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Modeling & Simulation of a Predictive Customer Churn Model for Telecommunication Industry

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ABSTRACT

In this paper, a representation of the Adaptive Neuro Fuzzy Inference System – based prediction model for customer churn in telecommunication industry was emulated. Exhaustive search algorithm was employed for feature selection of the most significant variables influencing churn tendency. This was with a view to identifying the key performance indicators for churn tendency. Fuzzy rules were set up to represent the antecedents with their corresponding consequents. The Fuzzy Inference System (FIS) was then trained to fine-tune the parameters. The trained FIS was then simulated, validated and verified for churn tendency prediction using MATLAB programming language tools. The proposed model will help the telecommunications industry have advanced knowledge of their customer behavior better by identifying subscribers that are likely to churn at some later date in advance. This will help keep the bottom line of Telecommunications Company in a competitive environment.

Keywords: *Churn, adaptive neuro-fuzzy inference system, fuzzy inference system, call detailed record*

1. INTRODUCTION

The evolution of video and Internet technologies and the rate at which mobile phone networks are growing have raised the enormous pressure on the telecommunications industry because they have huge amount of data being generated and stored, therefore requiring intelligent tools to acquire effective analysis. Data mining techniques are powerful mechanisms that have different features and abilities suitable for analyzing great amounts of data due to the fact that they allow the selection, exploring and modeling of large volume of dataset to uncover previously unknown data patterns for business advantage.

Data mining combines statistical analysis, machine learning and database technology to extract hidden patterns and relationships from large databases [15]. It is defined as a process of non - trivial extraction of implicit, previously unknown and potentially useful information from the data stored in the database [4].Data mining (DM) has been applied in so many industries. For businesses, it is used to unveil patterns and relationship in the data in order to help make better business decisions. It can help reveal trends of sales, develop smarter marketing campaigns, and accurately predict customer loyalty. Some of the specific uses of data mining are market segmentation, customer churn, fraud detection, market basket analysis and trend analysis.

There are many DM techniques that can be used in classification and clustering data to make predictions in the near future. These techniques may use Decision Tree (DT), Support Vector Machine (SVM) in addition to Neural Networks (NN), Genetic Algorithms (GA) or Fuzzy Logic (FL) to make predictions.

Earth wide users of telecommunications are increasing at an impressive rate. Mobile telecommunications providers are working hard to add more and more customers to their system as this helps them to keep the price of service low. With all this effort being put in place by the telecommunications industry, more competitors entering the industry, new and innovative business models and better services are pushing up the cost of this customer acquisition.

Customers, on the other hand, are always left with a decision of choosing a telecommunications provider. They become more demanding and tend to migrate from a previous service provider to a better one.

In this kind of situation, mobile providers have deemed it fit to place more attention on the retention of existing subscribers. Therefore, providers are left with no other option but to put more effort on the prediction and prevention of churn.

Customer churn in mobile telecommunications, as defined [16], refers to the movement of subscribers from one service provider to another. It is a word derived from “change” and “turn”. It means the discontinuation of a contract. In the telecommunications industry, the broad definition of churn is the action that a customer’s telecommunications service is cancelled. This includes both service provider initiated churn and customer initiated churn. Churn is also called attrition and often used to indicate a customer leaving the service of one company in favor of another company. Customer churn are classified into three categories [5], as depicted in Figure 1. These are voluntary and involuntary churners.

Involuntary churners are the easiest to identify. These are the customers that a telecommunications industry decides to remove from their subscribers' list.

Therefore, this set includes people that are churned for fraud or non-payment of their bills as well as customers who don't use their phones. Voluntary churner is not easy to determine. It happens when a customer makes a decision to put an end to his/her service with the provider.

When a telecommunications churn comes to mind, it is usually the voluntary kind that strikes the mind.

Voluntary churn can be sub-divided into two main categories. These are incidental churn and deliberate churn. Incidental churn occurs, not because the customers planned on it but because something happened in their lives. For example, change in financial condition churn, change in location churn, etc. Deliberate churn happens for reasons of newer technology, price changes, quality of service, social or psychological factors, and convenience reasons. Deliberate churn is the problem that most churn management solutions try to solve [10].

The customer churn management is of importance in the daily operation of a telecommunications company. The reason behind this is that they maintain very huge amount of information about their customers.

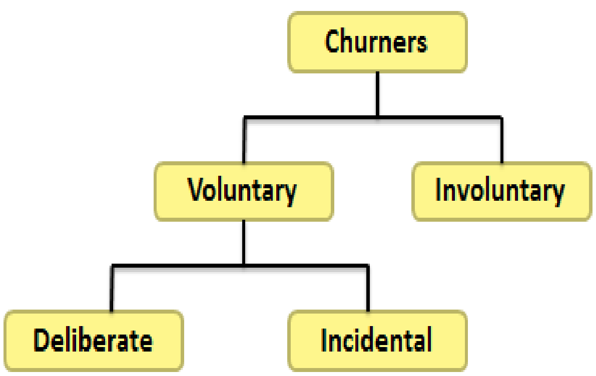

Figure 1: Churn taxonomy [12]

As such companies need to recognize and monitor customer behavior to predict their behavior and desires earlier than competitors and generate customer's profiles for marketing purposes. The main objective of the telecommunications industry is trying to improve customer relationship, combat high cost of churn and to keep the bottom line of the company in a competitive environment. This objective can only be met only if the telecommunications industry has advanced knowledge of their customer behavior i.e. the patterns of behavior of customers.

So, it has developed into an industry-wide belief that the best core marketing strategy for the future is to retain existing customers and avoid customer churn [10].

Marketing research literature has noted that churn management is a term that describes an operator's process to retain profitable customers [1]. Similarly, the term churn management in the mobile network services industry is used to describe the practices of securing the most important customers for a company [9]. In essence, effective customer management presumes an ability to predict the customer decision to migrate from one service provider to another.

[2] indicated that there are two types of targeted approaches to managing customer churn: reactive and proactive. Targeted proactive promotion programs have potential advantages of having lower incentive costs.

However, these strategies may be very wasteful if churn predictions are inaccurate because companies will be wasting money to offer incentives to customers who will not churn. Therefore, an accurate customer-churn prediction model is critical for ensure the success of customer incentive programs [2].

Various churn prediction model have been proposed by some researchers to forecast, in advance, likely subscribers that might want to migrate at a later date. Accuracy has been the major aspect that past researchers has focused on in evaluating a churn prediction model. The capability of the model to express the behavior of the system in an understandable way is also an important part that must not be left out in evaluating a churn prediction model. Therefore there is the need for the development of a comprehensible and accurate churn prediction model that will be used to answer question of why and when a customer is willing to migrate to other service providers.

This paper attempts to address this problem by introducing the principle of fuzzy logic techniques with emphasis on Adaptive Neuro Fuzzy Inference System (ANFIS). ANFIS integrates both neural network (NN) and fuzzy logic principles. It has potential to capture the benefits of both in a single framework.

The rest of this paper is arranged as follows: Section 2 discusses the related works while section 3 presents the proposed framework for customer churn prediction model. Section 4 described the expected result while section 5concludes the paper.

2. RELATED WORK

Customer attrition or churn is an important problem that needs urgent attention in any subscription based company. Mainly for this reason, churn prediction model is the most common method that is applied in such companies. Long-distance companies, mobile phone service providers, insurance companies, cable companies (Pay-TV) [2], financial service companies, Internet service providers, newspapers, magazines, and some retailers all share subscription model where customers have formal, contractual relationships which must be explicitly ended.

There has been quite a good amount of work regarding the prediction of churn in telecommunications industry. Customer churn problem in subscription based company, most especially, the telecommunication industry have been looked into analytically by reviewing the theory and models of formal churn prediction models.

A prediction model that studied the defectors of saving and investment (SI) customers of a large Belgian financial service provider was designed by [3] in order to gain insight into the timing of the SI churn event. A multi-dimensional probity model and a proportional hazard model are performed to find the most convenient products to cross sell in terms of customer preferences and the likelihood to lower the customer defection process respectively.

[17] Developed a data mining approach for customer churn management in a two phase process. The first phase considered selecting customers with equal characteristics using clustering K – means method and in the second phase, reasons of customer churn were analyzed using churn index and decision tree to extract patterns. A well-known data mining methodology - CRISP – DM - was used in investigating network usage behaviors of the internet service provider (ISP) subscribers in Taiwan [11]. Attribute - Oriented Induction (AOI) method was used for discovering characteristics and discrimination knowledge of ISP customers from the ISP traffic data.

Towards dealing with customer churning problem in ISP companies, an empirically tested model was developed by [3] to examine the antecedents of consumer loyalty toward ISPs. The outcome of the study reveals that service quality and not only pricing was a major concern among users.

The telecommunication service market has become more competitive than ever because of the deregulation, new technologies and new competitions appearing in the telecommunications industry. And in this kind of environment customer churn has turned into a very serious issue. Many subscribers frequently churn from one provider to another in search of better rates/service or for the benefits of signing up with new carrier.

It is estimated that the average churn rate for the mobile telecommunications is 2.2% per month, i.e. about 27% of given carrier's subscriber are lost each year [17]; making it essential to develop an effective churn reduction method. The cost of acquisition of new mobile service subscriber is estimated to be from $300 to $ 600.

However, the cost of retaining an existing subscriber is generally much lower than that [16].

To achieve a predictive model in telecommunication industry, a customer churn prediction technique that predicts churning from subscribers' contractual information and call patterns changes extracted from call details was designed for mobile telecommunications company in Taiwan by [16]. The designed technique by [16] incorporates the multi-classifier class combiner approach to address the challenge of highly skewed class distribution between churners and non-churners. The outcome of the study suggested that the designed call-behavior based churn prediction technique exhibits satisfactory predictive effectiveness when more recent call details are employed for the churn prediction model construction.

In another attempt to identify the determinants of subscriber churn and customer loyalty in Korean mobile telephony market; [10] used binomial logit model based on the survey of 973 mobile users. The outcome of this study shows that the probability that a subscriber will switch carrier is dependent on the level of satisfaction with alternative-specific service attributes including call quality, tariff level, handsets, brand image, as well as income, and subscription duration. However, factors such as call quality, handset type, and brand image were identified to affect customer loyalty as measured by the intention/non-intention to recommend the service provider to other people.

[13] Proposed a neural network based approach to predict customer churn in subscription of cellular wireless services. The model was implemented on the widely used applied quick method available within the Neural Net node of Clementine 12.0. The model was experimented with multiple hidden layers in the neural network, containing three to seven neurons, but the best results were obtained having one hidden layer with three neurons. The outcome of the study by [13] indicates that neural network based approach can predict customer churn with accuracy more than 92%, indicating the proportion of the test set correctly predicted. Further, it was observed that medium sized NNs perform best for the customer churn prediction when different neural network's topologies were experimented.

[12] Proposed a new prediction model based on data mining (DM) techniques. The proposed model is composed of six steps which are; problem domain identification, data selection, investigate data set, classification, clustering and knowledge usage. A data set with twenty three attributes and five thousand instances were used to train and test the model. Using three different techniques which are DT, SVM, and NN for classification and simple K Means techniques for clustering results indicated that the best output for the data set in hand is SVM technique.

In furtherance, a decision support system that can discriminate between churning and not churning customer using data mining technology was proposed by [7]. The authors found MATLAB to be the most suitable for the model, because it supports many algorithms. Back propagation algorithm was used for the model building.

The whole dataset for the model building was divided into three subsets (training sets, the validation tests and the test set). The training set was used to train the network, the validation set was used to monitor the error during the training process and the test set was used to compare the performance of the model.

Similarly, a dual step model which consists of clustering phase and classification phase was developed by [8].The customer base was first divided into four clusters, based on their RFM (Recency, Frequency and monetary) related features, with the aim of extracting a logical definition of churn, and secondly, based on the churn definitions that were extracted in the first step, different algorithms were utilized with the intention of constructing predictive models for churn in the developed clusters. The performance of the employed algorithm (Neural Network, Decision Tree (C5.0), Decision Tree (CART), and Decision Tree (CHAID) were evaluated and compared based on "gain measure". The results indicate that Decision Tree algorithms in all clusters outperform Neural Networks, based on "gain measure" for top 10% and 20% of their customer base. The outcome of the study reveals that the decision tree algorithm does not possess the same performance in all the developed clusters. Thus it was concluded by the researchers that adopting a combination of decision tree algorithms for model building in the developed clusters will bring maximum model performance.

Also, a better and more accurate churner prediction technique that incorporates hybrid learning method was proposed by [18]. The hybrid method is a combination of tree induction system and genetic programming to derive the rules for classification based on the customer behavior. The game theory techniques were used to identify the community effect of churn. The predicted score which is the churn value of a mobile customer were calculated and the proposed model was used for prediction of various user defined groupings based on usage time, location and their underlying social network, thus making it a pragmatic approach which models churn on human level than a mathematical level.

In addition preliminary study of applying data mining to solve real – world customer churn (attrition) problem was reported by [17]. Customer information was used to make predictions about the likelihood of churn.

Data mining methodology (decision tree and logistic regression) was used to develop customer churn prediction models using real data from a major Taiwan mobile service company. The outcome of the study indicates that the target rate was very small, around 0.5% monthly churn rate with predictive model delivering excellent performance on Lift in field test.

[6] investigated an approach of the suitability of customer complaints and repairs data for churn prediction.

The best variables were identified and neural classification trees and regression were compared for their suitability for churn prediction. The outcome of the study by [6] shows that neural network with Bayesian architecture was the best technology for predicting churners, while the regression model was the best at predicting non – churners and it also shows significant accuracy for predicting customer churn using repairs and complaints data, proving that repairs and complaints influence customer's decisions to stay with their service providers.

In this paper, an attempt is made to develop a comprehensible and accurate customer churn predictive model for managing customer churn in telecommunications industry. A thorough study of the related works indicates that more emphasis has been placed on accuracy of a predictive model and not on interpretability of the model to end users.

3. THE PROPOSED PREDICTIVE CUSTOMER CHURN MODEL

The proposed churn prediction model is presented in Figure 2. The process starts with the preparation of the call detailed record (CDR) followed by the assignment of membership functions to the identified variables. Thereafter, an exhaustive search algorithm is employed for feature selection of the most significant variables influencing churn tendency. This will assist to identify the key performance indicators for churn tendency. After which fuzzy rules are set up to represent the antecedents with their corresponding consequents. The fuzzy inference system (FIS) is then trained to tune the parameter using Adaptive Neuro Fuzzy Inference System (ANFIS). The trained FIS is then simulated for churn tendency prediction. In the ANFIS model development, Sugeno's fuzzy approach was used to obtain the values for the

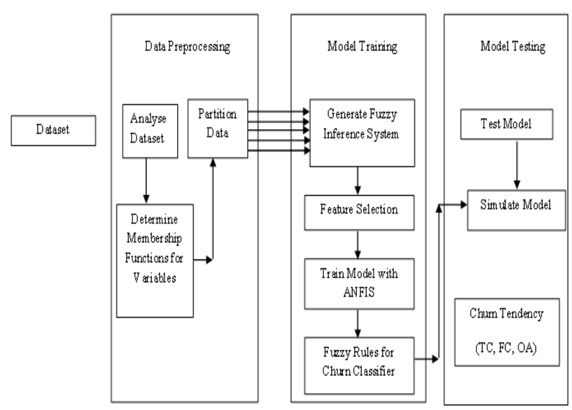

Figure 2: Proposed churn prediction model

output variable from the input variables provided to the fuzzy inference system structure. The Sugeno FIS type was used due its ability to handle non-linear relationships.

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The FIS model was developed using the Call Detail Record (CDR) of some subscribers of the network over a period of time.

3.1 Data collection and preparation

This section describes the nature of variables of the CDR used as inputs to the FIS. Numerical standard data sets were collected from an anonymous operator which contain historical records of customer churn, how they turned out in hindsight, i.e., their previous behaviour – if it turned out that they are churners or not.

This dataset has a total number of 5000 subscribers with 21 variables each. The number of predictors was therefore reduced from 21 to 9. The target variable is Churn, which has two values, one of them for each subscriber: Yes or No, telling if a subscriber is a churner or not. The variables needed and used in the dataset are presented in Table 1. The variables fall under the following categories:

a) **Demographic profiles:** Demographic information is used to describe a demographic grouping of a market segment. The only demographic data considered was Age (AG).
b) **Contractual information:** The payment type (PT), length of service (LS) as well as call information which include Total Minutes of Calls (#M) and Total Number of Calls (#C).
c) **Complaint information:** This includes variables such as Number of Disconnected Calls (DC), Abortive Calls (AC), Number of Calls to Customer Service (CS) and Number of Repaired Service due to Complaints (RC).

In order to properly evaluate the performance of the FIS classifier model, the dataset was randomly partitioned into five (5) equal sets, with each containing 1,000 records. From these, five (5) new datasets were obtained by combining four sets as the training data while the remaining set as the validation data. In other words, the training process is repeated 5 times. Then, the results of the five training process was averaged to obtain the final result. This process is represented in Figure 3.

Table 1: Churn dataset variables

No	Variable Category	Variable	ID	Range
1	Demographic Profile	Age	AG	[15 71]
2	Contractual Information	Payment Type	PT	[0 1]
3		Length of Service	LS	[1 243]
4		Number of Call Minutes	#M	[284.3 885]
5		Total Number of Calls	#C	[191 416]
6	Complaint Information	Customer Service Calls	CS	[0 9]
7		Disconnected Calls	DC	[0 30]
8		Abortive Calls	AC	[0 33]
9		Repaired Calls	RC	[0 6]

3.2 Membership functions

Membership functions (MF) were assigned to each of the variables identified in the dataset as depicted in Table 2. A membership function $u_{Ai}(x)$ is a continuous and piecewise differentiable function that transforms the input value x into a membership degree in the range [0, 1]. It is a graphical representation of the magnitude of participation of each input. For most of the input variables, the generalized bell-shaped MF "*gbellmf*" was chosen while the linear MF "*linear*" was chosen for output membership function factor. The generalized bell-shaped function represents a value (x) as a membership value [0, 1] within a linguistic term (A_i). *gbellmf* is described by the function given in Equation 3.1.

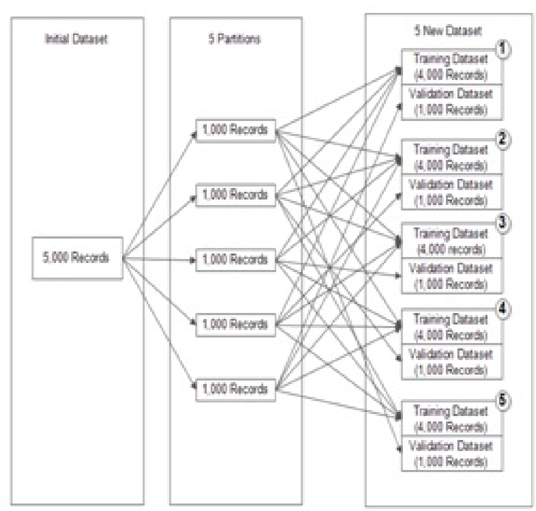

Figure 3: Data partitioning process

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$$\mu_{Ai}(x; a_i, b_i, c_i) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \qquad (1)$$

Where $a_i \neq 0$, a_i controls the width of the curve, b_i controls the slope of the curve, and c_i indicates the center of the curve.

The *trimf* is a function that depends on three scalar parameters '*a*', '*b*', and '*c*', as shown in Equation 2.

$$\mu_{Ai}(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{cases} \qquad (2)$$

Table 2: Parameters of variables' membership functions

Variable	Membership function	MF categories	a_i	b_i	c_i
AG	Gbellmf	Young	14	2	15
		Adult	14	2	43
		Old	14	2	71
PT	Trimf	Direct	0.25	2	0
		Cash	0.25	2	0.5
LS	Gbellmf	Short	60.5	2	1
		Medium	60.5	2	122
		Long	60.5	2	243
#M	Gbellmf	Low	149.5	2	284.3
		Average	149.5	2	583.3
		High	149.5	2	888.2
#C	Gbellmf	Low	56.25	2	191
		Average	56.25	2	303.5
		High	56.25	2	416
CS	Gbellmf	Low	2.25	2	0
		Average	2.25	2	4.5
		High	2.25	2	9
DC	Gbellmf	Low	7.5	2	0
		Average	7.5	2	15
		High	7.5	2	30
AC	Gbellmf	Low	8.25	2	0
		Average	8.25	2	16.5
		High	8.25	2	33
RC	Gbellmf	Low	1.5	2	0
		Average	1.5	2	3
		High	1.5	2	6

The parameters '*a*' and '*c*' locate the "feet" of the triangle and the parameter '*b*' locates the peak.

4. FEATURE SELECTION PROCESS

To demonstrate the churn prediction process, a Graphical User Interface (GUI) was developed to integrate the data handling, feature selection, model training process and model simulation process. The feature selection process starts with an input and proceeds gradually through the addition of more input. This approach is known as sequential search process, which is depicted in Figure 4. In this study the interest was in obtaining the top three (3) most significant inputs. To begin the sequential search process, a number of inputs were selected from the feature selection panel. Once the search process was completed, the result was displayed.

The results for the selection of 1, 2 and 3 inputs are shown in Tables 3 with the most significant input #M, 4 with the most significant input #M CS and 5 with the most significant input #M CS RC, and their corresponding training errors are shown in Figures 5, 6 and 7 The combination with the least training error was then selected.

The outcome of the feature selection using three (3) inputs reveals that the following inputs are the most significant inputs:

a) #M: The total number of minute calls
b) CS: Number of customer service calls
c) RC: Number of repaired calls.

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In order to investigate the appropriateness of these inputs, they were selected as inputs for the FIS model. The model was then trained using the partitioned churn data set earlier imported into the system.

4.1 Training and simulation of FIS

The FIS was created using grid partitioning and trained using Adaptive Neuro Fuzzy Inference System (ANFIS). The ANFIS model structure is shown in Figure 8. The model contains three (3) inputs (#M, CS, RC), 27 fuzzy rules and one output (churn tendency). The model was trained five (5) times using different dataset earlier partitioned. After the training process was completed, the FIS models were simulated. The rule view helps to visualize how changes of the inputs influence the output (churn tendency) as shown in Figure 9. The set of rules obtained, when the model was trained with dataset1, is shown in Table 6. The ANFIS simulator was used to simulate multiple record instances with different dataset.

The simulation threshold value was assumed to be 0 to 0.5 for non – churners and 0.5 to 1.0 for churners. The simulation process was repeated five (5) times and the values of the true churn, false churn, true non-churn and false non-churn were observed.

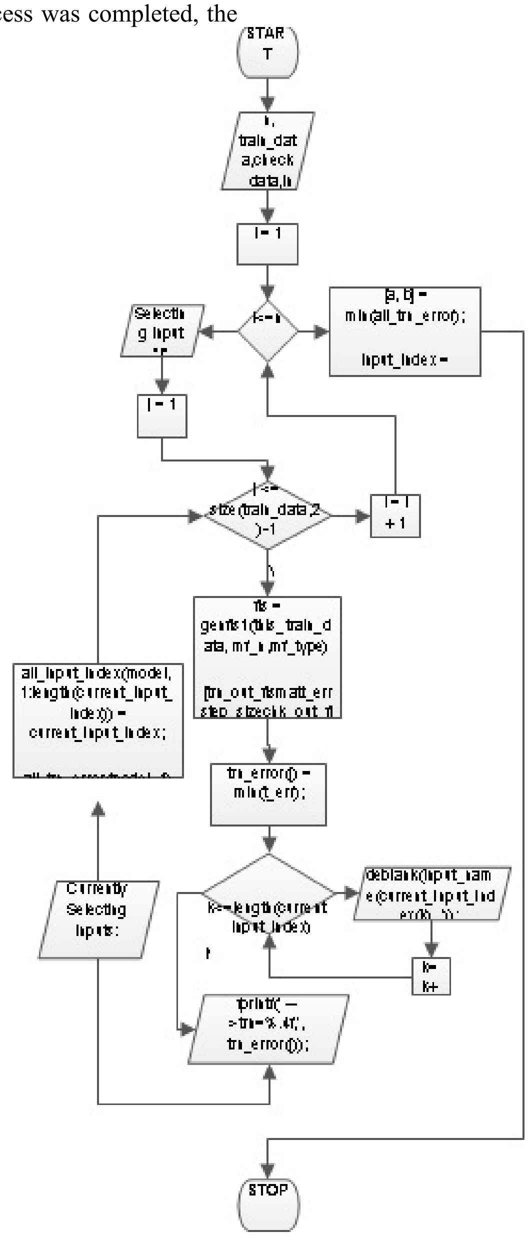

Figure 4: Feature selection process

4.2 Performance evaluation of the model

Various performance assessment methods can be used to check whether or not the proposed prediction model is effective and has an impact on churn management. In this study, the performance metrics employed are Prediction Accuracy, effectiveness in terms of Precision Rate and Recall Rate.

4.2.1 Prediction accuracy

Assessment of the prediction model accuracy is required to trust the data that are collected, develop consensus about the results and consistently predict values with acceptable accuracy. Prediction Accuracy (PA) is computed as the ratio of the number of correctly predicted samples to the total number of samples. In this study, the prediction accuracy is assessed by measuring the following prediction quality indicators:

Table 3: Sequential search for one input

ANFIS model	Input	Training error
1	AG	0.3481
2	PT	0.3483
3	LS	0.3481
4	#M	0.3250
5	#C	0.3483
6	CS	0.3333
7	DC	0.3479
8	AC	0.3479
9	RC	0.3441

Table 4: Sequential search for two inputs

ANFIS model	Input	Training error
1	#M AG	0.3241
2	#M PT	0.3248
3	#M LS	0.3242
4	#M #C	0.3241
5	#M CS	0.2876
6	#M DC	0.3239
7	#M AC	0.3234
8	#M RC	0.3152
1	#M AG	0.3241

Table 5: Sequential search for three inputs

ANFIS model	Input	Training error
1	#M CS AG	0.2941
2	#M CS PT	0.2968
3	#M CS LS	0.2925
4	#M CS #C	0.2932
5	#M CS DC	0.2921
6	#M CS AC	0.2918
7	#M CS RC	0.2914
1	#M CS AG	0.2941
2	#M CS PT	0.2968

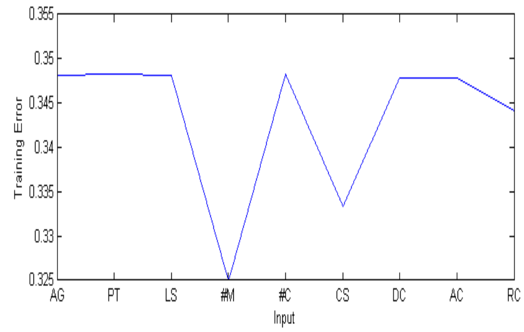

Figure 5: Training error for one input

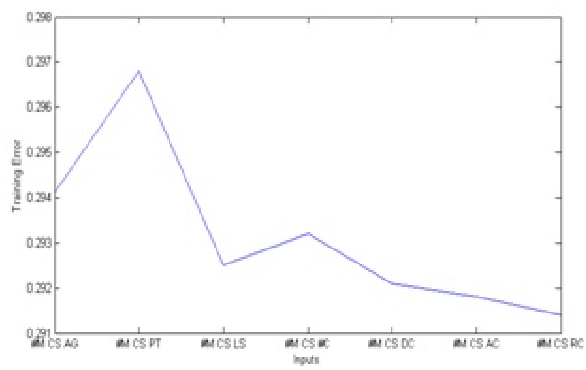

Figure 6: Training error for two inputs

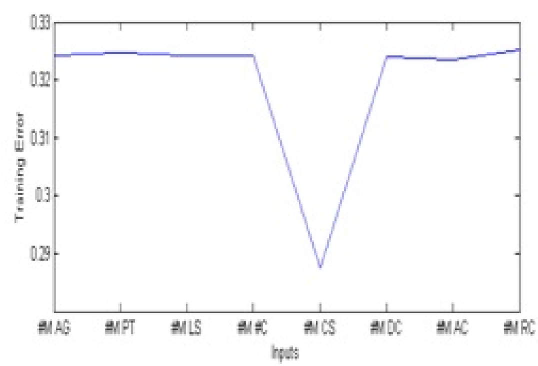

Figure 7: Training error for three inputs

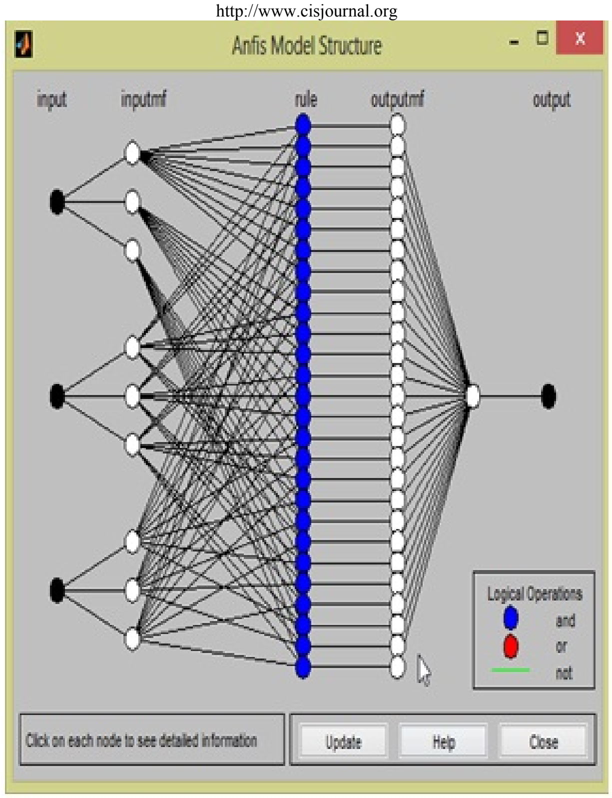

Figure 8: ANFIS model structure for the churn predictor

Table 6: Trained model rules for dataset1

No	Rule
1	if (#M is Low) and (CS is Low) and (RC is Low) then (churn is out1mf1)
2	if (#M is Low) and (CS is Low) and (RC is Average) then (churn is out1mf2)
3	if (#M is Low) and (CS is Low) and (RC is High) then (churn is out1mf3)
4	if (#M is Low) and (CS is Average) and (RC is Low) then (churn is out1mf4)
5	if (#M is Low) and (CS is Average) and (RC is Average) then (churn is out1mf5)
6	if (#M is Low) and (CS is Average) and (RC is High) then (churn is out1mf6)
7	if (#M is Low) and (CS is High) and (RC is Low) then (churn is out1mf7)
8	if (#M is Low) and (CS is High) and (RC is Average) then (churn is out1mf8)
9	if (#M is Low) and (CS is High) and (RC is High) then (churn is out1mf9)
10	if (#M is Average) and (CS is Low) and (RC is Low) then (churn is out1mf10)
11	if (#M is Average) and (CS is Low) and (RC is Average) then (churn is out1mf11)
12	if (#M is Average) and (CS is Low) and (RC is High) then (churn is out1mf12)
13	if (#M is Average) and (CS is Average) and (RC is Low) then (churn is out1mf13)
14	if (#M is Average) and (CS is Average) and (RC is Average) then (churn is out1mf14)
15	if (#M is Average) and (CS is Average) and (RC is High) then (churn is out1mf15)
16	if (#M is Average) and (CS is High) and (RC is Low) then (churn is out1mf16)
17	if (#M is Average) and (CS is High) and (RC is Average) then (churn is out1mf17)
18	if (#M is Average) and (CS is High) and (RC is High) then (churn is out1mf18)
19	if (#M is High) and (CS is Low) and (RC is Low) then (churn is out1mf19)
20	if (#M is High) and (CS is Low) and (RC is Average) then (churn is out1mf20)
21	if (#M is High) and (CS is Low) and (RC is High) then (churn is out1mf21)
22	if (#M is High) and (CS is Average) and (RC is Low) then (churn is out1mf22)
23	if (#M is High) and (CS is Average) and (RC is Average) then (churn is out1mf23)
24	if (#M is High) and (CS is Average) and (RC is High) then (churn is out1mf24)
25	if (#M is High) and (CS is High) and (RC is Low) then (churn is out1mf25)
26	if (#M is High) and (CS is High) and (RC is Average) then (churn is out1mf26)
27	if (#M is High) and (CS is High) and (RC is High) then (churn is out1mf27)

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- TP: This denotes the number of churn instances that are correctly predicted as churn.
- FN: This denotes the number of churn instances that are incorrectly predicted as non- churn.
- FP: This denotes the number of non-churn instances that are incorrectly predicted as churn.
- TN: This denotes the number of non-churn instances that are correctly predicted as non-churn.

The Prediction accuracy is computed as follows:

$$PA = \frac{TP+TN}{TP+TN+FN+FP} * 100 \qquad (3)$$

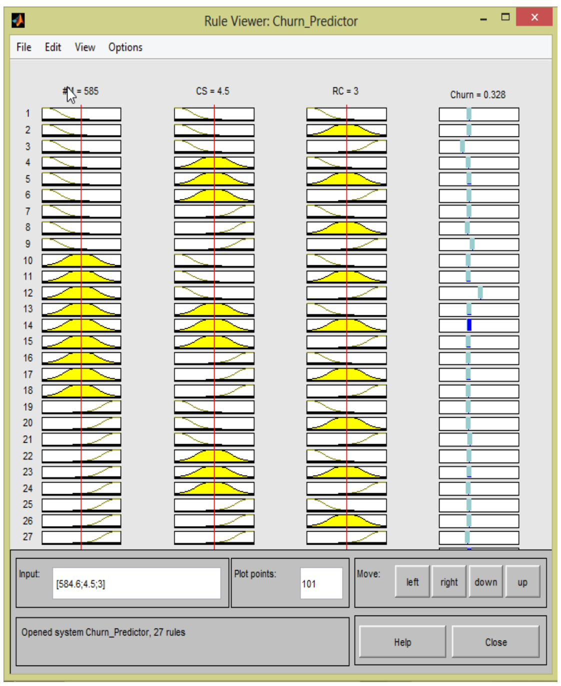

Figure 9: Rule viewer for the FIS

4.2.2 Precision rate

Precision is the proportions of retrieved instances that are relevant i.e. proportion of churn instances that were correct i.e.

$$P = \frac{TP}{TP+FP} * 100 \qquad (4)$$

4.2.3 Recall rate

Recall is the proportion of relevant instances that are retrieved or the ratio of correctly classified instance mong all instances i.e. rates of true churn or true positive rates. The recall rate is computed as follows:

$$R = \frac{TP}{TP+FN} * 100 \qquad (5)$$

4.2.4 Prediction accuracy, precision and recall measures of the model

A simulation was performed to evaluate the prediction accuracy, precision and recall rates of the prediction model quantitatively using the measures presented in Equation (3, 4, and 5). The true positives (TP), false negatives (FN), false positives (FP) and true negatives of the model are presented in Table 7. Table 8 shows the simulation results for the performance evaluation. The fuzzy churn model has achieved overall predicted accuracy Precision and Recall values of 95.8%, 80.86% and 92.7% respectively.

5. CONCLUSION

As customer churn prediction model have become the major tool for telecommunications industry for sustaining and maintaining a stable profit level at top line and bottom line in a competitive environment, it means that this model must be structure in a way that is reliable. Therefore, the ANFIS model structure proposed in this paper would ensure accurate and comprehensible prediction of churners and non - churners and further help to effectively control and manage customer churn in other to retain existing customers. This study will contribute to available knowledge from studies leading to increased prediction accuracy, and interpretability in terms of the model generated in predicting churners in telecommunications industry.

Table 7: True positives, false negatives, false positives and true negatives of the fis model

	Test Set 1	Test Set 2	Test Set 3	Test Set 4	Test Set 5
TP	130	121	154	130	121
FN	11	9	10	13	8
TN	830	840	802	820	846
FP	29	30	37	37	25

Table 8: Simulation results

Prediction Accuracy, Precision and Recall Rates (%)					
Dataset	1	2	3	4	5
Accuracy	96	96.1	95.6	95	96.7
Precision	81.7	80.1	81.9	77.8	82.8
Recall	92.1	93.0	93.9	90.9	93.7

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