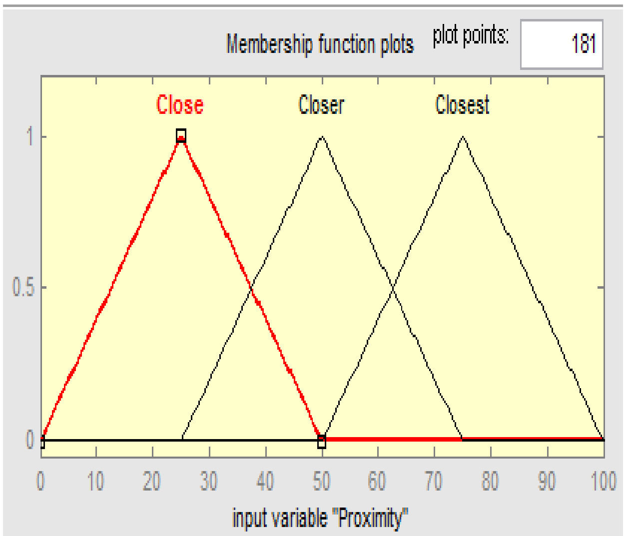

Fig. 6: Membership Function Plot for Proximity

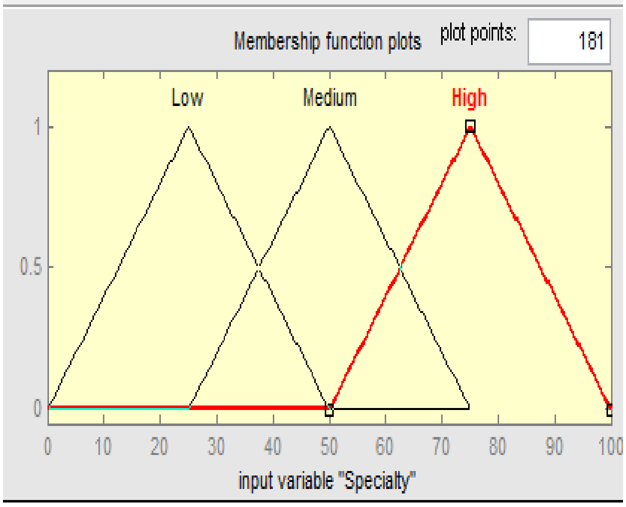

Fig. 7: Membership Function Plot for Specialty

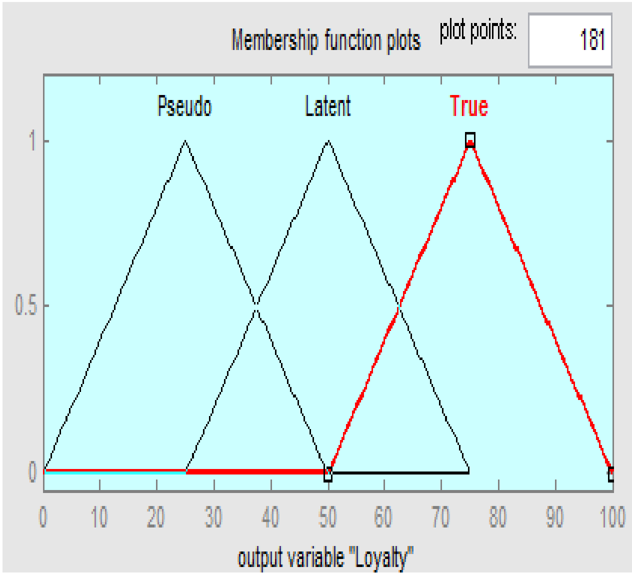

Fig. 8: Membership Function Plot for Loyalty

TABLE 1: RULE BASE FOR LOYALTY ANALYSIS AND RELATIONSHIP MANAGEMENT

1. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Close) and (Specialty is Low) then (Loyalty is Pseudo) (1)
2. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Close) and (Specialty is Medium) then (Loyalty is Pseudo) (1)
3. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Close) and (Specialty is High) then (Loyalty is Pseudo) (1)
4. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Closer) and (Specialty is Low) then (Loyalty is Pseudo) (1)
5. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Closer) and (Specialty is Medium) then (Loyalty is Pseudo) (1)
6. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Closer) and (Specialty is High) then (Loyalty is Latent) (1)
7. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Closest) and (Specialty is Low) then (Loyalty is Pseudo) (1)
8. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Closest) and (Specialty is Medium) then (Loyalty is Latent) (1)
9. If (Turnover is Low) and (Payment_Behaviour is Less_Attractive) and (Proximity is Closest) and (Specialty is High) then (Loyalty is Latent) (1)
10. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Close) and (Specialty is Low) then (Loyalty is Pseudo) (1)
11. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Close) and (Specialty is Medium) then (Loyalty is Latent) (1)
12. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Close) and (Specialty is High) then (Loyalty is Latent) (1)
13. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Closer) and (Specialty is Low) then (Loyalty is Pseudo) (1)
14. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Closer) and (Specialty is Medium) then (Loyalty is Latent) (1)
15. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Closer) and (Specialty is High) then (Loyalty is Latent) (1)
16. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Closest) and (Specialty is Low) then (Loyalty is Pseudo) (1)
17. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Closest) and (Specialty is Medium) then (Loyalty is Latent) (1)
18. If (Turnover is Low) and (Payment_Behaviour is Attractive) and (Proximity is Closest) and (Specialty is High) then (Loyalty is Latent) (1)

Fuzzy Inference

Inference is the process of drawing conclusions from existing data. The inference process for loyalty analysis and relationship management is shown in Figure 9. For each rule, the inference mechanism looks up the membership values in the condition of the rule. Fuzzy inputs are taken to determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The aggregation operation is used to calculate the degree of fulfillment or firing strength. A rule, say rule 1, generates fuzzy membership values T1 coming from the turnover, PB1 coming from payment behavior, P1 coming from proximity and S1 coming from specialty measurements. T1, PB1, P1 and S1 are combined by applying fuzzy logical AND to evaluate the composite firing strength of the rule. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. The degrees of truths (R) of the rules are determined for each rule by evaluating the nonzero minimum values using the AND operator. Only the rules that have strength higher than 0, would “fire” the output. The firing levels of the 81 rules are computed by the formula;

$$\alpha_i = T_i(v_0) \wedge PB_i\,(x_0) \wedge PR_i(y_0) \wedge S_i\,(z_0),\ T_i(v_0) \wedge PB_i\,(x_0) \wedge PR_i(y_0) \wedge S_i\,(z_0),...T_{in}(v_0) \wedge PB_i(x_0) \wedge PR_i(y_0) \wedge S_i(z_0) \qquad (10)$$

Where, α_i is the matching degree of a given input which satisfies the condition of the ith rule and i= 1, 2,.., 81. Then $\alpha_i$is assigned to the rule’s consequence L_i (w) as;

$$L_i\,(w) = \alpha_i \qquad (11)$$

The Mamdani max-min inference engine is employed and evaluates to obtain the individual rule outputs as;

$$L'_i(w) = (\alpha_{i1} \quad L_{i1}(w)),\ (\alpha_{i2} \quad L_{i2}(w)),\ \ldots(\alpha_{in} \quad L_{in}(w)) \quad (12)$$

where Li(w) is the individual rule’s consequence.

The overall system output is computed by aggregating the individual rule outputs from all the rules using OR operator as;

$$L(w) = L'_1(w) \quad L'_2(w) \quad L'_3(w) .. \quad L'_n(w) \qquad (13)$$

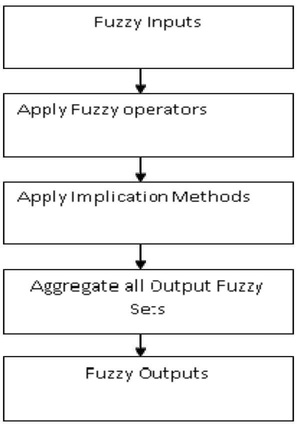

Fig. 9: Fuzzy inference process for loyalty analysis and relationship management

Defuzzification

Defuzzification of data into a crisp output is a process of selecting a representative element from the fuzzy output inferred from the fuzzy control algorithm. Many defuzzification techniques are proposed and four common defuzzification methods are center-of-area (gravity), center-of-sums, max-criterion and mean of maxima. According to (Umoh et al, 2011) (Obot, 2008), max-criterion produces the point at which the possibility distribution of the action reaches a maximum value and it is the simplest to implement. The center of area (gravity) is the most widely used technique because, when it is used, the defuzzified values tend to move smoothly around the output fuzzy region, thus giving a more accurate representation of fuzzy set of any shape (Cochran and Chen, 2005). The technique is unique, however, and not easy to implement computationally.

Our defuzzification is obtained using the Centroid of Gravity method (COG). Center of gravity (CoG) often uses discretized variables so that CoG, y can be approximated to overcome its disadvantage which uses weighted average of the centers of the fuzzy set instead of integration. This is used to map the fuzzy rules output to a crisp point as shown in (14).

$$\text{Crisp Output} = (\sum \mu(x).X)/(\sum \mu(x)) \qquad (14)$$

Where $\mu_A(x)$ = Membership value in the membership function and x = Center of membership function.

Model Experiment

The study adopts Matlab®/Simulink® and its Fuzzy Logic tool box functions to develop a computer simulation showing the user interface and fuzzy inference to assist the experimental decision for the best control action.

For example, we select four fuzzy inputs values, Turnover = 65, Payment Behavior = 35, Proximity=40, and Specialty = 65, evaluate their corresponding membership functions (Fuzzification) as presented;

TABLE 2: RULE BASE EVALUATION FOR T, PB, PR AND S AT 65 35 40 AND 65

Rule No.	Premise Variables				Conclusion Part of rule	Min.Value (non-zero)
	Turnover	Payment Behavior	Proximity	Specialty		
29	0.40	0.55	0.40	0.40	Pseudo	0.40
30	0.40	0.55	0.40	0.60	Latent	0.40
32	0.40	0.55	0.60	0.40	Latent	0.40
33	0.40	0.55	0.60	0.60	True	0.40
38	0.40	0.45	0.40	0.40	True	0.40
42	0.40	0.45	0.60	0.60	True	0.40
56	0.6	0.55	0.40	0.40	Latent	0.40
57	0.6	0.55	0.40	0.60	True	0.40
59	0.6	0.55	0.60	0.40	Latent	0.40
60	0.6	0.55	0.60	0.60	True	0.55
65	0.6	0.45	0.40	0.40	True	0.40
68	0.6	0.45	0.60	0.40	True	0.40
69	0.6	0.45	0.60	0.60	True	0.45

Turnover = 65 => Low =0.00, Medium=0.40, High=0.60.

Payment Behavior = 35 =>Less Attractive = 0.55, Attractive = 0.45, More Attractive = 0.00.

Proximity = 40 => Close = 0.40, Closer = 0.60, Closest = 0.0.

Specialty= 65 => low = 0.00, Medium=0.4, High=0.6.

Results of evaluation are shown in Tables 2.

For example, if Rules 29, 30, 32, 33, 38, 42, 56, 57, 59, 60, 65, and 68 fire from the rule base presented in this work when Turnover, Payment Behavior, proximity and specialty are selected to be 65, 35, 40 and 67.5, their corresponding degrees of membership evaluate to Low= 0.00, Medium = 0.40, High = 0.60 for turnover and Less Attractive=0.55, Attractive=0.45, More Attractive = 0.30 for payment Behavior, Close =0.40, Closer =0.60, Closest = 0.00 for proximity, Low=0.00, medium=0.50, High=0.50 for specialty. The respective output membership function strengths (range: 0-1) from the possible rules are computed using MAX-MIN inference for Pseudo Loyalty, Latent Loyalty (LL) and True Loyalty (TL) are computed as follows;

For Pseudo Loyalty, α_{29} = 0.40; L_{29} (w) = 0.40; L'_{29} (w) = (0.40 $\wedge$ 0.40) = 0.40

For Latent Loyalty, α_{30}= 0.40; L_{30} (w) = 0.40; L'_{30} (w) = (0.40$\wedge$ 0.40) = 0.40

α_{32}= 0.4; L_{32} (w) = 0.40;

L'_{32} (w) = (0.40$\wedge$ 0.40)= 0.40(15)

α_{56}= 0.40; L_{56} (w) = 0.40;

L'_{56} (w) = (0.40$\wedge$ 0.40) = 0.40

α_{59} = 0.40; L_{59} (w) = 0.40;

L'_{59} (w) = (0.40 $\wedge$ 0.40) = 0.40

For True Loyalty, α_{33} = 0.40; L_{33} (w) = 0.40; L'_{33} (w) = (0.40 $\wedge$ 0.40) = 0.40

α_{38} = 0.4; L_{38} (w) = 0.40;

L'_{33} (w) = (0.40 $\wedge$ 0.40) = 0.40

α_{42} = 0.40; L_{42} (w) = 0.40;

L'_{42} (w) = (0.40 $\wedge$ 0.40) = 0.40

α_{57} = 0.40; L_{5} (w) = 0.40;

L'_{57} (w) = (0.40 $\wedge$ 0.40) = 0.40

α_{60} = 0.55; L_{60} (w) = 0.55;

L'_{60} (w) = (0.55$\wedge$ 0.55) = 0.55 (16)

α_{65}= 0.40; L_{65} (w) = 0.40;

L'_{65} (w) = (0.40$\wedge$ 0.40) = 0.40

α_{68} = 0.40; L_{68} (w) = 0.40;

L'_{68} (w) = (0.40$\wedge$ 0.40) = 0.40

α_{69} = 0.45; L_{69} (w) = 0.45;

L'_{69} (w) = (0.45 $\wedge$ 0.45) = 0.45

Overall system output for Loyalty is computed as;

$$L(w) = L'_{29}(w) \vee L'_{30}(w) \vee L'_{32}(w) \vee L'_{33}(w) \vee L'_{38}(w) \vee L'_{42}(w) \vee L'_{56}(w) \vee L'_{57}(w) \vee L'_{59}(w) \vee L'_{60}(w) \vee L'_{65}(w) \vee L'_{68} \vee L'_{69} = 0.55 \quad (17)$$

Finally, we employ a defuzzification strategy in (16) to evaluate crisp output for the stated range as.

$$\text{Crisp output} = \frac{25x0.40+50x0.50+75x0.50}{0.40+0.50+0.50} = 52.79 \cong (53\%) \text{ Latent Loyalty} \quad (18)$$

These particular input conditions indicate value of 52.79 (53% LL) therefore latent loyalty is expected with 53% possibility as the required system response.

The values of the turnover, payment behavior, proximity and specialty indicated in Table 2 are inserted into the rule base under the view rule editor and the outputs computed for all the cases are recorded. The graphical construction of inference mechanism of fuzzy sets in Table 2 is shown in Figure 10 and Figure 11 shows the performance surface for Loyalty (Pseudo=0.4, Latent=0.4 and True= 0.55), generated in the Matlab Fuzzy Logic Toolbox.

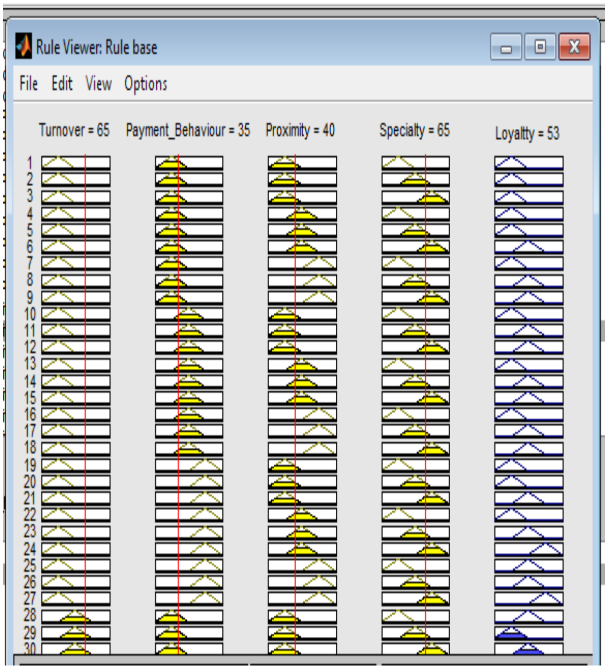

Figure 10: Graphical Construction of the Inference Mechanism of Fuzzy Sets in Table 2.

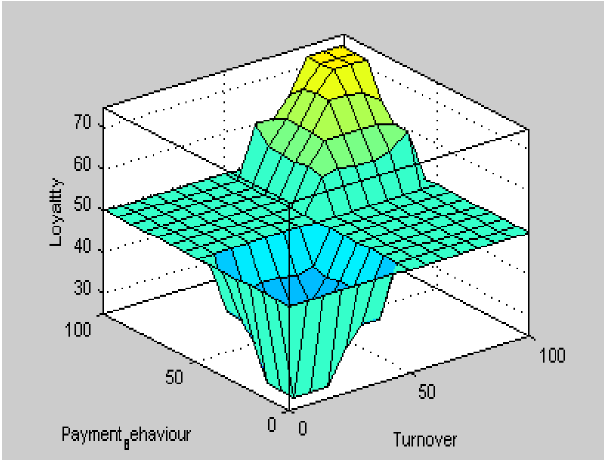

Figure 11:Performance surface for Loyalty (Turnover=65, Payment-Behaviour=35, Proximity=40 and Specialty=65)

RESULTS

In this paper, we present the design and implementation a fuzzy logic model for customer loyalty analysis and relationship management, based on Mamdani's direct approach. The selection of membership functions and rule base determine the output. We employ Triangular membership function; the variables in the system are manipulated and represented judiciously. We select the rule base from the experience of system expert. From the study, input and output linguistic variables are assigned to both input and output variables such as Turnover (low, medium, high), Payment Behaviour (less attractive, attractive, more attractive), Proximity (Close, closer, closest), (Specialty (low, medium, high), Loyalty(pseudo, latent, true) to the loyalty. The degree of influence or severity of each linguistic variable is evaluated. Table 2 shows fuzzy logic model of the variables, Turnover (TO), Payment behavior (PB), Proximity(PR), and Specialty (SP) in order to remove uncertainty, ambiguity and vagueness. The crisp output in (18) shows the linguistic label and degree of influence on loyalty. From the crisp output obtained from the graph of fuzzy logic model in figure 10, it is observed that this particular input condition indicate value of 53% (53% Latent), therefore latent is expected with 53% possibility.

Considering the degree of relationship between linguistic label and value of fuzzy output membership function, say "Pseudo", when its value equals 1.0, it indicates the totality of feelings or attitudes that a customer would not consider the repurchase of a particular product, service or brand or re-visit a particular company or shop. This condition will affect the success and profitability of the company with 100% possibility. When the fuzzy output (Pseudo) value is 0.7, it indicates 70% possibility effect on success and profitability.

Considering the relationships strength among fuzzy outputs in Figure 8, it indicates that only when "Latent" output value equals 1.0, (100%) that we can conclude that these customers have a very positive attitude or a strong preference towards company , vendor, etc, yet they have weak purchase behaviour. These customers are difficult for marketers to influence because there are factors out of the marketer's control that cause this latent loyalty such as reduced disposable income or unemployment. Relating "Pseudo with "Latent" for instance, when the value of "Pseudo" output is 0.6 showing possibility 60%, it indicates that there is 0.40 (40%) possibility of latent. This implies that it is not likely that the company will experience pseudo loyalty altogether when the customers have seemingly positive attitude or a weak preference towards a company by 60%. Relating "pseudo" with "latent" with the relationship strength of 0.5 (50%), it shows pseudo loyalty with 0.5 (50%) possibility and 0.5 (50%) of latent loyalty in this case. Relating "Latent" with "True" with the relationship strength of 0.35 (35%), it shows latent loyalty with 0.35 (35%) possibility and 0.75 (75%) of true loyalty, showing that these customers are regularly and repeatedly purchase products and services from the same company with 75% possibility in this case.

Several responses can be observed during the simulation of the system. The system is tuned by modifying the rules and membership functions until the desired system response (output) is achieved. The system can be interfaced to the real world via Java programming language.

Conclusion

Application of fuzzy logic technique in CRM is an emerging trend in the industry. It is important to make evident the great potential that fuzzy logic has to offer, such as an effective mean for managing customer relationships. Fuzzy Logic Controllers can provide more effective control of non-linear systems than linear controllers, as there is more flexibility in designing the mapping from the input to the output space. Fuzzy logic is capable of resolving conflicts by collaboration, propagation and aggregation and can mimic humanlike reasoning.. In this way, the system can learn the control parameters to take. By providing accurate information about the control elements, it allows companies to drive the customer equity, to better retain loyal and potentially good. With the help of linguistic variables and terms, the fuzzy logic approach also enables an intuitive querying process based on the terminology of the marketing department. All those tools help companies to maximize the value of their customers and, this way, their profits.

In our study, we represent the customer loyalty components using linguistic variables. We consider “turnover”, “payment behaviour”, “proximity” and “specialty” approaches in a vague, ambiguous and uncertain situation. It is shown that fuzzy logic is able to represent common sense knowledge and address the issue of vagueness, ambiguity and uncertainty as it is used to find the exact degree of pseudo, latent and true in customer loyalty of a company. To this end, fuzzy logic can be used to control and ensure the desired output in a model since it can tolerate wide variation in input variables. Fuzzy logic control model shows that true loyalty can be achieved at various levels, but maximum loyalty is achieved when these customers are regularly and repeatedly purchase products and services from the same company with by 100% (1.0). Also pseudo loyalty can be incurred at different levels when the customers have seemingly positive attitude or a weak preference towards a company. The exact level and exact pseudo, latent or true loyalty has been clearly defined by fuzzy logic control system thereby resolving the conflict of uncertainty and vagueness.

Our proposed fuzzy logic model for customer analysis and relationship management is implemented in Jane and Juliet supermarket, Uyo, Akwa Ibom State, being our case study, in order to show the utilization of the model. Since the ultimate aim of any capitalist industry is to make profit, the concept of customer loyalty is of great significance and it is evident that the fuzzy logic model developed, if implemented is an effective tool to effectively control customer loyalty in the company to achieve maximum profit. Our future efforts will be to further optimize the results of our work by integrating fuzzy logic and neural network or fuzzy logic and genetic algorithm. To focus and continue with a more complete investigation on identifying customers’ needs factors that influence on loyalty in companies. To represent linguistic variables by other types of fuzzy membership functions such as trapezoidal, bell shape, etc.

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