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Performance Tuning and Evaluation of Fuzzy Agent Model using ANFIS for Consumer-Relationship Management

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ABSTRACT

In the present paper a fuzzy agent model has been applied in retail scenario in order to improve the relationship with consumers. Simulation and testing of the model has been done using fuzzy reasoning system in MATLAB and performance of fuzzy agents has been analyzed using root mean square error measure. The performance of this model has further been evaluated using Adaptive Neuro Fuzzy Inference System (ANFIS). Evaluation was done with different input configurations by varying the number and type of membership functions using ANFIS. The evaluation of the model tries to analyze the effect of parameter tuning using ANFIS on decision making capability of fuzzy agents in strengthening consumer-relationship management. The simulation result shows that changing number and member function types impacts the performance of the model and the ANFIS model gives a better result in terms of root mean square error thereby improving the decision making capability of fuzzy agents. The paper clearly demonstrates that parameter tuning using ANFIS may provide an opportunity to optimize the design of the model with best input configuration to effectively evaluate the consumer response overtime.

Keywords - adaptive, adaptive neuro fuzzy inference system ANFIS, fuzzy inference system FIS, intelligent agent, multi-agent system MAS, optimization.

I. INTRODUCTION

Achieving the objective of runtime adaptation of evolving new and changing requirements still remains a challenging area in the field of software engineering. This volatility problem has been a major factor that requires a mechanism to identify and analyze changing requirements [1] [2]. In our previous work, we have used agentoriented approach to handle this volatility by proposing a dynamic adaptive multi-agent system (MAS) architecture that has been presented in Fig. 1[3]. Interface Agent (IA), Requirement gathering Agent (RGAgent), Service Provider Agent (SPAgent) and Task Agents (TA) are the four main components of the proposed MAS architecture. Description of each component has been detailed in the previous work [3].The proposed MAS architecture was then evaluated for its applicability in retail scenario to capture the underlying trend of customer satisfaction towards refund policy. Fuzzy inference system (FIS) was used to analyze the customer satisfaction using customer feedback and its acceptance towards current refund policy. The main function of requirement gathering (RGAgent) agent was to capture any sudden changes in customer satisfaction, analyzing its effect and recommending decision regarding retaining or replacing the refund policy. Today's retail market has become very competitive as it goes global via digital marketing as large amount of choices are now available for customers so there is a need to attract customers by establishing a strong relationship with customers. With an objective to improve relationship with customers in retail market, first the effectiveness of the model in gathering changing requirements and decision making with respect to runtime adaptation was evaluated and simulated using Mamdani FIS [4]. Since fuzzy agents use the linguistic representation of the gathered knowledge stored as rules, fuzzy logic reasoning was used to propose a mechanism for automatic modification of fuzzy rules dynamically.

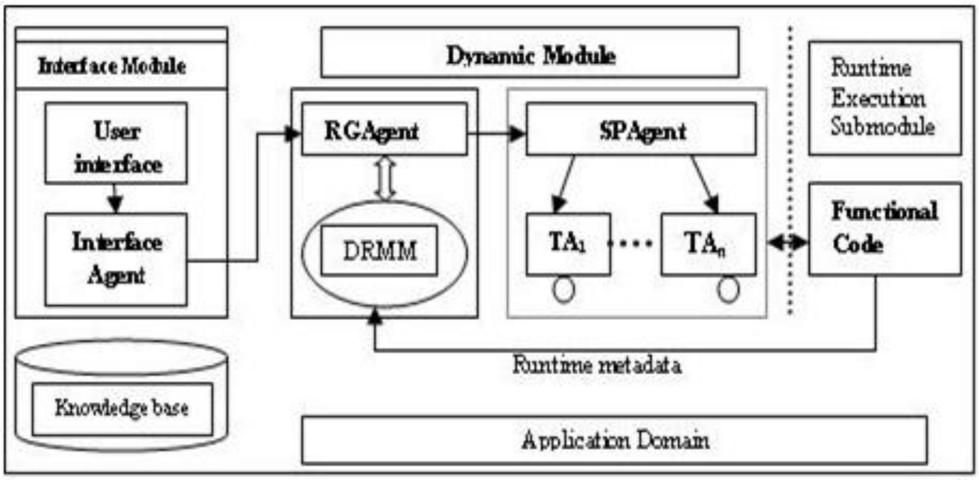

Fig 1. proposed multi agent architecture

II. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is a neuro-fuzzy intelligent architecture proposed by Jang [8]. This inference system combines the significant properties of artificial neural networks (ANN) and fuzzy logic set theory. It is an adaptive learning technique that uses fuzzy rule based reasoning along with neural network based training approach to identify adaptable membership function parameters. ANFIS attempts to minimize error by tuning input parameters, thus it is a suitable approach for modeling applications in an uncertain and complex environment. ANFIS modeling technique is applied onto Sugeno type FIS, which is characterized having either constant or linear output membership function [9]. The standard ANFIS uses hybrid learning technique but apart from hybrid learning other meta-heuristic techniques for learning can also be applied to enhance the efficiency of ANFIS model [10]. Shihabudheen and Pillai have presented a survey of neuro- fuzzy models using different learning techniques including meta-heuristic techniques classified as gradient based, hybrid, population based (genetic algorithm, differential evolution, ant colony optimization, particle swarm optimization, artificial bee colony optimization), Extreme Learning Machine (ELM) based and using Support Vector Machine (SVM). Authors have thoroughly compared each neuro-fuzzy learning technique and summarized the result on different attributes. The neuro-fuzzy system using hybrid learning is self organizing in nature with high classification capability so this technique can be applied for tuning parameters in our application [11]. It is the frequently used performance optimization technique as it is capable of processing non-linearity in the underlying structure, ease in implementation, computationally cost effective, adaptive to surrounding scenario with learning capability [10][12][13]. Applicability of ANFIS approach has also been found in diverse domains such as for wind speed prediction, business and economics, sports, energy planning and environment modeling [9] [10] [12] [14] [15][16].

This section presents a brief introduction of ANFIS and detailed information can be referenced from original work by Jang [8]. The standard ANFIS framework uses hybrid of backpropagation gradient descent and least square methods as training mechanism with an objective to minimize error between input set and predicted output set and the 5-layered architecture of ANFIS is presented in Fig. 2. Hybrid learning approach in forward pass optimizes the consequent parameters using least square method whereas premise parameters are optimized in backward pass using gradient descent method [8][17]. The fuzzy rules in Sugeno FIS model are framed using IF-THEN rules which have two parts antecedent and consequent and for two input parameters it has the following form:

IF x is A_1 and y is B_1 then $f_1 = (p_1x + q_1y + r_1)$ (1)

IF x is A_2 and y is B_2 then $f_2 = (p_2x + q_2y + r_2)$ (2)

where x_i, y_i are input parameters, A_i, B_i are fuzzy sets, f_i gives the output and p_i,q_i,r_i are corresponding consequent parameters of fuzzy rule.

ANFIS architecture with the two variables has been shown in Fig. 2 and it consists of five layers. Layer 1 presents parameterized membership functions (μ) from fuzzy sets A_i and B_i. Any membership function μAi(x), μBi(y) can be used at this layer for inputs which are antecedent and for Gaussian membership function it is represented by (3):

$$\mu A_i(x) = e^{-\left(\frac{x-c_i}{\sigma_i}\right)^2} \quad (3)$$

where c, σ represents center and width of fuzzy set (premise) respectively.

Output at this layer is specified by (4) and (5):

$$O_{1,i} = \mu_{Ai}(x) \text{ , for i = 1, 2} \quad (4)$$

$$O_{1,i} = \mu_{Bi-2}(y)\text{, for i = 3, 4} \quad (5)$$

Layer 2 determines firing strength or weight w_i using equation (6) for each of the rules which are then normalized in layer 3 as $\overline{w}_i$ using (7). Layer 4 is an adaptive layer which computes product of weight w_i and output f_i using (8).

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y)\text{, for i = 1, 2} \quad (6)$$

$$O_{3,i} = \overline{w}_i = \frac{w_i}{\sum_i w_i}\text{ , for i = 1, 2} \quad (7)$$

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad (8)$$

At layer 5, overall network output is computed by (9) which summate all the incoming input signals:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (9)$$

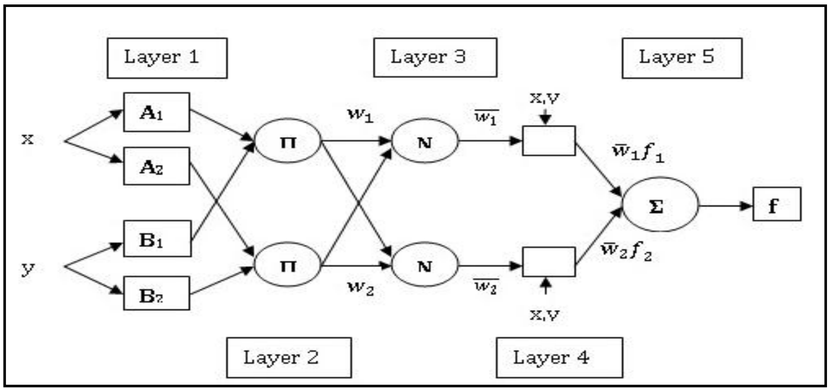

Fig 2. architecture of ANFIS [12]

III. EXPERIMENTATION

This study carries out experimentation on the test case Consumer-Relationship Management with an objective to improve the relationship between consumer and commodity by optimizing the performance of proposed multi agent model by parameter tuning. The experimentation first simulates the test case using Mamdani FIS and analyzes the performance of RGAgent which predicts the potential and sound consumers overtime [4]. Potential consumers are those key consumers which may play a key role in increasing sales by availing various discounts and other similar artifacts whereas sound consumers are those potential consumers which are financially wealthy and are the target for planning advance promotional policy. In the next step, ANFIS is applied for training and testing of the system under varied contexts to identify and analyze the best input configuration by parameter tuning in order to optimize output which in this case is predicting potential and sound consumers. Noureen Talpur *et al* have applied ANFIS on classification problems and carried out experimentation to evaluate the effectiveness of the ANFIS model on different membership functions [18]. This paper thus explores the way to improve the performance of system by testing application using ANFIS and experimenting with different shapes of member function on different count of member functions.

The experimentation is carried out in following steps.

III.I Parameter Determination

As a first step towards experimentation, the most effective input and output parameters were decided for the test case "Consumer-Relationship Management". The test case has been modeled using two fuzzy agents and named as FRGA1 and FRGA2 for fuzzy requirement gathering agent 1 and 2. The combined functionality of FRGA1 and FRGA2 enact as requirement gathering agent (RGAgent) of proposed MAS. The fuzzy agent model simulation mainly concentrates on the functionality of RGAgent and its performance evaluation which is represented in Fig. 3. Brief description of selected input and output parameters to carry out FIS simulation is presented in Table 1 and the functionality of RGAgent for the test case is visually presented in Fig. 4. Agent FRGA1 takes two input parameters {Vf, Texp} and determines those consumers who have the highest probability of being potential consumers {Pc}. Similarly, FRGA2 takes two input parameters {Pc, In} and determines those potential consumers who are highly sound {Sc}. Root mean square error (RMSE) performance metrics is used as an outcome of experimentation for evaluation of the FIS model.

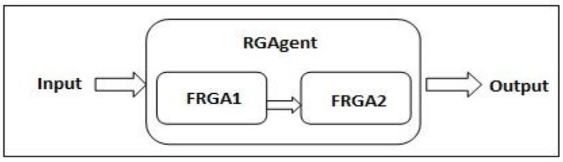

Fig. 3. modeling requirement gathering agent RGAgent as FRGA1 and FRGA2 for the test case

Table 1. Input and output determinants for the test case simulation

Input Parameters	**Description**
Visit frequency (Vf)	Number of times a consumer visits a retail store in a month
Income (In)	Annual income of consumer
Total Monthly Expenditure (Texp)	Expenditure per month
Output Parameters	
Potential Consumers (Pc)	Future key consumers
Sound Consumers (Sc)	Financially sound potential consumers

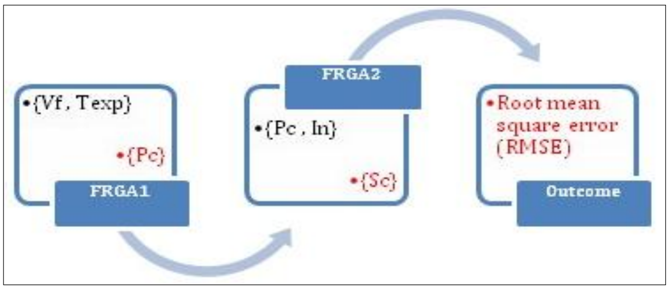

Fig. 4. Functionality of RGAgent as FRGA1 and FRGA2 for the test case

III.II Fuzzy Simulation

Secondly, the data for 224 salaried consumers were collected manually according to the input determinants specified in Table 1. 152 samples of data were used for training and 72 samples for testing. All the input data values were then normalized in the interval [0, 1]. Mamdani FIS was then applied to the test case input data with the fuzzy input configuration as shown in quantization Table 2 with linguistic range specified as VERY LOW (VL), LOW (L), MED (M), HIGH (H), VERY HIGH (VH). Two FIS namely CCR1 and CCR2 representing functionality of FRGA1 and FRGA2 has been designed as shown in Fig. 5 and 6. Fuzzy rules using IF-Then conditional structure were then designed and FRGA1 using fuzzy reasoning CCR1 identified the potential consumers and FRGA2 using CCR2 identified sound consumers. Fuzzy simulation was done in 5 iterative runs by increasing the visit frequency to maximum. In each run potential and sound customers were identified by CCR1 and CCR2. Assuming this prediction output as actual result, the ANFIS simulation of the system was carried out in the next step in order to achieve the optimized design configuration using parameter tuning.

Table 2. Input and output determinants used for test case simulation using FIS

Input/Output Determinants	**Linguistic Range**				
Vf	L	M	H		
In	VL	L	M	H	VH
Texp	VL	L	M	H	VH
Pc	L	M	H		
Sc	L	M	H		

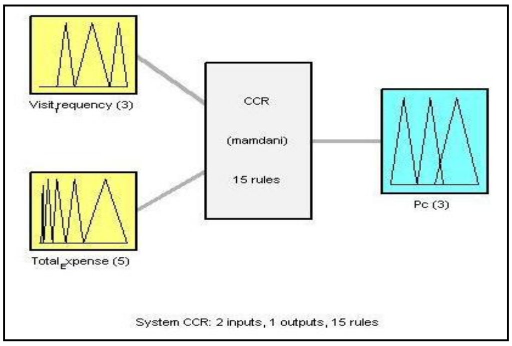

Fig. 5. FIS CCR1 as FRGA1 for the test case

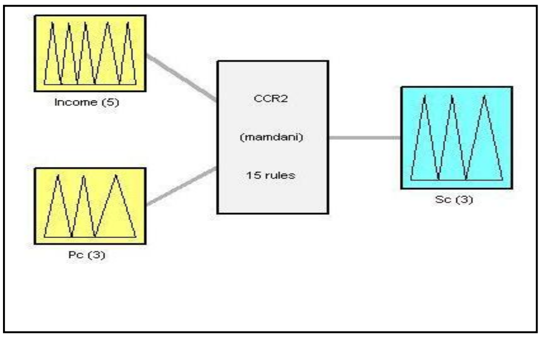

Fig. 6. FIS CCR2 as FRGA2 for the test case

III.III ANFIS Simulation

ANFIS simulations uses:

- 152 data samples as training data pairs.
- 72 data samples as checking data pairs for validation

ANFIS is then applied onto the experimental dataset and the system is trained, tested and evaluated for two different scenarios. The simulation evaluates the prediction performance of ANFIS models using RMSE measure and analyzes the effect of changing number and type of membership functions.

Scenario 1: Performance evaluation on different number of membership functions (μ). For evaluation the model is configured and tested for 3, 4, and 5 member functions for each input variables in fuzzy agents FRGA1 and FRGA2.

Scenario 2: Performance evaluation on different shapes of member functions. In this scenario, the model is configured for three different types of membership functions Triangular shaped (trimf), Gaussian (gaussmf) and Generalized bell-shaped (gbellmf) respectively and tested for each configuration of scenario 1.

The ANFIS model simulation of test case was done with coding using commands of Fuzzy Control Toolbox in MATLAB® [19].

Following steps were carried out:

1. Initializing the fuzzy system to start with is the first step to ANFIS training. Command ‘genfis1’ is used to generate an initial fuzzy system configuration with specified member function type and number of membership functions on all inputs to the system.
2. After the initial FIS has been configured, command ‘anfis’ is used to train the ANFIS system using training data as input to the system with specified options. ANFIS starts optimizing the system using initial configuration with options specified are number of epochs, number and type of membership functions. The best possible configuration of ANFIS system can be generated using ‘anfis’ command from initial FIS matrix as generated by ‘genfis1’ in

terms of membership functions. Also, training error (RMSE) as output is also computed for further evaluation of system.

3. Checking data set has also been applied simultaneously along with the training data set to prevent overfitting and for improving prediction accuracy.
4. Command 'evlalfis' is used for evaluating the system performance by comparing the actual output with output of fuzzy system with training data and check data.

With an aim to identify the best optimized ANFIS system performance, the system was trained on settings under scenarios 1 and 2. The model ANFIS1was used to evaluate the best fuzzy configuration for agent FRGA1 and ANFIS2 for agent FRGA2. Both the model was first trained on 3 membership functions on all inputs by varying membership function types to trimf, gaussmf and gbellmf. Then the number of membership functions was changed to 4 and 5 respectively for all inputs by varying shapes of member function using trimf, gaussmf and gbellmf. Table 3 and 4 summarizes the structure information of ANFIS models generated while training. Finally, among the entire design configuration set, performance evaluation was done using RMSE to determine the best configuration.

Table 3. ANFIS1 structure property for 9 different input configurations.

FRGA 1									
ANFIS 1	**μ = 3**			**μ = 4**			**μ = 5**		
Info	**trimf**	**gaussmf**	**gbellmf**	**trimf**	**gaussmf**	**gbellmf**	**trimf**	**gaussmf**	**gbellmf**
Number of nodes	35	35	35	53	53	53	75	75	75
Number of linear parameters	27	27	27	48	48	48	75	75	75
Number of nonlinear parameters	18	12	18	24	16	24	30	20	30
Total number of parameters	45	39	45	72	64	72	105	95	105
Number of training data pairs	152	152	152	152	152	152	152	152	152
Number of checking data pairs	72	72	72	72	72	72	72	72	72
Number of fuzzy rules	9	9	9	16	16	16	25	25	25

Table 4. ANFIS2 structure property for 9 different input configurations.

FRGA 2									
ANFIS 2	**μ = 3**			**μ = 4**			**μ = 5**		
Info	**trimf**	**gaussmf**	**gbellmf**	**trimf**	**gaussmf**	**gbellmf**	**trimf**	**gaussmf**	**gbellmf**
Number of nodes	35	35	35	53	53	53	75	75	75
Number of linear parameters	27	27	27	48	48	48	75	75	75
Number of nonlinear parameters	18	12	18	24	16	24	30	20	30
Total number of parameters	45	39	45	72	64	72	105	95	105
Number of training data pairs	152	152	152	152	152	152	152	152	152
Number of checking data pairs	72	72	72	72	72	72	72	72	72
Number of fuzzy rules	9	9	9	16	16	16	25	25	25

IV. EXPERIMENTAL RESULT

The main aim of this paper is to determine the best possible configuration of system in terms of number and type of membership function in order to optimize the performance of the system. Thereby, the configuration will result in improving the prediction power of RGAgent in proposed MAS for decision recommendation process. To analyze the prediction performance of RGAgent as decision recommender, first fuzzy simulation was done and then optimization using neuro-fuzzy simulation was performed on normalized data samples for the test case.

IV.I FIS Evaluation

The performance of fuzzy RGAgent was evaluated by measuring RMSE and the results are shown in Table 5 and 6. The future pattern of consumers predicted will give an insight to future advance promotional planning to capture the predicted behavior of consumers. Lower RMSE will signify the better prediction capability of RGAgent by gathering changing requirements in a domain so to optimize the performance of RGAgent ANFIS simulation was performed.

Table 5. Predicted probability of Pc and Sc interms of percentage at each simulation run (R)

R	%Pc	% increase or decrease	%Sc	% increase or decrease
	H	H	H	H
1	71.5	-	14.6	-
2	78.1	+6.6	10.6	-4.0
3	80.1	+2.0	9.3	-1.3
4	94.7	+14.6	12.6	+3.3
5	100.0	+5.3	9.3	-3.3

Table 6. Performance measure RMSE of data sample

Data Set	**RMSE**
Training Sample	
Pc Vs R	3.468
Sc Vs R	2.356
Test Sample	
Pc Vs R	3.62
Sc Vs R	4.986

IV.II ANFIS Evaluation

Scenario 1 analyzes the effect of changing number of membership functions on the decision making capability of FRGA1 and FRGA2 by computing RMSE. As mentioned above, the model was configured on 3, 4 and 5 member functions respectively on a member function type whereas, scenario 2 analyzes the effect of using different member function types on predictive performance of FRGA1 and FRGA2. For this, the model was configured with triangular (trimf), gaussian (gaussmf) and generalized bell-shaped (gbellmf) member functions respectively for each input on a set of 3, 4and 5 member functions.

Since FRGA1 tries to predict the probable potential consumers from the input data set and FRGA2 probable sound consumers, the overall predictive power of RGAgent depends on combined prediction performance of FRGA1 and FRGA2. RMSE has been used as a measure for model evaluation, which gives the measure of deviation of actual value from the predicted value. Smaller the RMSE for a model configuration, the more refined predictive power for decision recommendation, thereby suggests an optimal model configuration to achieve better performance. The overall computational result as RMSE values for each configuration under scenarios 1 and 2 after experimentation are stored in Table 7 and 8.

ANFIS1: Model ANFIS1 evaluates the performance of agent FRGA1 in terms of RMSE by varying design constraints and the values are stored in Table 7. ANFIS1 uses two input parameters Vf and Texp each one with three membership functions quantized as LOW, MED and HIGH. The design configuration was then tested with trimf, gaussmf and gbellmf type respectively on each input with 3 membership functions. From Table 7, it is shown that while validation trimf produces the lowest value of RMSE (0.0013) on 3 membership functions. Similarly, for 4 membership functions on all inputs quantized as LOW, MED, HIGH and VERY HIGH, trimf gives the lowest RMSE value (0.054). Also, for 5 membership functions on all inputs quantized as VERY LOW, LOW, MED, HIGH and VERY HIGH, trimf generates the lowest RMSE (0.011) when compared with RMSE of gaussmf and gbell mf. Thus, Table 7 shows that among all the specified configurations for model ANFIS1, the lowest RMSE (0.0013) is generated with triangular membership function (trimf) type on 3 membership functions for all inputs. Thus, this configuration performs more efficiently than others in terms of generating minimum RMSE and selected as best configuration for agent FRGA1 to enhance the prediction capability. Each of the computed result has been pictorially presented in Fig. 7 that can be easily analyzed where 7(a) presents the changes in RMSE value obtained at each epoch for $\mu=3$, 7(b) RMSE at each epoch for $\mu=4$ and 7(c) RMSE at each epoch for $\mu=5$ on trimf, gaussmf and gbellmf.

ANFIS2: In a similar manner as specified for ANFIS1, ANFIS2 evaluates the performance of agent FRGA2 by computing RMSE on various design constraints and the results are presented in Table 8. The system takes two parameters as input Pc and In and the model is first evaluated for 3 member functions quantized as LOW, MED and HIGH for both the inputs on trimf, gaussmf and gbellmf respectively. From Table

8, it is clear that for this input configuration gbellmf shows the best performance result by generating minimum value of RMSE (0.448) as compared for trimf and gaussmf types. The system is further evaluated by increasing the number of membership functions to 4 quantized as LOW, MED, HIGH and VERY HIGH and 5 as LOW, MED, HIGH and VERY HIGH on all inputs with on trimf, gaussmf and gbellmf types respectively. For 4 membership functions, trimf generates the lowest RMSE (0.0386). For 5 membership functions, after sufficient training all the three trimf, gaussmf and gbellmf performs equally well but gaussmf and gbell remain consistent throughout the system training producing lowest RMSE (0.0382) value. This value is also the minimum RMSE among all testing configurations, thus system configuration with 5 membership functions with either gaussmf or gbellmf is the best configuration for agent FRGA2. Also, the computed result for ANFIS2 has been pictorially presented in Fig. 8 where 8(a) presents the RMSE value obtained at each epoch for μ=3, 8(b) RMSE at each epoch for μ=4 and 8(c) RMSE at each epoch for μ=5 on trimf, gaussmf and gbellmf.

Finally, the result of ANFIS simulation from Table 7 shows that using trimf with 3 membership functions on Vf and Texp is the best fit model for agent FRGA1. Table 8 clearly shows that, using gaussmf or gbellmf with 5 membership functions on Pc and In, generates best fit model for FRGA2. Using these design configurations decision making capability of RGAgent can be more effective in predicting potential and sound consumers thereby strengthening consumer-commodity relationship in retail scenario.

Also, the experimentation clearly shows that changing number and type of membership functions definitely impacts the performance efficiency of the system and ANFIS helps to evaluate the performance of each design configuration recommending the best fit one.

Table 7. RMSE obtained as a result of fuzzy simulation of test case for agent FRGA1 using model ANFIS1for 9 input configurations

FRGA1	**Output determinant – Pc**											
ANFIS1	**μ = 3**			**μ = 4**				**μ = 5**				
MF Type \ Epoch	**1**	**2**	**3**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**5**
Trimf	0.013	1.493	0.536	0.54	0.944	1.772	0.942	0.11	1.885	1.702	1.715	1.628
Gaussmf	1.408	1.417	1.455	1.236	1.315	1.398	1.459	2.677	2.233	1.591	1.265	1.214
Gbellmf	1.38	1.342	1.346	1.324	1.324	1.425	1.56	2.991	2.679	2.256	1.905	1.664

Table 8. RMSE obtained as a result of fuzzy simulation of test case for agent FRGA2 using model ANFIS2 for 9 input configurations

FRGA 2	**Output determinant – Sc**											
ANFIS	**μ = 3**			**μ = 4**				**μ = 5**				
MF Type \ Epoch	**1**	**2**	**3**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**5**
Trimf	0.509	0.505	0.499	0.435	0.386	0.409	0.387	0.411	0.386	0.382	0.382	0.382
gaussmf	0.473	0.47	0.467	0.453	0.448	0.443	0.437	0.382	0.382	0.382	0.382	0.382
Gbellmf	4.54	4.51	4.48	0.466	0.461	0.456	0.45	0.382	0.382	0.382	0.382	0.382

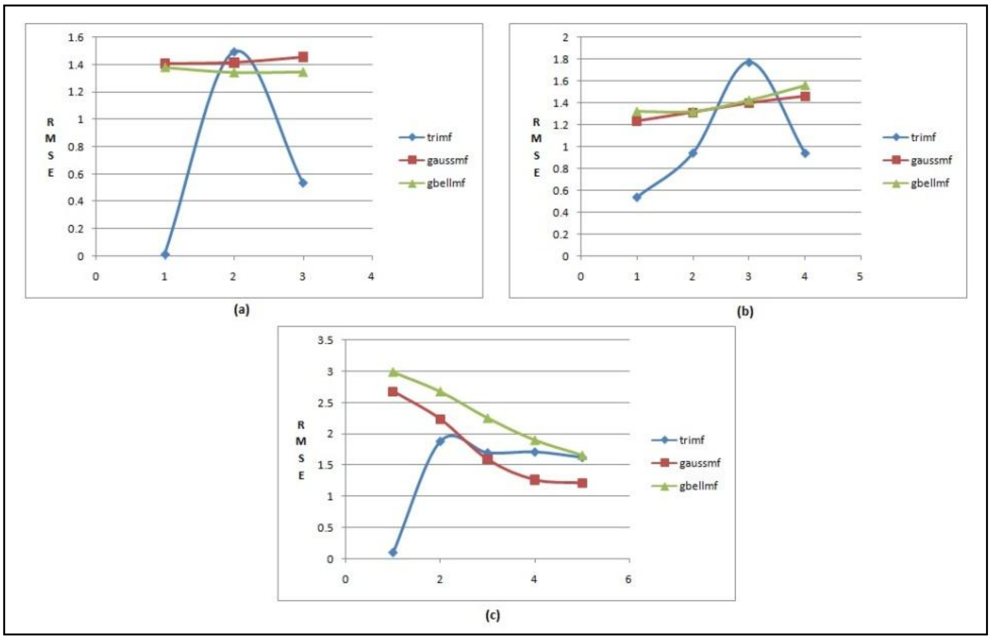

Fig. 7. Changes in RMSE on different epochs for each input configuration (ANFIS1)

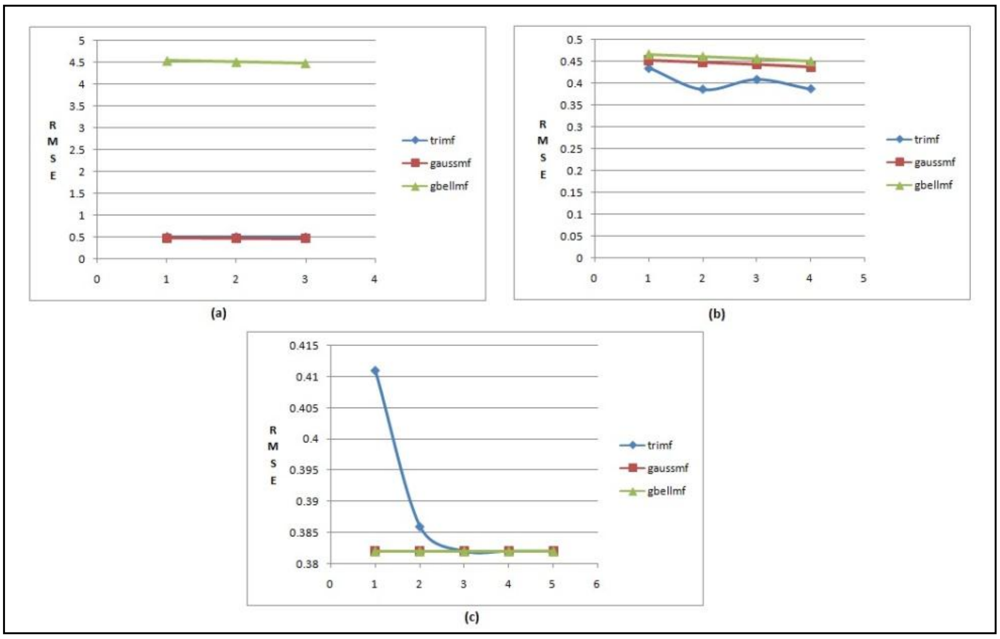

Fig. 8. Changes in RMSE on different epochs for each input configuration (ANFIS2)

On comparing the RMSE recorded for evaluating performance of RGAgent in Table 6 with RMSE values in Table 7 and 8, it is clearly visible that RMSE value has been significantly decreased as a result of ANFIS optimization and finally the comparison with best optimized input configuration is shown in Table 9.

Table 9. Lowest RMSE obtained as a result of fuzzy simulation using FIS and ANFIS for test case

Data Set	RMSE (FIS)	Lowest RMSE (ANFIS)	ANFIS Configuration
Pc Vs R	3.468	0.0013	μ = 3, trimf
Sc Vs R	2.356	0.0382	μ = 5, gaussmf or gbellmf

V. CONCLUSION

Contribution of ANFIS as an adaptive method using various learning techniques has made it a suitable approach to be applicable in various domains for optimizing the system performance. This paper aimed at performing ANFIS optimization of requirement gathering agent RGAgent for the test case 'Consumer relationship management' in retail market. Since ANFIS has combined features of both neural networks and fuzzy system, it has the capability to process numerical along with linguistic data, thereby used as a suitable technique for parameter tuning. Another advantage of using ANFIS for parameter training is that variety of membership function types can be used with ease in ANFIS to evaluate system performance in different simulation contexts. In this study, we have evaluated the prediction performance of RGAgent with 9 different input configurations using Triangular, Gaussian and Generalized bell shaped member functions on 3, 4 and 5 member functions. The experimental result demonstrates that triangular shaped is most preferable membership function with 3 member functions on each input for fuzzy agent FRGA1 and Gaussian or Generalized bell shaped membership function with 5 member functions on each input for fuzzy agent FRGA2 thereby enhancing prediction probability of RGAgent to identify potential and sound consumers. Experimentation also indicates that the effective design of input configuration in terms of type and number of member functions will definitely expedite the advance promotional planning process and its implementation in retail system for strengthening relationship with consumers. ANFIS thus emerged as a promising approach for parameter tuning. Future work in this regard will focus on applying and evaluating other metaheuristic learning techniques in ANFIS in order to explore different ways to further enhance the predictive capability of RGAgent in fuzzy agent based model by identifying the best input configuration.

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