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OPTIMISING CUSTOMER SUPPORT IN CONTACT CENTRES USING SOFT COMPUTING APPROACH

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Abstract

This paper describes the research and development of a methodology for optimising the customer support in contact centres (CC) using a soft computing approach. The methodology provides the categorisation of customer and customer service advisor (CSA) within CC.

Within the current contact centre environment there is a problem of high staff turnover and lack of trained staff at the right place for the right kind of customer. Business needs to assign any available advisor to a customer and provide consistent and good quality of service. There is a need to identify the right amount of information to be displayed on the screen considering both the customer and the assigned advisor background. On the basis of data collected through case studies carried out within five customer contact centres, two step clustering analysis was used to derive the categories for customers and advisors based on demographic, experience, business value and behavioural attributes.

We provide the methodology to develop a fuzzy expert system which assigns a new customer or advisor to the pre-defined categories. The authors have explained the steps which were followed for the development of the fuzzy expert system. A prototype system has been designed and developed to identify the type of customer and CSA based on the demographic, experience and behavioural attributes. The authors illustrate analysis with real data, based on the work with large scale customer contact centres. The CSA's can play different roles and have different level of autonomy, but at the end they are humans with heart and voice. While product purchases, lifestyle information and billing data provide important information about customers, it is call detail records that describe a customer's behavior and define their satisfaction with the services offered. Call detail records describe the transactions between customer and the company.

This study describes the research and development of methodology for categorizing customer and customer service advisor within contact centre environment. On the basis of the categories derived for customer and service advisor; the minimum amount of information required by the CSA to serve the customer is analysed and discussed within the paper. The information requirement framework provides the amount of information which is required by the CSA on the basis of {customer, advisor} relationship.

A promising area for future work is that of data mining the records within contact centres. The methodology for proposed fuzzy expert system and its application to CC setting should be of interest to many industry sectors including telecommunications and contact centre environments.

Keywords: Customer behaviour modelling, Categorisation, Customer Service Advisor, Soft Computing, Intelligent Information Modelling, Contact/Call Centre environment

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1. Introduction

The integration of contact centre into daily operations represents one of the most promising trends in the next century economy. In advanced technology and communication systems, it is very important for the industries to develop new customer contact centre (CCC) environment technologies for better customer contact requirements. The impact is such that contact centres are expected to affect all aspects of society from the private sector to public sector in all parts of the world. Whatever the nature and point of contact, customers want a seamless interaction throughout their experience with the company. Customers receive more personalised experience, while the company itself can now provide a consistent message across all customer interactions. Customers want to contact companies at their convenience, using the most convenient means. Good service is now a survival issue, and the competition is on the value that customers receive from their relationship with their suppliers. The companies are aware that it is easier to lose a customer than to gain one; it also knows that it is easier to sell additional services and products to customers who are satisfied with the service provided upon contact; and that a minority of the customer base accounts for the majority of an organisation revenues.

For identifying the type of information required, the research aims to develop a fuzzy expert system which identifies the type of customer and advisor based on the demographic, experience, business value and behavioural attributes. Identifying the type of customer and advisor through the categorisation process within an interaction, it can provide better information to the advisor to deal with the customer. A contact centre must both anticipate and react to customers changing needs and demands to achieve strategic customer care. This has major implications for the kinds of skills, knowledge and competencies of all CCC staff, the systems and the management. Within the current contact centre environment there is a problem of high staff turnover and lack of trained staff at the right place for the right kind of customer. Business needs to assign any available advisor to a customer and provide consistent and good quality of service. There is a need to identify the right amount of information to be displayed on the screen considering both the customer and the assigned advisor background.

The paper is organised as follows: In section 2 the authors have illustrated the use of customer and advisor categorisation within industry and marketing environment. In section 3, we present the related research which is carried out in the design and development of customer and customer advisor categorisation. Section 4 describes the proposed methodology and the design and development of the fuzzy expert system for the categorisation. Section 5 shows the results from the experiments carried out with the model. Section 6 briefly decribes the information requirement framework to provide sufficient information to the advisor. Section 7 of the paper shows the discussions and suggestions for future work with the part of the research. And finally Section 8 highlights the major conclusions drawn from this paper.

2. User Behaviour & Marketing Strategy

Understanding and adapting to changes of customer behaviour is an important aspect of surviving in a continuously changing environment (Chaochang, 2002). Research in understanding customer preferences, known as 'consumer behaviour study', has been the subject of investigation in psychological marketing area for few decades. It is necessary to understand individual customers from designer side, as well as from the customer's side to provide guidance for customers to find what they want. Customer choice of a product depends on explicit requirements, implicit requirements, available options and latent requirements implied by the product (Zeelenberg and Pieters, 2004). Studies have also shown that complete understanding of service advisor satisfaction requires knowledge of the customers situation before the communication begins (Heckman and Guskey, 1998). The study of customer helps firms and organisations improve their marketing strategies by understanding issues such as:

- The psychology of how customers think, feels, reason, and select between different alternatives.
- The psychology of how the customer is influenced by his or her environment (e.g. culture, family, signs, media etc.
- The behaviour of customers while shopping or marking other marketing decisions.

In contact centres, customer contact employees (i.e. those employees who interact directly with customers over the phone) are called "contact centre advisors (CSA's) (Malhotra and Mukherjee, 2004). They are important for service organisation since they provide a link between the external customer and environment and the internal operations of the organisation (Zeithaml and Bitner, 2000). Although research has suggested that customer service advisor (CSA's) performance is critical to create customer satisfaction, little has been done to analyse which employee behaviours influence customer encounter satisfaction and which behaviours influence relationship satisfaction. The performance of a CSA during interactions with customers has been the subject of considerable research, in both sales and service settings. There are five dimensions of CSA's behaviour that influence customer's perceptions: mutual understanding, authenticity, extra attention, competence, and meeting minimum standards (Dolen, Ruyter and Lemmink, 2004). As suggested by Bushey and others for modeling the users can include statements of how the users within a specific user group behave in certain situations or perform certain functions. A system can be designed to accommodate the behavioural diversity of the user groups that most strongly contribute to meeting business goals (Bushey, Mauney, and Deelman, 1999). Many telecoms service sector are subjected to failures in service delivery and better customer satisfaction values because they much depend on customer service advisor (advisors) to deliver service to their customers. Because of the delivery of the service occurs during the interaction between contact advisors and customers, the attitudes and behaviours of advisors can influence customer's perceptions of the services (Hartline and Ferrell, 1996).

The development and widespread use of the Internet for communication and commerce is creating a skills gap within the modern contact centre. It has been suggested that as web-chat/collaboration becomes more popular among customers there will be a shortage in the number of qualified or trained CSA's (Martin and Azvine, 2003). Further, there is not enough focus and attention given to the training of CSA's in the area of Internet related support (Rose and Wright, 2005). It is not surprising that employee retention within the contact centre is becoming critical to the success of an organization. Employee turnover results in a substantial expense for a company particularly as it relates skilled CSA's. The efficiency and effectiveness of a department may suffer as new staff progress through the learning curve. Depending on the industry sector and the required level of skill and education, this can be a very lengthy process (Calvert, 2001). The loss of an experienced CSA can now be viewed as a major blow to the organization, even more so if they are hired away to a competitor. There is another school of thought that believes that modern contact centre technologies will reduce the necessity to hire technologically advanced CSA's (Mohr and Bitner, 1995). Through the implementation of advanced CTI and case management systems, the skills required by CSA's will evolve from product, service and technological knowledge to skills associated with efficient navigation of a Case Management system. Experts we interviewed suggested that as long as CSA's possess good interpersonal skills and are friendly, then screen pops, etc. – should provide them with automated and pat responses to effectively handle customer inquiries. As part of the CRM process, CSA's are increasingly required to identify and act upon cross-selling and up-selling opportunities (Storey and Cohen, 2002)

3. An Overview of Literature

3.1. Customer Contact Centres

Technology has changed the way organizations manage their relationships with their customers. While some organizations may argue this new reality, the consumer is increasingly in a position of power, as comparison-shopping on a wider-scale becomes the norm. A strong relationship with the customer is of utmost importance to today's organization, and the modern contact centre can facilitate this. The modern contact centre enables the organization to create a two-way dialogue with their customers (Boyd, Blood, and Wright, 2002). Each 'contact' with the customer is an opportunity for that organization to develop a better understanding of its customer base. Customer issues, positive or negative, are now documented and tracked on an individual basis, for future action (Swinyard, 2003). Historically, change within organizations has meant a focus on cost reduction (Koole, Mandelbaum, Gans, Ramdas and Fisher, 2003). However, given the shift in the balance of power from organizations to the customer, cost reduction with stable customer satisfaction has become the priority for organizations (Hawkins, Meier, Nainis, and James, 2001). Nonetheless, it is necessary to carefully determine which channels are effective at meeting the needs of the customers. As an example, while the Internet may be an effective self-service technology, certain customer groups, such as the elderly, may be limited in their ability to effectively manoeuvre through such channels (HeeSeok, JaeKyeong and SoungHie, 2001). Understanding your customers' capabilities and needs is a necessity when transitioning to a multi-channel environment. A firms ability to understand its own customers is, however hidden in the data it accumulates about their activities, and their likes and dislikes – not external inputs (Meltzer, 2001). Figure (1) shows the changing shift of call centre to contact centre.

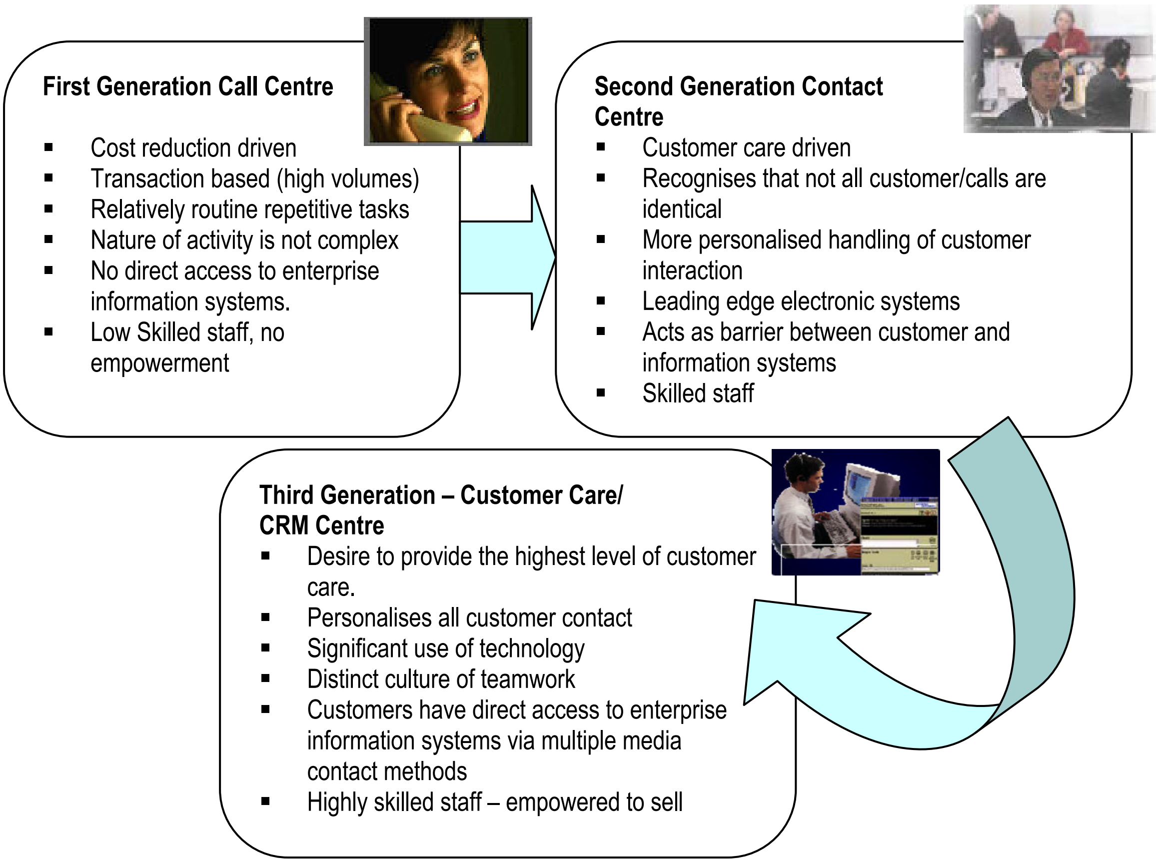

Figure 1 – Changing shift of call centre to contact centre

Not surprisingly, the increased use of channels through which customers can interact with organizations has resulted in increased expectations across all channels. No longer are customers satisfied with merely having access to multiple channels. Customers are expecting the same level and quality of service across all channels (Hsipeng and Lin, 2002). Because customers are able to access online retailers through the Internet 24 hours a day and 7 days a week (as opposed to the hours of shopping constrained by traditional retailers), customers have come to expect comparable support during this experience. The failure to offer such support could be the impetus that motivates a customer to click to a competitor's site which offers a more customer oriented shopping and service experience. Shopping on the Internet also changes the channels through which customers expect to receive support. As an example, some contact centres now allow CSA's to shadow a customer while they are browsing a website. CSA's are able to make recommendations and to push value-added information to the customers instantaneously (Langerak, 2001). The role of the CSA is also evolving with the changes taking place around them. Whereas historically, interactions with the CSA have been transaction based, modern day CSA's are dealing with far more complex and varying customer issues. As had been stated earlier, the simpler interactions are increasingly being moved to self-service technologies, such as company websites and Interactive Voice Response (IVR). As such, this technological change is not simply transforming the methods by which the organization operates, but is impacting the level of skill and education required by both CSA's and management within the contact centre environment. The role of the CSA has now been expanded to provide value across the entire engaging in customer retention programs. CSA's will need to develop skills that are far more complex than the simple general information questions which have historically been handled within this department (Goff, Boles, Bellenger and Stojack, 1997).

3.2. Soft Computing in Telecommunications

Soft computing differs from hard (conventional) computing in that it is tolerant of imprecision, uncertainty and partial truth (Zadeh, 1996). Soft computing technologies provide an approximate solution to all ill-defined problems and can create user models in an environment, such as behaviour modeling, in which users are not willing to give feedback on their actions and/or designers are not able to fully define all possible interactions. (Frias-Martinez, Magoulas, Chen and MacRedie, 2005). Fuzzy logic has proved useful for developing many practical applications, especially in the field of engineering, as it can handle inexact and vague information. For all the available research been carried out in fuzzy logic and the development of fuzzy expert system for customer modelling, little has been done to categorise the advisor (CSA) within the contact centre domain. Since the expert knowledge captured in If…Then statements is often not naturally true or false, fuzzy sets afford representation of the knowledge in a smaller number of rules, and smooth mapping can be obtained between input and output data (Ngai and Wat, 2003).

Soft computing technologies provide an approximate solution to an ill-defined problem and can create user models in an environment, such as contact centre environment, in which customer willingness to buy or companies prediction towards customer purchase intentions, advisors reaction towards the customers attitude and behaviour, and in turn the customer's behaviour towards the communication with the service advisor within the environment (Stylios and Groumpos, 1999). The elements that a user model captures (goals, plans, preferences, common characteristics of users) can exploit the ability of soft computing of mixing different behaviour and capturing human decision processes in order to implement a system that is more flexible and sensible in relation to user interests. Fuzzy logic provides a mechanism to mimic human decision making that can be used to infer goals and plans; Neural Networks is a flexible mechanism for the representation of common characteristics of a user (Frias-Martinez et al, 2005). It also can be seen as rule based systems that use fuzzy logic in their knowledge base and derive conclusions from user inputs and fuzzy inference process, while fuzzy rules and the membership functions make up the knowledge base of the system. The goal of fuzzy expert system is to take in subjective, partially true facts that are randomly distributed over a sample space, and build a knowledge based ES that will apply to them certain amount of reasoning and aggregation strategies to produce useful decisions. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani-type inference, as defined it for the Fuzzy Logic Toolbox, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. Sugeno-type systems support this type of model. In general, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant (2005). A fuzzy set allows for the degree of membership of an item in a set to be any real number between 0 and 1, this allows human observations, expressions and expertise to be modelled more closely (Wong, 2001); (Zadeh, 1994; Zadeh, 1988).

4. Proposed Methodology

The proposed research methodology of this work was to categorise customer and advisors within contact centre environment with the use of soft computing techniques. A model was developed to assign any customer or advisor within contact centre environment to a pre-determined category through clustering analysis.

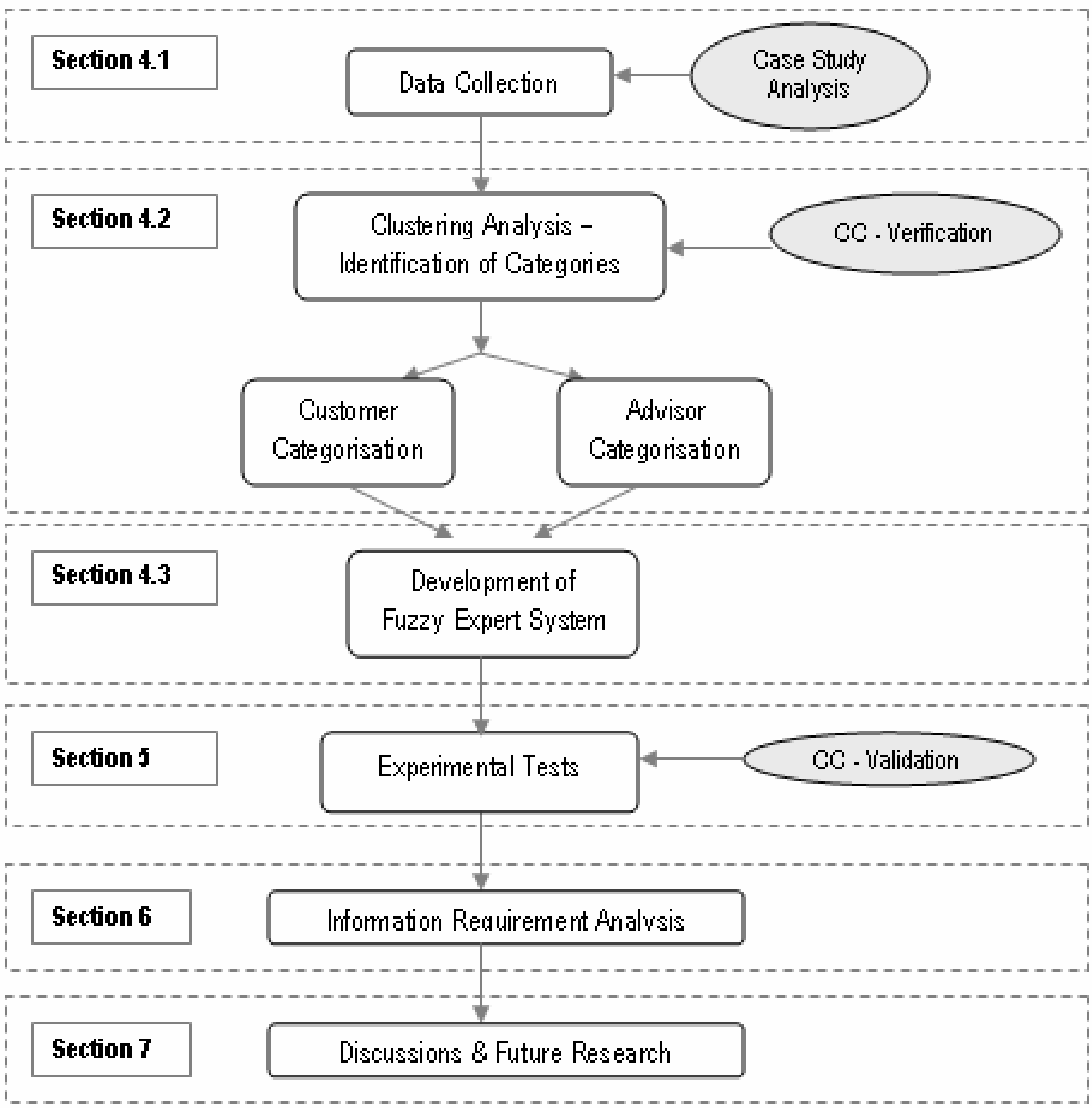

Figure 1: Flowchart for proposed methodology of development of the fuzzy expert system

4.1 Data Collection

Data was collected with the help of semi-structured questionnaires for advisors (CSA) and team leaders/managers with respect to their demographic variables, experience and behavioural variables within five customer contact centre focussing on fault and sales and looking on single to multi profile business customers. A total of 84 advisors were interviewed and assessed, 60 customer calls were monitored, and total of 19 team leaders and managers were interviewed through the questionnaires. The authors first had a thorough conversation with the team leaders understanding the current environment, the work done within the centre, the strength of advisors within the centre, and portfolio of advisors which were working at the centre. Based on the information which was provided from the team leader, the authors then identified the types of advisors which were going to be used for monitoring and observation on the basis of few important attributes such as; Age Group & Gender, Experience within the company, Education background, and Attitudes (positive and negative).Once the identification was completed, the authors then asked the team leaders, to arrange a sitting with the advisors and monitoring the call conversation of the customer. The key observations which the authors noticed for the data collection were advisors characteristics and customer observations (voice).

4.1.1 Advisor Questionnaire Format

The data was collected through observation by the authors and was verified by the advisors at the contact centres. The variables which were used for the questionnaire were from the author's knowledge and understanding developed through literature (Mohr and Bitner, 1995; Lian, Wolniewicz and Dodier, 2004) (Berson, Smith, and Thearling, 2000) and many more, and also verified with expert judgement of the team leaders at the contact centre. The set of criteria used for advisor data collection were demographic variables, service experience, IT experience, characteristics behaviour, speed of service, positive and negative emotions, understanding and competence of the advisor towards the customer. The author carried out the check list of the following criteria and attributes of the advisor during the monitoring process and was later verified with the advisors and the team leaders respectively. The criteria used for the monitoring process are as shown in table (1).

Situation / Condition	Criteria	Attributes
▪ CSA's Demographic Values	Age & Sex	Age 18 – 30, 30 – 50, Above 50 Sex Male, Female
▪ CSA's Knowledge of service	Knowledge Level	Knowledge - School, College, Graduate
▪ Level of experience	Service Experience	Service Experience - Novist (<1 yr), Experienced (> 1yr)
▪ Computer experience	IT experience	IT experience – Little, moderate, extensive
▪ Characteristics Behaviour with customer	Char.Behaviour	Char. Behaviour – Competence, Attitude, Comm.
▪ Speed with the service	Speed	Speed with Service – Slow, Medium, Fast
▪ Relationship with the customer	Relationship	Relationship – Helpful, Very helpful
▪ CSA's positive and negative emotions while dealing with customers	Positive & Negative	Positive – Attentive, Concentrated, Joyful, Happy Negative – Sad, Discouraged, Angry, Mad
▪ Mutual understanding of the situation	Understanding	Understanding – Open, Close
▪ CSA's Competence	Competence	Competence – Capable, Efficient, Organized,
▪ Performance	Performance	Performance – Understanding, Attention, Meeting standards

Table 1: Criteria used for Advisor Categorisation

4.1.2 Customer Questionnaire Format

For customer data collection, the collection was done on the basis of the information provided on the screen of the advisor when the call conversation was in progress, and also the author's monitoring to the calls to identify the behavioural aspect of the customer, before the call and once the call was finished.

Situation / Condition	Criteria	Categories
• Customer Demographic Values	Age & Sex	Age 18 – 30, 30 – 50, Above 50 Sex Male, Female
• Different types of customers	Customer Types	Customer Types – Prospectus, Responders, Active, Former
• Customer's education	Education Level	Education - School, College, Graduate, Professional
• Financial Level of the customer	Income Group	Income – Poor, Average, Good
• How long the customer been with the company	Relationship	Relationship – Old – > 2 yrs, < 2 yrs , New
• How often customer buys from company	Lifecycle	Buying Patterns – Frequently, Rarely
• What is the customers purchasing power	Purchasing Power	Purchasing Power – Low, High
• Customers payment difficulty	Payment Problems	Payment – Regular, Irregular
• Customers method & frequency of complaints of service	Complaint Frequency	Comp. Freq. – Rarely, Regular, Often
• Customer Emotions	Positive & Negative	Positive – Attentive, Concentrated, Joyful, Happy Negative – Sad, Discouraged, Angry, Mad

Table 2: Criteria used for Customer Categorisation

The set of criteria used for customer data collection and analysis were demographic variables, education level, the income and financial details, time with company, purchasing power of the customer, payment related problems, complaint frequency and positive and negative attributes of the customer towards the advisor and the company. Similar to the advisor collection of the data, the authors had the check list of the criteria and attributes, and were used during the call monitoring process. Once the collection was made, it was later verified with the advisors and the team leaders on their knowledge towards the customer attitude within the CC environment. The criteria and attributes used for customer during the monitoring process are as shown in table 2

(Shah, Roy, and Tiwari, 2005). Based on the data collection and analysis of data; attributes derived for customer and advisor are as follows:

- Customer – age, education, financial status, time with company, business value and behavioural analysis.
- Advisor – age, education, experience, previous experience, IT speed, and behavioural analysis.

Once the data was collected and analysed it was verified with the team leaders and managers within the contact centres. Based on the verification the data was structured and analysed using statistical data analysis tool. Through the data analysis tool, the customers and advisor were then grouped according to the attributes shared among each other. The next stage for the development was to identify the categories for customers and advisors through the process of clustering analysis.

4.2 Clustering Analysis – Categorisation of Customer and Advisor

This section shows the method followed for identification of customer and advisor categorisation through clustering analysis by using two – step process within SPSS analysis. The final set of attributes used for customer and advisor (CSA) for the clustering analysis to derive the categories are as shown in table (3).

Advisors (CSA)	Customer
1. Age – young, middle age, old	1. Age – young, middle age, old
2. Education – school, college, graduate, professional	2. Education – school, college, graduate, professional
3. Experience – novice, medium, senior	3. Financial Status – poor, average, good
4. IT Speed – slow, medium, fast	4. Time with Company– low, moderate, high
5. Previous Exp – low, moderate, extensive	5. Business Value – low, medium, high
6. Positive Behaviour – attentive, friendly, customer focus	6. Positive Behaviour – joyful, co-operative, understanding
7. Negative Behaviour – unaware, annoyed, angry	7. Negative Behaviour – angry, annoyed,

Table 3: Advisor and Customer Variables within Clustering Analysis

The set of advisor categories derived from the clustering analysis is as shown below in table (4). Six advisor categories (A1-A6) were derived out of the 84 data sets for the advisors.

Categories / Attributes	A1 (Novice Advisor)	A2 (Customer Focus Advisor)	A3 (Annoyed Advisors)	A4 (Experience – Cust. Focus)	A5 (Experienced – Friendly)	A6 (Attentive Advisor)
AGE	18-25	18-25	25-40	40-50	50+	18-25
EDUCATION	SCHOOL	GRADUATE	GRADUATE	PROF.	PROF.	COLLEGE
EXPERIENCE	<1 YRS	<1 YRS	5-10 YRS	10-15 YRS	15+ YRS	1-5 YRS
IT SPEED	LOW	MEDIUM	HIGH	HIGH	MEDIUM	MEDIUM
PREVIOUS EXPERIENCE	NONE	NONE	EXTENSIVE	EXTENSIVE	MODERATE	NONE
POSITIVE BEHAV.	-	CUSTOMER FOCUS	ATTENTIVE	CUSTOMER FOCUS	FRIENDLY	ATTENTIVE
NEGATIVE BEHAV.	ANGRY & UNAWARE	ANNOYED	ANNOYED	-	-	UNAWARE
Total Cases (out of 84)	16	18	20	4	7	19

Table 4: Advisor Categorisation

Based on the data structuring done from the case studies, a data set was designed with 60 samples of customer records and 84 samples (cases) of advisors (CSA's) within the SPSS database. Ten different types of experiments were carried out within the two step cluster analysis method ranging from automatic clustering to a maximum of 10 clusters within SPSS. Based on the clustering few results were noted which were:

1. Because of the number of clusters increased from 6-10, the total number of cases each cluster is taking is not normally distributed.
2. The number of people (customers and advisors) in each cluster is too low for making it a significant cluster.
3. The rules derived from the cluster results are repeated and are too close to each other.

The set of categories derived for customer from the clustering analysis is as shown below in table (5) (Shah et al, 2005).

Categories / Attributes	C1 (Angry Customer)	C2 (Understanding Customer)	C3 (Joyful Customer)	C4 (Good Customer)	C5 (Aggressive Customer)	C6 (Old Customer)
AGE	18-25	25-40	18-25	40-50	25-40	40-50
EDUCATION	SCHOOL	GRADUATE	COLLEGE	PROF.	PROF.	COLLEGE
FINANCIAL STATUS	POOR	GOOD	POOR	AVERAGE	GOOD	AVERAGE
TIME WITH COMPANY	1-5 YRS	5-10 YRS	>1 YRS	10+ YRS	5-10 YRS	5-10 YRS
BUSINESS VALUE	LOW	MEDIUM	MEDIUM	HIGH	HIGH	LOW
POSITIVE BEHAV.	-	UNDERSTANDING	JOYFUL	JOYFUL	UNDERSTANDING	CO-OPERATIVE
NEGATIVE BEHAV.	ANGRY & AGGRESSIVE	ANGRY	ANNOYED	-	AGGRESSIVE	ANNOYED
Total Cases (out of 60)	12	9	13	6	11	9

Table 5: Customer Categorisation

4.3 Development of Fuzzy Expert System

This section discusses the steps followed for the development of the fuzzy expert system for customer and CSA categorisation. Fuzzy expert system was developed by using Matlab Fuzzy Logic Toolbox to assign any customer and advisor to that of pre-defined category which was derived from the clustering analysis. On the basis of the expert system, the authors can determine the type of category the customer and the advisors are given which would enable to identify the categorisation of the customer and the advisor. Once the assignment of the category is done, it would enable the model to identify the type of information which is required to be displayed on the screen of the advisor to enable them to help the customer more efficiently and thus providing better customer satisfaction.

4.3.1 Step 1 – Define membership functions and fuzzy sets

The first step of the process involved the combination of a list of critical factors based on the literature review and in-depth interviews with the advisor, team leaders, centre managers and systems expert within the environment. The critical factors were the input variables of the fuzzy ES which were as age, gender, and education, and financial background, time with the company, business value and behaviour from the customer side which would identify the type of category they belong to. The development of the model was done by authors own understanding of the current contact centre environment and from the literature studies.

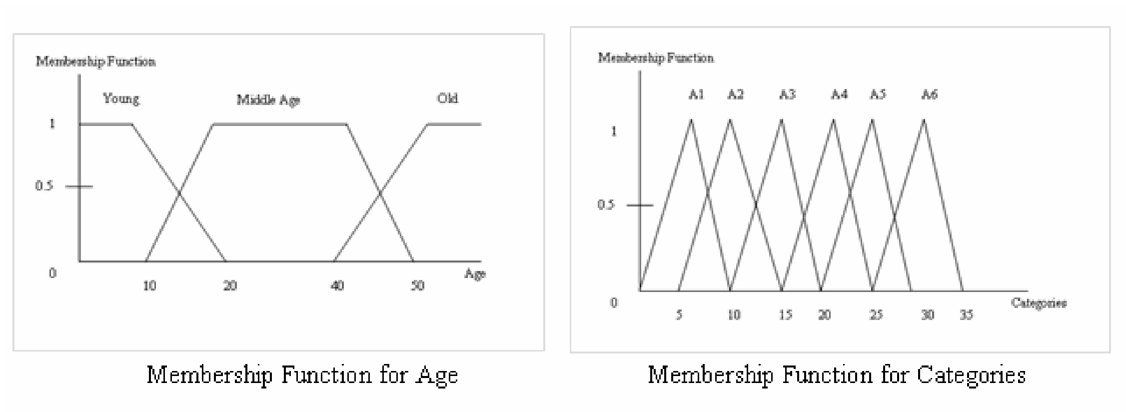

Figure 2: Sample Membership Functions for Input (Age) and Output (Categories)

Once the selection was done and the model was developed, it was validated with expert judgment from the team leaders at the centre through nine team leaders and managers at three of the case study contact centres. Each linguistic term is defined by a membership function which helps to take the crisp input values and transform them into degree of membership [figure 2].

4.3.2 Step 2 – Construct the Fuzzy Rules

Within the fuzzy expert system model once the membership functions of the input and output variables for customers and advisors were derived, fuzzy if…then rule were written which identified the type of input for customers and advisors. The rule base specifies qualitatively how the output of the system "Category" for the advisor and the customer is determined for various instances of the input variables of Age, Education, Financial Status, and Time with Company, Business Value, Experience, and Behavioral attributes. Samples of the derived rules for system are explained as below:

Sample Advisor Rules

The rules for advisors were selected from the understanding of the advisor input attributes and the results from the clustering analysis are explained below. **IF** age is young, education is school, experience is novice, previous exp is low, IT speed is slow, positive behaviour as friendly and negative behaviour as unaware **THEN** the selected category is A1[Table 6].

Age	Education	Experience	Previous Experience	IT Speed	Positive Behaviour	Negative Behaviour	Category
Young	School	Novice	Low	Slow	Friendly	Unaware	A1
Middle	Graduate	Medium	Moderate	Medium	Attentive	Annoyed	A3
Old	Profess.	Senior	Extensive	Medium	Focus	None	A5
Young	College	Novice	Moderate	Fast	Focus	Unaware	A6
Young	Graduate	Novice	Low	Fast	Attentive	Annoyed	A2
Old	Graduate	Senior	Extensive	Fast	Friendly	None	A4
Young	Graduate	Medium	Moderate	Fast	Attentive	None	A2

Table 6: Sample of Advisor Fuzzy If….Then Rules

Sample Customer Rules

If…Then rules for customer were derived similarly to that of the advisors within the fuzzy expert system model. Some of the rules derived for the system are as explained below. **IF** age is young, education is school, financial status is poor, time with company is low, business value is low, positive behaviour is none and negative behaviour is aggressive **THEN** the category selected is C1 [Table 7].

Age	Education	Financial Status	Time with Company	Business Value	Positive Behaviour	Negative Behaviour	Category
Young	School	Poor	Low	Low	None	Aggressive	C1
Middle	Graduate	Good	Moderate	Low	None	Annoyed	C2
Old	Graduate	Average	Moderate	Medium	Understanding	Angry	C6
Young	College	Poor	Low	Medium	Co-operative	None	C3
Middle	Professional	Good	Moderate	High	Joyful	None	C5
Old	Professional	Average	High	High	Joyful	Annoyed	C4
Middle	School	Poor	High	Medium	None	Aggressive	C1

Table 7: Sample of Customer Fuzzy If….Then Rules

5 Validation of the Fuzzy Expert System

With respect to the model, the authors carried out some experiments with the fuzzy expert system model by changing the input variable values and monitoring the change in the output which showed the change in the category for customer and advisors. The results which we analysed are the set of new data points from 16 random sampling for customer and advisors [Table 8 and 9]. The results derived from the experiments carried out within the expert system model were validated within the contact centre environment with the team leaders and managers.

5.1 Advisors Experimental Examples

This section highlights the experimental examples which were carried out within the fuzzy expert system model to assign the customer and advisor to that of the pre-defined category from the clustering analysis. Experiment 5 and 7 shown below are the ones which were different during the validation process.

Ex. 5 - If Age = 51, Education = 27, Experience = 8.6, IT Speed = 2.8, Previous Exp = 5, Positive Behaviour = 5, Negative Behaviour = 1.2. Then Advisor Category output is 25 which determines that the category for advisor is A5

Ex. 7 - If Age = 22.8, Education = 18, Experience = 2, IT Speed = 2.5, Previous Exp = 2.1, Positive Behaviour = 3.2, Negative Behaviour = 1. Then Advisor Category output is 26.1 which determines that the category for advisor is A6

No	Age	Education	Experience	Previous Experience	IT Speed	Positive Behaviour	Negative Behaviour	O/P	Category	CC Validation
1	21.5	12	2	1.8	1.5	5.5	3.8	25	A6	A6
2	30	21	4.2	5	4	1.8	5	10	A3	A3
3	20	5	1	0.5	1.3	1.2	1.8	5	A1	A1
4	28	24.6	0	1.5	3	8	4	5	A2	A2
5	51	27	8.6	5	2.8	5	1.2	25	A5	A4
6	43	16.5	7	5.1	4.2	6	0	20	A4	A4
7	22.8	18	2	2.1	2.5	3.2	1	26.1	A6	A2
8	15	2	1	1	0.8	7	0	2.33	A1	A1

Table 8: Experimental Results for Advisor Expert System Model Summary

The input values for the advisor variables define the type of advisor and output value determines the category for the advisor. For example, the input values in the first experiment is for age=21.5, and from our membership functions it justifies that the input variable for age is young; education=12=college, experience=5=5-10 yrs, previous exp=1.8=low, IT Speed=1.5=slow, positive behaviour=5.5=friendly. As shown above in table (8) the CC validation shows the results from the validation carried out with the team leader's expert judgment at the contact centre. The validation is further explained later in section 5.3 of the paper (Shah, et al. 2006)

5.2 Customer Experimental Examples

The customer experimental results from the expert system, which differ during the validation process, are discussed as below and shown in table (9).

Ex. 6 - If Age = 40, Education = 25, Financial Status = 5, Time with company = 10, Business Value = 8.5, Positive Behaviour = 9, Negative Behaviour = 0.4. Then Customer Category output is 20 and category is C4

Ex.7 – If Age = 50, Education = 10, Financial Status = 4.3, Time with company = 6.5, Business Value = 0, Positive Behaviour = 7, Negative Behaviour = 3. Then Customer Category output is 30 and category is C6.

No	Age	Education	Financial Status	Time with Company	Business Value	Positive Behavior	Negative Behavior	Output Value	Category	CC Validation
1	20	10.2	2	0.8	4	10	1	15	C3	C3
2	25	5	3	5	2.5	1.2	5	5	C1	C1
3	30	7	8.9	9	6.8	5	0	25	C5	C5
4	36	16.5	6.5	4.5	5	6.2	10	10	C2	C2
5	28	10.7	0	0	5	10	2.1	15	C3	C3
6	40	25	5	10	8.5	9	0.4	20	C4	C6
7	50	10	4.3	6.5	0	7	3	30	C6	C4
8	18	1.2	1.5	3	1.2	1.2	8	5	C1	C1

Table 9: Experimental Results for Customer Expert System Model Summary

Based on the model, the authors identified that the results derived from the model, assigned a customer with the pre-determined category which were derived from the clustering. These results were also validated with the team leaders at the contact centre to verify that the given selection of the pre-determined categories for customer was properly justified. The categories derived from the fuzzy expert system for customer and advisor will assign each customer call a defined category from the list. On the basis of the categories defined; the authors have demonstrated the next steps for the research to find the minimum amount of information which is required by the CSA to serve the customer. The discussions for some of the experiments related to the expert system are explained later in the paper within the discussion and conclusions. The next section of the paper describes briefly the framework developed to identify the amount of information based on {customer, advisor} combinations.

6. Information Requirement Analysis

This section explains the complete list of information that can be required to be displayed to the advisor to help him to understand and resolve the query of the customer. Information requirement development was done on the basis of the set of categories for customer and advisor derived from the clustering and determined from the fuzzy expert system model. The main objective of this section was to identify the minimum amount of information which is required to be displayed on the screen to the advisor which would enable the advisor to help the customer. This information should always satisfy the three important business aspects of customer contact which were (i) Customer Satisfaction, (2) Resolving the conflict and (3) Cross Sell – Up Sell opportunities. Information Requirement framework was developed to overcome the *information overload* with the current contact centre environment.

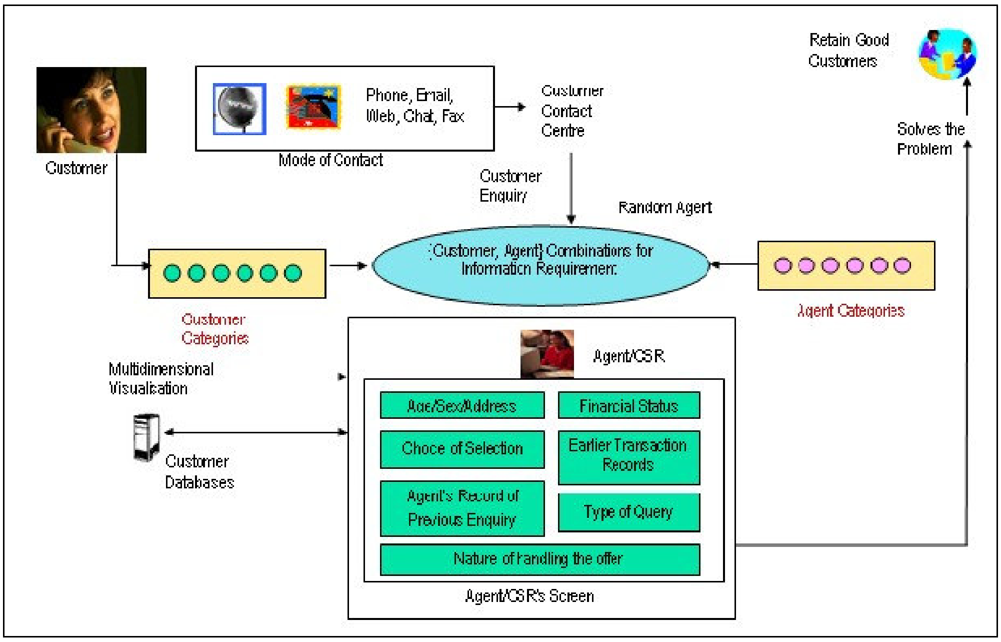

Figure 3: Conceptual Contact Centre Model

Also from the point of customer satisfaction *speed of response* was crucial and the *right amount of information* which is required to be displayed to the advisor under particular customer – advisor situation was important (Roy, et al. 2006).

Information Requirement framework was developed to overcome the *information overload* with the current contact centre environment. Also from the point of customer satisfaction *speed of response* was crucial and the *right amount of information* which is required to be displayed to the advisor under particular customer – advisor situation was important. Once the information to be displayed to the advisor is known from the possible combinations of {customer, advisor}; the information is then grouped into master list of information screen (Shah, Roy, Tiwari, and Majeed, 2006).

6.1 Contact Centre Information

From the initial understanding of the contact centre, and from the literature; the author designed a template with the complete list of information which would be used during a particular customer-advisor conversation. This list is mainly divided into three sections with customer information, business service details and advisor details. Once the total information to be displayed was known, it was again validated with the industry experts of team leaders and advisors within the centre. Based on the list of the information screen to be displayed to the advisor, a master screen was derived and as shown in the figure (5) (Shah et al, 2006). The detailed description for each of the section is as follows:

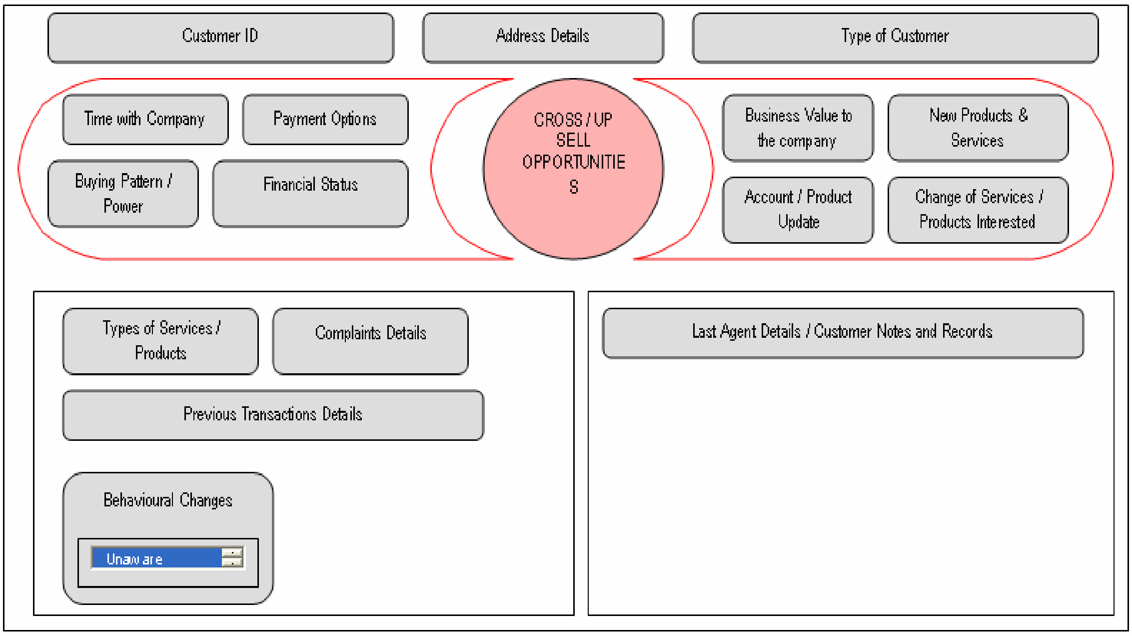

Figure 5: Information Requirement Frameworks – Master Screen Information

1. Customer Information

i. Customer ID info - Customer information about name, telephone number and other details
ii. Type of customer - Customer type – business, residential, single, etc.
iii. Address details. – customer address details
iv. Demographic data – other demographic data (marital status)

This information is the basic information about the customer based on the data provided by the customer to the company during the initial registration. This information is always needed in all the cases as the advisor can verify whether they are dealing with the customer only, or someone on behalf of the customer. Depending on the nature of the query; the advisor can only deal with the customer directly and no with someone else on their behalf. Because of the data protection and privacy act the advisor is also not allowed to disclose any of the personal information to any third party.

2. Business (Service) Details

i. Type of services and products ordered -
ii. Time with the company – the length of time the customer is been with the company
iii. Previous transaction details – the last communication of the customer with the company
iv. Behavioral changes – any change in the behaviour of the customer
v. Financial Status – financial status, job status etc.

vi. Buying Power – the buying power, regularity of buying
vii. Complaint Details – customer complaints in the past history.

This information relates to the customers service details with the company. It also shows the type of services and products the customer is currently subscribed to (in case of a telecoms or internet service provider) or the products the customer has bought in the past years (Past History in case of retail and financial sector). In many cases of the {customer, advisor} combinations, it would also show the financial status and buying power of the customer, which would enable the advisor to have any cross / up sell opportunities. Any change in the behaviour is recorded by the advisor in the customer database.

3. Advisor Details

i. Business value to the company – the value the customer is bringing to the company (business customer – high value)
ii. New products and services (cross / up sell) – according to the customer likes and dislikes; a list of new products and services which can be offered to the customer.
iii. Last advisor details – the last advisor notes and communication message
iv. Account update – any change in account status, cancellation etc.
v. Change of services – any change in services
vi. Product update – awareness to the product to the customer.

This category of information is based on the business value of the customer towards the company. This information section would help the advisor to identify the customer potential of buying new products / services. It would show the advisor the possibility of the cross sell and up sell opportunities. It would also show the advisor, all the information of the previous transaction of the advisors who dealt the particular customer, which would enable them to deal with the customer in the most efficient manner. Once the total information to be displayed was known, it was validated with the industry experts of six team leaders and three advisors within the centre.

6.2 Validation

The information and the results from the model were verified through team leaders and managers at three of the contact centres where the case studies were carried out. A total of nine team leaders and managers were interviewed with the help of an open set questionnaire, showing the categories derived and the assignment of a particular customer or advisor to these categories through the help of the fuzzy expert system tool developed. The team leaders at the contact centre were shown the possible combinations of the customer and advisor categories, and on what basis these categories were derived.

Best Advisor – Worst Customer Scenario (Advisor A5 and Customer C1)

A5 – Male, 50+ (age), Professional (education), 10+ yrs (experience), Medium (IT speed), Moderate (prev.exp.), Friendly (behaviour)
C1 – Female, 18-25, School (education), Poor (financial status), 1-5 yrs (Time with company), Low (business value), Angry and Aggressive (behaviour)
Information Display - Customer ID, address details, type of customer, time with company, buying pattern/power, financial status, type of services, business value to company, new products/service

The rules within the expert system were fine tune in respect to the validation from the team leaders at the contact centres. The changes within the rules were made in behaviour attributes and experience level within the customer and advisor categorisation.

Worst Advisor – Best Customer Scenario (Advisor A1 and Customer C4)

A1 – Female, 18-25, School (education), >1yrs Experience, Slow (IT speed), None Previous experience, Angry and Unaware (behaviour)
C4 – Female, 40+ (age), Professional (education), Average (financial status), 10-12 yrs (time with company), High (business value), Joyful (behaviour)

Information to Display - Customer ID, address details, type of customer, time with company, buying pattern/power, financial status, type of services, business value to company, new products/service.

The information requirement framework was validated within the contact centres by identifying the best and worst case scenarios of customer and advisor communication as shown below. A total of thirty six scenarios were considered identifying the best case and worst case of customer and advisor contact. The scenario identifies the type of customer and advisor and selects the required information based on the customer and advisor attributes from the categorisation (section 4.2).

7. Discussion and Future Research

The authors have demonstrated the steps which were followed for the development of a fuzzy expert system to assign the customer and advisor to the pre-determined category. The experimental results in table (8) and (9) shows that 80% of results are as expected, and were assigning a particular customer and advisor to the categories which were derived from clustering. Based on experiment 5, the expert system assigned category A5 to the advisor. However from validation with team leaders it revealed that the category should be A4. On the basis of the validation the changes were made with respect to behavioural attributes from friendly behaviour to customer focus behaviour. Experiment 7 revels that the expert system assigned category A6, which on further validation with team leaders at the contact centres fall into A2 category. The reasons for this swift change in selection of category were due to:

a) Education level to be high.
b) Positive behaviour to be attentive.
c) Less amount of negative behaviour.

The rules were fine tuned to predict A2 category and share characteristics of that category. For customer categorisation, the results from the expert system for experiment 6 and 7 did not match that to the validation from the team leaders at CC. Necessary modifications were carried out within the expert system to assign a category to customer to match with the validation results from the team leaders. As seen in experiment 6, the changes made were education level was changed from graduate to college level to assign customer with C6 category. Experiment 7 revealed that expert system assigned C6 category which on further validation fall into C4 category. The changes made within the expert system were:

(a) Customer time within company.
(b) Positive attitude towards the advisor and
(c) Less amount of negative attitude shown from the customer.

The next step of this research is to further develop the framework which would identify the type of information required by the advisor. The cost and maintenance of the framework will be considered and further validation will be carried out with respect to the information requirement framework with more {customer, advisor} combinations and the information required to be displayed. A simulation approach is going to be used to validate the entire system and framework which would comprise of fuzzy expert system and the information requirement framework. The simulation environment would assign a particular customer call to the advisor, identify the type of customer and advisor based on categorisation, fuzzy expert system will be used to assign each customer and advisor with a category and on the basis of the {customer, advisor} combination show the required information to be displayed on the screen of the advisor which would enable them to serve the customer more efficiently and thus satisfying the important business aspects.

8. Conclusions

This paper reports on a long term research project that was set to investigate the feasibility of soft computing techniques for categorising customer and advisors with specific application in the contact centre sector. However, the findings can have implications far beyond this specific case study. The reported results are considered significant for a number of reasons.

Firstly, the study involved a real life problem. This means that the data used, the requirements and objectives set and the scale of the experiment corresponds to a real problem, as defined by a major telecommunications operator. Since modern telecommunication companies have similar characteristics in terms of services provided to their customers, databases and information systems design for monitoring customer characteristics used, the findings of the experiment are applicable to other sectors of service industry.

Secondly, throughout this study, it was recognised that domain experts were continuously providing expertise and intuition by directing and pointing to the matters that were important for the company and its customers. It was also shown that the original steps of the process required a mixture of tools and experts intuition, relating to the problem of defining the data set and selection of variables describing the required modelling features. Further research should develop a framework to map customer and advisor behavioural and demographic information directly to the type of information required to be presented on the screen; rather than a fixed template based approach. This paper is focused on the development of customer and advisor (CSA) categorisation within contact centre environment. A fuzzy expert system was developed to assign any customer or advisor to that of the pre-determined category from the clustering analysis. The results showed the assignment from the expert system for the categorisation of the customer and advisor which was validated with the team leaders at the case study contact centres. The proposed methodology can be applied in contact centre environment to minimise the problems of information overload, right amount of information at the right time, retention of advisors, and customer satisfaction through speed of response.

Finally an interesting discussion concerns the degree to which the study can be generalised and reused in other problems in service industry. Some of the findings and specific techniques used are of general value such as the clustering approach used for customer and advisors and the discussion on the use of soft computing based approach to assign each customer and advisor to a pre-defined category. More specifically, a large area of problems related to the identification of information and categorisation of customer in the service industry. They bear many similar characteristics to the one described here, and can be based on very similar process, where apart from the initial stages of problem definition and original variables selection, the rest of the process can be repeated. Also for the specific problem of behavioural modelling of customer and advisor within contact centres, the methodology described in the paper can be reused, except of definition of the advisor data. A data mining tool to handle such exception of data can be used as one of the objective for further research.

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