Multi-criteria decision-making for purchasing cell phones using machine learning approach

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Abstract: The process of selecting and purchasing cell phones is a multi-criteria decision-making (MCDM) problem with conflicting and diverse objectives. This study discusses various techniques involved in selecting and purchasing a cell phone by using machine learning approach. The responses of the participants were sought through a questionnaire which gave them different options with regard to the latest features available in a cell phone. Seven independent input variables – cost, battery backup, rear camera, weight, size, memory and operating system, were provided to the participants to elicit their responses. Each of the input variables was measured on a scale expressed in linguistic terms as low, medium and high. Mamdani approach, traditional fuzzy reasoning tool (FLC) and neuro-fuzzy system (ANFIS) were used to design three input and one output processes. The back-propagation algorithm formed the basis for application of the neuro-fuzzy system. Two traditional fuzzy reasoning tools – the artificial neural network (ANN) approach and the neuro-fuzzy system, were used to arrive at more accurate understanding of the process of selecting a cell phone for personal use.

Keywords: cell phone selection; multi-criteria decision-making; MDCM; artificial neural network; ANN; approach neuro-fuzzy system ANFIS; fuzzy reasoning tool; FLC.

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1 Introduction

In the present times, a cell phone/mobile is extremely essential for people as well as for the society. Selecting a cell phone requires a person to decide before selecting a cell phone. Decision-making (DM) is the process of choosing out of varied sets of options. It is a fundamental aspect of everyday mental processes. Decisions are often to be made in the midst of uncertainty the payoffs are probabilistic and unknown. The study of DM has been approached from different perspectives which include behavioural, biological, mathematical and computational aspects, however, a large number of challenges remain unexplored in understanding this higher function of human cognition.

In India as well as across the globe, the present scenario has become more complicated due to tough competition among mobile phone manufacturing companies; they launch different models and also update versions of mobiles within short interval of time. With addition of some new features which usually vary from one version to another, cell phones are made available at different costs ranging from high to low. The vast majority of the mobile manufacturing companies focus on maximising their profits and to achieve this goal, they add new features when they launch different versions. Adoption of new technology escalates cost significantly which in turn makes it difficult for the customers with low income to make a choice out of this plethora of available options. Hence it is essential to implement some methodology in selecting an optimal mobile among several choices available in the market at affordable price. Besides the customers, the designers and manufacturing companies also face challenge to manufacture a mobile phone which suits the customer's requirement and enhances his satisfaction. Selection of appropriate mobile for the common people is multi-criteria decision-making (MCDM) problem and so it is for the entire mobile industry as it involves many input/output criteria and alternatives.

This paper is an attempt to understand the processes involved in making of decision while purchasing a cell phone. The paper is organised as follows: the introduction is followed by literature review of MCDM, the next section describes data collection, and the Section 4 elaborates methodology adopted in this study. In the last section, the results of two methods are discussed and the paper ends with concluding remarks and also provides direction for future research.

2 Literature review

MCDM methods were evaluated using many models like analytical hierarchy process (AHP), analytical network process (ANP), and technical for order preference by similarity to the ideal solution (TOPSIS) and fuzzy sets to determine the best model for the suitable problem.

AHP is very operative in the DM process as it ensures procedural rationality. It also states that AHP is very similar to the human behaviour in DM and also the pair-wise comparison ensures that all possibilities are explored so that the best outcome can be provided. Chen (2005) also supports this evidence when he also suggests AHP may be used for qualitative and quantitative aspects as it provides the best alternative depending on the criteria.

ANP is a simple and easy model to use. It has flexibility of approach in solving complex procedures that require a lot more calculation as compared to AHP. It also states that due to its complex and the time-consuming nature, only a few applications of ANP are valid/ useful. However, in contrast to AHP, ANP considers the dependency among the criteria and alternatives thereby giving more precise results.

In 2004, Olsen suggested that TOPSIS requires only limited subjective inputs in comparison to some other MCDM methods and it can also identify the best alternative. In certain situations, TOPSIS gives a better solution than another model. TOPSIS seems to be an effective method in solving MCDM problem, however, although in limited sense only, it uses some subjective information which may bias the results.

All the approaches for solving MCDM problem are not suitable for inconsistency data (Mohanty et al., 2015). Saaty (2007c) states that people now use fuzzy sets to determine the nature of the data. AHP is a consistency technique whereas fuzzy is the least consistent.

Any decision process with multiple criteria dealing with human judgement is not easy to model. Decisions are subject to professional judgements usually based on imprecise information. Machine learning approach is suitable for subjective judgement, making decisions with imprecise data (Mohanty et al., 2015).

3 Method

3.1 Participants

A total of 200 students in the age group of 19 to 28 years (male = 118, age = 24.08 yrs; female = 82, age = 23.24 yrs), including graduate and postgraduate engineering students, management students, and research scholars from the Kalinga Institute of Industrial Technology University (KIIT University) Bhubaneswar, Odisha, (India), participated in this study. Prior to their participation, the subjects were informed about the opportunity to cooperate in a study related to DM process of selecting a cell phone for personal use. Informed consent was sought, and those who signed the informed consent form were the participants in this study.

3.2 Selection under linguistic variable

The questionnaires consisting of seven input variables such as cost, power backup, rear camera facilities, weight, screen size, memory and operating system, and output variable as select or not select as per the individual choice of the participants were prepared. Each input parameter was expressed in linguistic variables like low, medium and high except one input variable – operating system. The participants were asked to give opinion while making their choice.

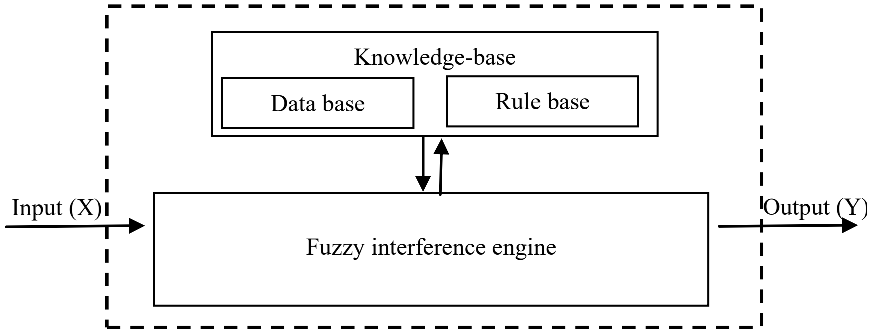
3.3 Measuring the variables: cost, battery backup, size, weight, rear camera, memory, and operating system

For each problem, the participants were asked to choose the option which they prefer by putting tick mark in front of their choice. After collecting the questionnaires, we evaluated the participant's choices to each problem for the dimensions of cost, talk time, size, weight, rear camera, memory, operating system on the basis of the ranges and values provided. Each dimension was measured on a one-point scale, '0' representing the lowest value of the dimension and '1' indicating the highest value of the dimension. We evaluated the choice of 200 participants.

4 Fuzzy rule-based systems

A knowledge base (KB) and inference engine (IE) are two main components of fuzzy rule-based systems (FRBS). There are various ways to represent knowledge. Perhaps, the most common way to represent human knowledge is to form it into natural language expression. The KB generally represents the knowledge about the problem being solved in the form of fuzzy linguistic IF-THEN rules, and the IE, which puts into effect the fuzzy inference process, is needed to obtain an output from the FRBS, when an input is specified. This form in expression is commonly referred to as the IF-THEN rule-based form like IF premise (antecedent), THEN conclusion (consequent) parameters. The schematic view of an FRBS is shown in Figure 1.

Figure 1 A schematic view of an FRBS



An FRBS consists of three modules, namely fuzzification, inference, and defuzzification. Fuzzification is the process, in which the input parameters are converted into appropriate fuzzy sets to express measurement uncertainty. The fuzzified measurements are then used by the IE to evaluate the control rules stored in the fuzzy rule base and a fuzzified output is determined. The fuzzified output is then converted into a single crisp value. This conversion is called de-fuzzification.

4.1 Fuzzy linguistic variable and membership functions

Fuzzy linguistic approach provides a systematic way to represent linguistic variables in a natural evaluation procedure (Nauck and Kruse, 1996). A fuzzy linguistic label can be represented by a fuzzy number, which is represented by a fuzzy set (Zadeh, 1965). Fuzzy sets capture the ability to handle uncertainty by approximation methods (Nauck and Kruse, 1996).

A fuzzy set α is represented by a pair of two things – the first one is the element x and the second one is its membership value $\mu_\alpha(x)$ (varying in the range of [0, 1]), as given below.

$$\alpha = \{(x, \mu_\alpha(x)) : x \in X\} \tag{1}$$

For the inputs and output, triangular membership functions were used in order to keep the design of the FLCs simple. A degree of overlapping of two was used, as shown in Figure 2. Furthermore, a universe of discourse normalised to the range of [0.0, 1.0] was utilised. This value, called membership value or degree of membership (as given below), quantifies the grade of membership of the element in X to the fuzzy set A.

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{m-a}, & a < x \le m \\ \dfrac{b-x}{b-m}, & m < x < b \\ 0, & x \ge b \end{cases} \tag{2}$$

Here, a, b, m are real numbers. In this formula, b and a are the upper and lower values of the support of A, respectively, and m is the median value of A.

4.2 *Description of fuzzy input variables*

The input fuzzy variables were V_1 = {cost}, V_2 = {Talk time} and V_3 = {Rear camera}, V_4 = {Size}, V_5 = {Weight}, V_6 = {Memory}, V_7 = {Operating system} and each of them was represented using three linguistic terms, such as Low (L), Medium (M), High (H) the linguistic terms and their ranges are shown in Figure 3.

Figure 2 Input variable 'cost', 'talktime', 'Rcam', 'weight', 'size', 'memory', 'OS'

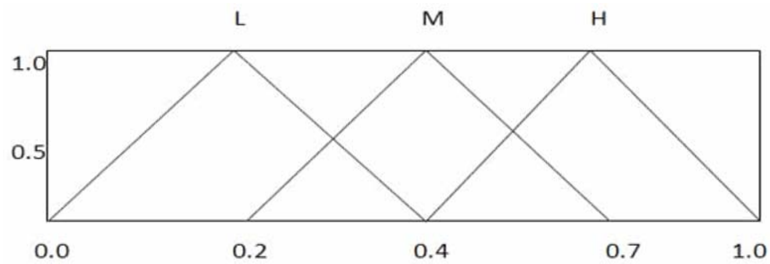


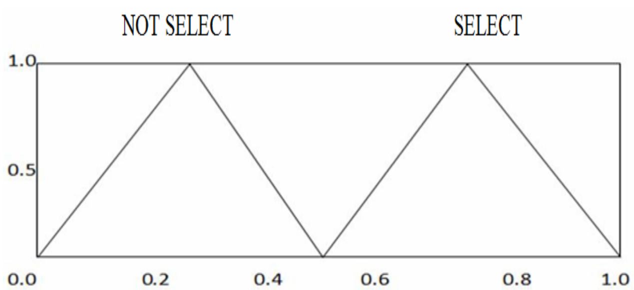
Table 1 Linguistic term and their ranges for the variables: V_1 = {cost}, V_2 = {talktime}, V_3 = {Rcam}, V_4 = {weight}, V_5 = {size}, V_6 = {memory}, V_7 = {OS}

Linguistic terms	*Membership function*	*Range of parameter*
Low (L)	Trimf	[0.0, 0.4]
Medium (M)	Trimf	[0.2, 0.7]
High (H)	Trimf	[0.4, 1.0]

4.3 *Description fuzzy output variable*

Two linguistic terms, namely select and not-select were used to represent the output variable: V_8 = {output as a decision} (refer to Figure 3). The Mamdani min-operator was utilised for aggregation and defuzzification was done using the centre of the sums (COS) method (Pratihar, 2008).

Figure 3 Membership function distributions for output fuzzy variable: V_8 = {select/non select}



4.4 Determining fuzzy rule base from input and output variables

Rules are the cores of the FRBS, which represent the relationships between its inputs and output. In the present problem, seven input variables were considered and each of them was represented using three linguistic terms. Thus, there could be a maximum of rules in the FRBS. In this study, we have generated 344 fuzzy rules.

For instance, the first and last rules were as follows:

IF V_1 is L AND V_2 is L AND V_3 is L AND V_4 is L AND V_5 is L AND V_6 is M AND V_7 is M
THEN output is Not-Select.

Similarly,

IF V_1 is H AND V_2 is L AND V_3 is M AND V_4 is H AND V_5 is H AND V6 is M AND V_7 is H THEN output is Select.

4.5 Fuzzy rule encoding

Three input variables each having four linguistic terms constitute 344 rules. Linguistic terms are represented with their index values, as given in Table 2.

Table 2 Description of fuzzy linguistic term

Abbreviation	*Expression*	*Index representation*
L	Low	0.25
M	Medium	0.35
H	High	0.55

5 Working principle of traditional FLC (Mamdani approach)

An FLC consists of a set of rules presented in the form of IF (a set of conditions are satisfied) THEN (a set of consequences can be prepared). Here, the antecedent is a condition in its application domain and the consequent is a control action for the system under control. Both the antecedents and consequents of the IF-THEN rules are represented using some linguistic terms. The inputs of FRBSs should be given by fuzzy sets, and therefore, we have to fuzzify the crisp inputs. Moreover, the output of an FLC is always a fuzzy set, and therefore, to get the corresponding crisp value, a method of defuzzification is to be used. The fuzzification of input variables involves the following steps:

a measure all the input variables

b perform a scale mapping that transfers the ranges of values of input variables into corresponding universes of discourse

c perform the function of fuzzification that converts input data to suitable linguistic values, which may be viewed as the label of fuzzy sets.

The rule base comprises knowledge of the application domain by using the information of the database. Thus, the database provides necessary data to design the control rules involving linguistic terms. The rule base characterises the control goals and policy of the domain experts by means of a set of linguistic control rules.

The IE of an FLC has the capability of simulating human DM based on fuzzy concepts and of inferring fuzzy control actions by employing fuzzy implication and the rules. A method of defuzzification is used to obtain the crisp value corresponding to the fuzzified output. In this study, COS method of defuzzification was utilised, this is given below.

$$U'_{f'} = \frac{\sum_{j=1}^{P} A(\alpha_j) \times f_j}{\sum_{j=1}^{P} A(\alpha_j)} \tag{3}$$

where $U'_{f'}$ is the output of the controller, $A(\alpha)$ represents the firing area of j^{th} rule, p is the total number of fired rules and f_j represents the centre of the area.

6 Design and development of adaptive neuro-fuzzy system based on Mamdani approach

A neuro-fuzzy system inherits properties from both fuzzy logic-based systems and neural networks. Here, an FLC is represented using the structure of a neural network, which is trained in order to develop its optimised KB. The incorporated neural network, part of the same system can, by using its learning capability, perform online tuning of all the rules and gradually improve the performance of the entire hybrid system. A neuro-fuzzy system works based on a fuzzy system, which is trained by a learning algorithm derived from neural network theory. The heuristic learning procedure operates on local modification in the underlying fuzzy system. These concepts became very popular in real-world applications (Berenji and Khedkar, 1992). Neuro-fuzzy systems are usually represented as multilayer feed-forward neural networks (Buckley and Hayashi, 1994), but fuzzifications of other neural network architectures, like a self-organising map, are also considered (Vuorimaa, 1994). In this study, a neuro-fuzzy system based on Mamdani approach was adopted, which is described below.

It consists of five layers: layer 1, called the input layer; layer 2, that is, fuzzification layer; layer 3 is the implementing layer; layer 4 is known as the fuzzy inference layer and finally, layer 5, the defuzzification layer (refer to Figure 4). The role of each layer of the neuro-fuzzy system is described below in detail.

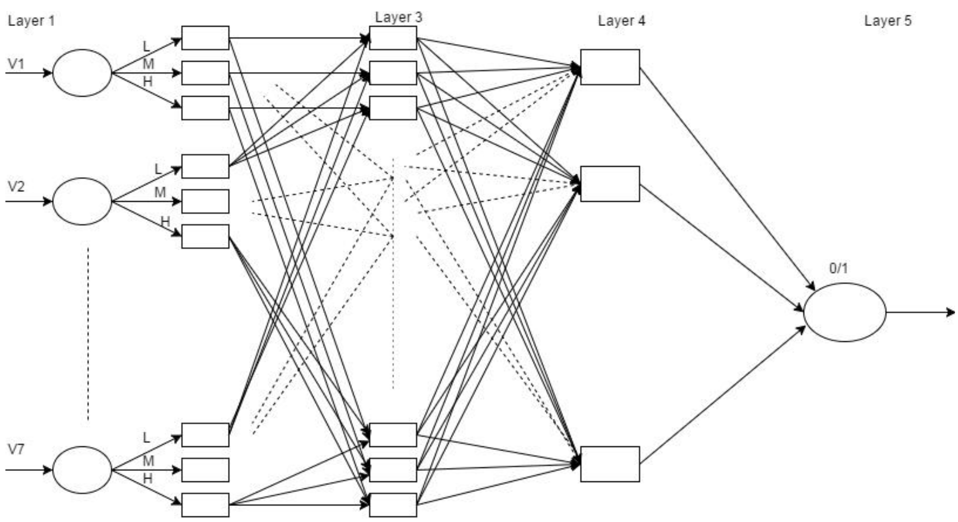
- *Input layer:* The variables, namely cost (V_1), talk time (V_2), rear camera (V_3), weight (V_4), screen size (V_5), Memory (V_6) and operating system (V_7) were fed as inputs to the network.

  The output would be the same as the input as a linear transfer function was considered in this layer, for simplicity. Each of the input variables (that is V_1, V_2, V_3,

V_4, V_5, V_6 and V_7) was expressed using three linguistic terms (L: low, M: medium, H: high).

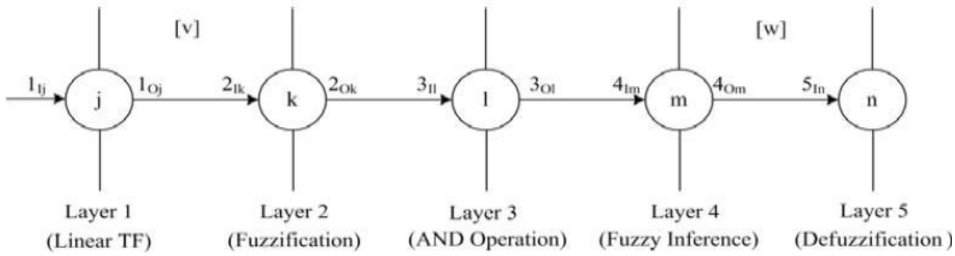
- *Fuzzification layer:* The inputs of this layer were taken to be equal to the outputs of the first layer. Thereafter, these crisp values of the inputs were converted into the fuzzy membership function values, with the help of membership function distribution. For all seven inputs, the membership function distributions were assumed to be triangular.
- *AND implementing layer:* This layer computes the task of original AND operation. Each neuron lying in this layer is connected to three neurons of the previous layer, as shown in Figure 4. Membership function values calculated in the previous layer were considered as the inputs of a particular neuron (say n^{th}) lying in this layer. These seven membership function values were compared and the minimum of these seven was taken as the output of the n^{th} neuron (Malakooti and Zhou, 1994).
- *Fuzzy inference layer:* This layer could identify the fired rules corresponding to seven input variables, each having three linguistic variables and as a result of which, the fired rules were identified along with their strengths for a set of inputs.
- *Defuzzification layer:* In this layer, the connecting weights between the fourth and fifth layers (refer to Figure 5) were used to indicate the membership function values of the output variables. Once the membership function distributions were known, this layer could calculate the outputs of all fired rules (in terms of areas under the membership function distributions). After the outputs of all the fired rules were determined, they were superimposed to get the fuzzified output by considering all the fired rules together. As the fuzzified output (nothing but an area) was not suitable for implementation as a control action, a crisp value corresponding to it was calculated. This process is called de-fuzzification. A COS method was adopted for the de-fuzzification.

Figure 4 A schematic view of the neuro-fuzzy system based on Mamdani approach



In this study, a neural network toolbox of MATLAB 13 was used. A back-propagation learning algorithm had been used here. TRAINLIM (that is, Levenberg-Marquardt back-propagation) algorithm was also used in this work, as it was seen to be more efficient than other learning techniques when a network contains not more than a few hundred weights (Hagan and Menhaj, 1994).

Figure 5 A specific neuron at each layer of the network



Source: Pratihar (2008)

7 Results and discussions

The performance of all the three methods, FLC, ANFIS (both developed base on Mamdani approach) and ANN were measured using root mean square error and R^2 value. The results of all the method are stated and discussed as follows.

7.1 Results of FLC

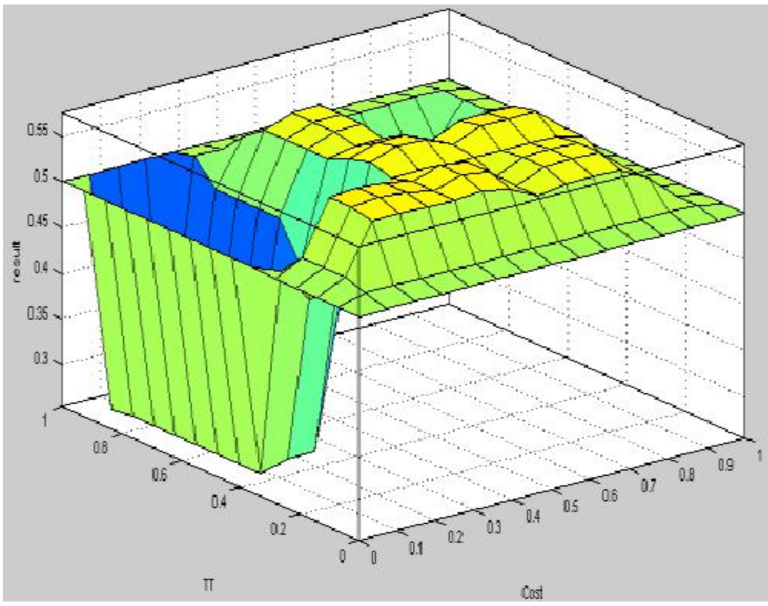
Traditional fuzzy reasoning tool was developed using seven inputs, namely, cost, talk time, rear camera, weight, size, memory and operating system, and each having three different responses (that is, low, medium, high). A set of 344 rules were designed manually, as shown in Appendix A.

The result of this approach suggest that the cost, operating system and talk-time (battery backup) are essential for selecting a cell-phone [refer to Figure 6(a) to Figure 6(f)]. The values of input parameters such as cost, operating system, talk-time were high with respect to the other input parameters. The outcome variables (SELECT) significantly respond with these three input parameters. The result of this approach is shown in Table 3.

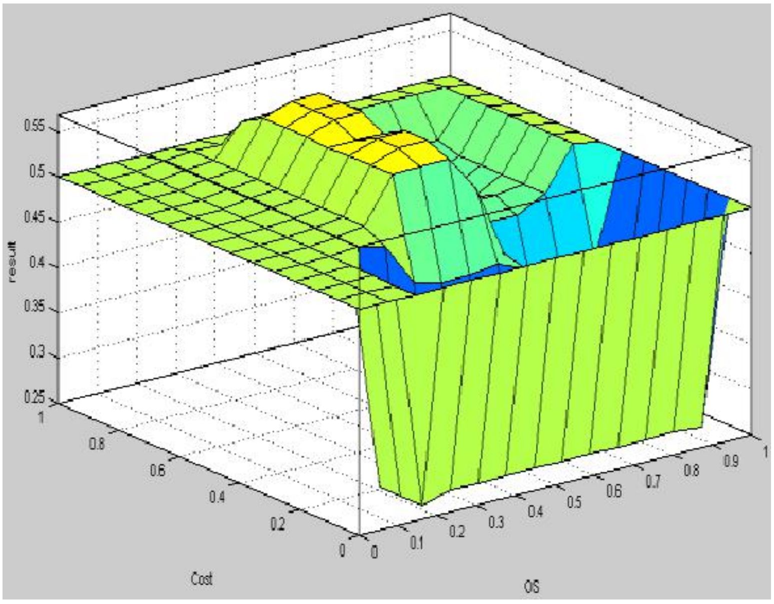
Table 3 Comparison between fuzzy reasoning tool and neuro-fuzzy approach

Architectures	*Process*	*Sample*	*MSE*	R^2
Neuro-fuzzy using Mamdani approach	Training set	120	0.9994	0.9998
Fuzzy reasoning tool using Mamdani approach	Testing set	60	0.9878	0.9521
	Validation	20	0.9994	0.9998

Figure 6 (a) Cost vs. TT (b) OS vs. cost (c) TT vs. OS (d) OS vs. TT (e) Cost vs. TT (f) Cost vs. OS (see online version for colours)

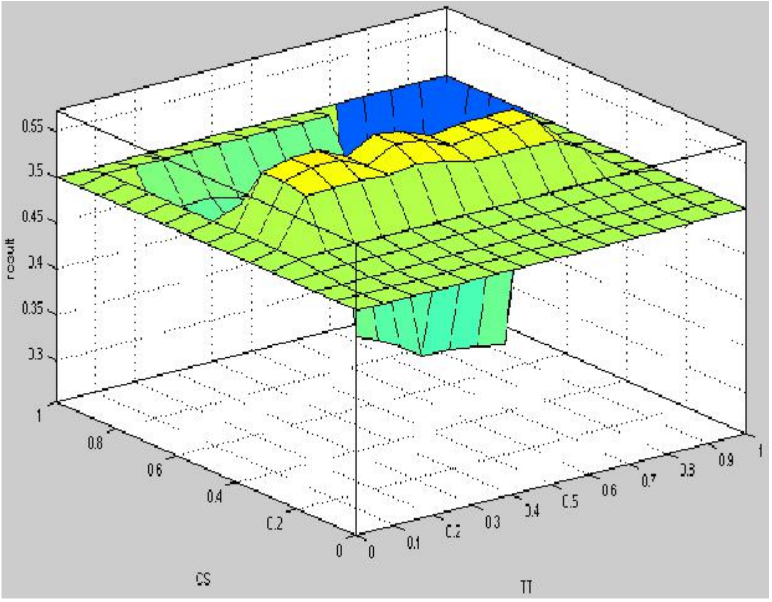


(a)

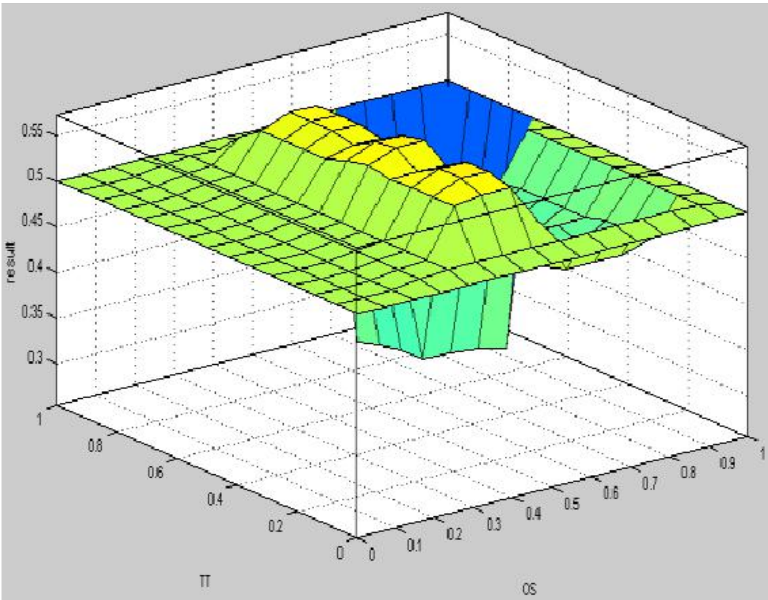


(b)

Figure 6 (a) Cost vs. TT (b) OS vs. cost (c) TT vs. OS (d) OS vs. TT (e) Cost vs. TT (f) Cost vs. OS (continued) (see online version for colours)

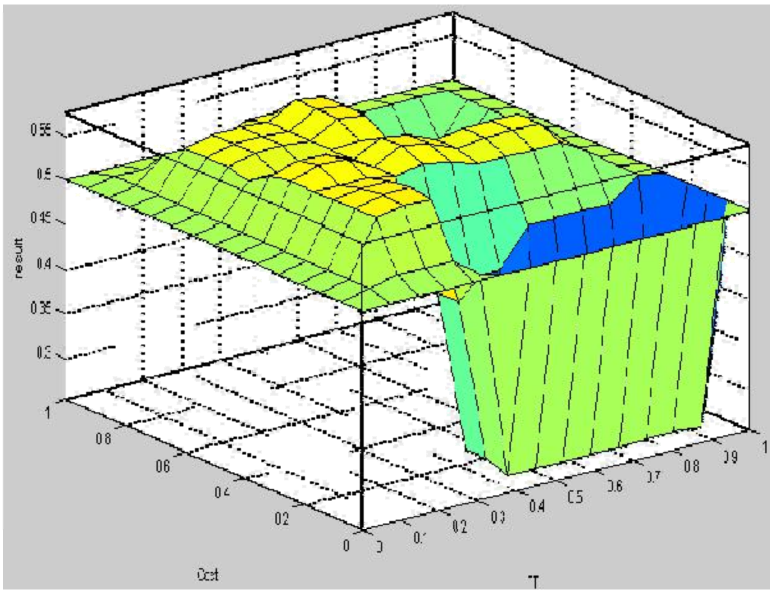


(c)

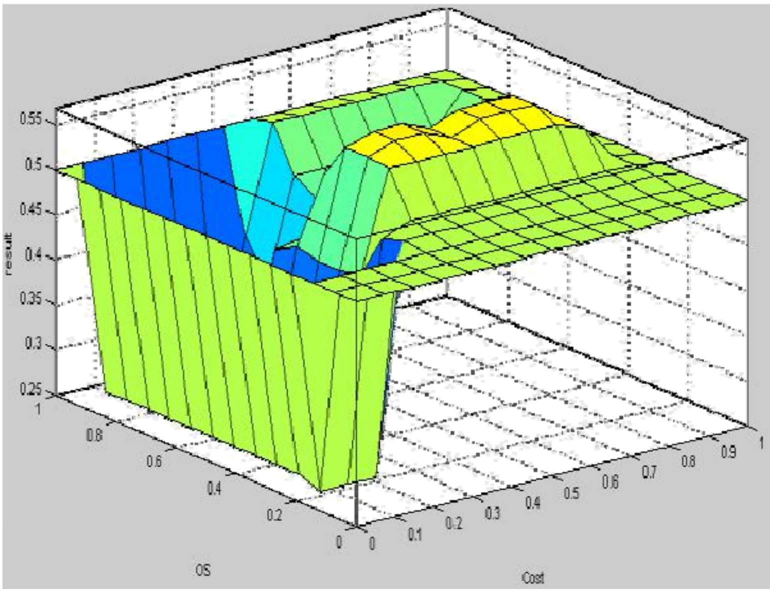


(d)

Figure 6 (a) Cost vs. TT (b) OS vs. cost (c) TT vs. OS (d) OS vs. TT (e) Cost vs. TT (f) Cost vs. OS (continued) (see online version for colours)



(e)

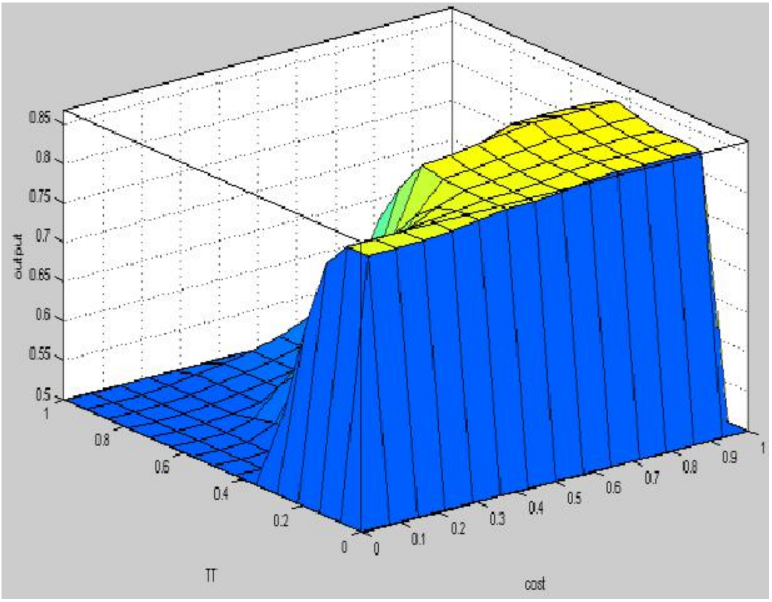


(f)

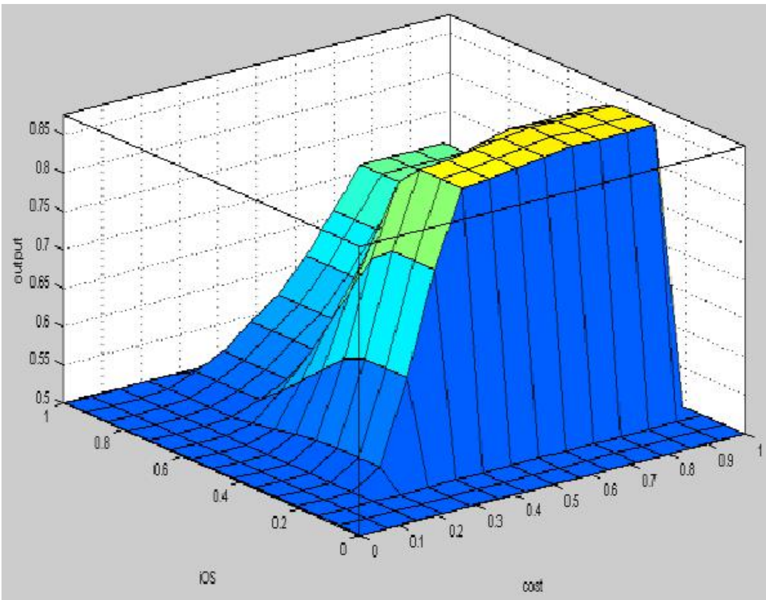
7.2 Result of neuro-fuzzy approach

The purpose of this neuro-fuzzy system developed using Mamdani approach was to predict the outputs of the complete system for a set of input variables. An online (that is incremental) mode of training had been adopted in this analysis. Out of a total of 200 data, 120, 60 and 20 were utilised for the training, testing and validation respectively. The results of this approach are shown in Table 3 and graphically in Figure 7(a) to Figure 7(f). It yielded better and more accurate result than compare to FLC and ANN.

Figure 7 (a) Cost vs. TT (b) Cost vs. OS (c) OS vs. cost (d) OS vs. TT (e) TT vs. OS (f) TT vs. cost (see online version for colours)

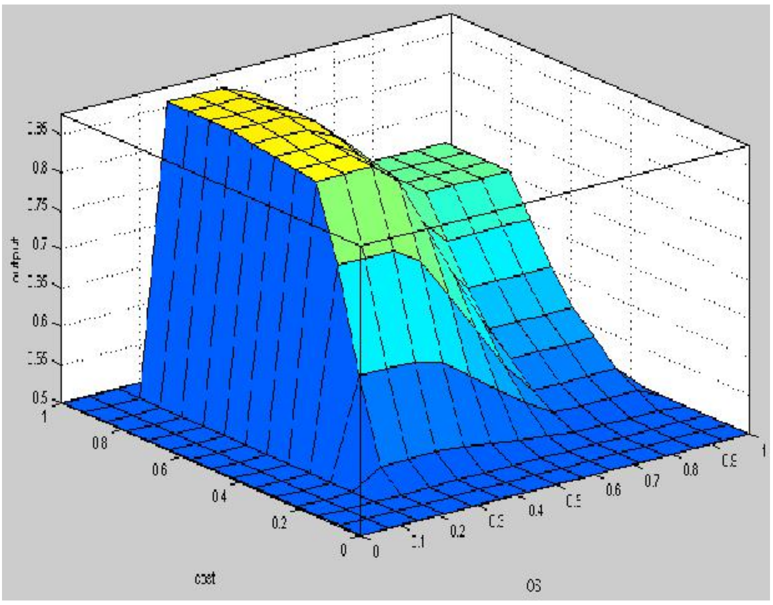


(a)

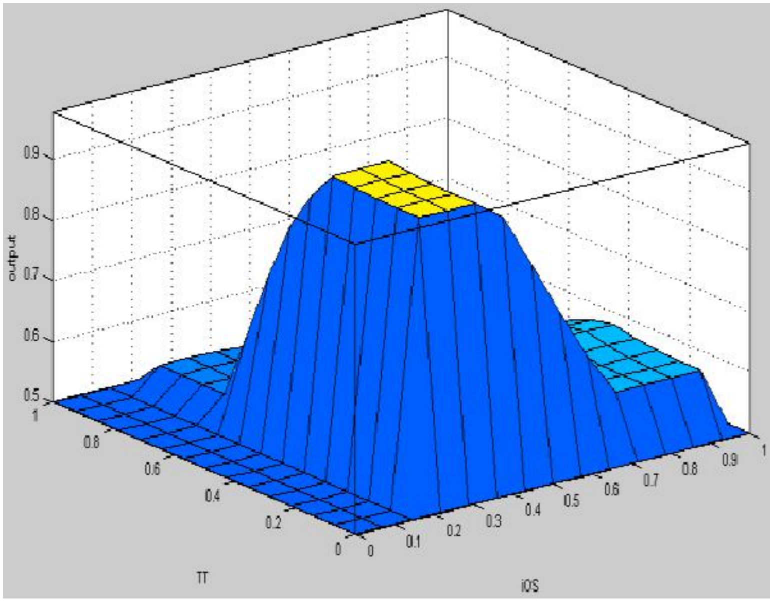


(b)

Figure 7 (a) Cost vs. TT (b) Cost vs. OS (c) OS vs. cost (d) OS vs. TT (e) TT vs. OS (f) TT vs. cost (continued) (see online version for colours)

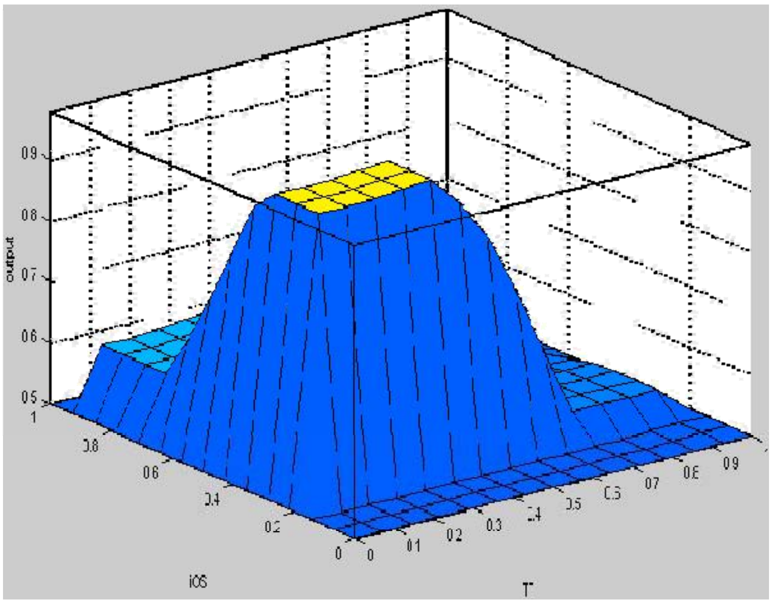


(c)

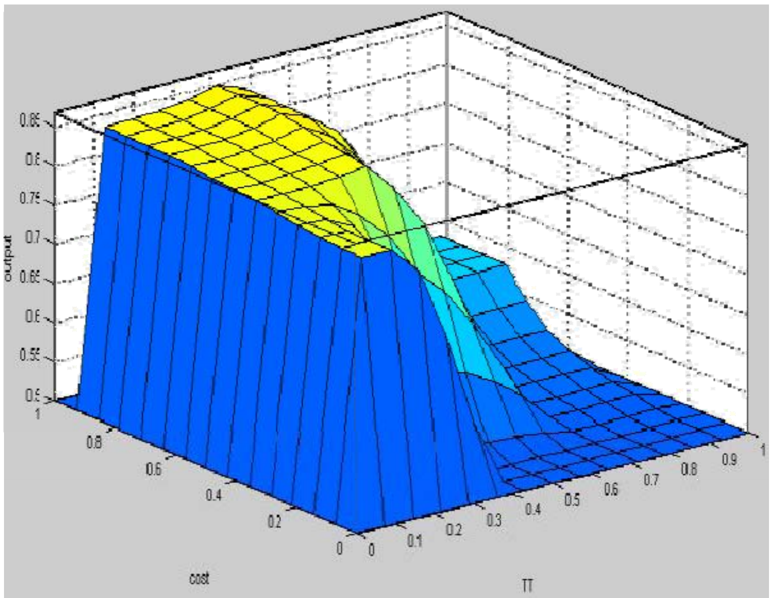


(d)

Figure 7 (a) Cost vs. TT (b) Cost vs. OS (c) OS vs. cost (d) OS vs. TT (e) TT vs. OS (f) TT vs. cost (continued) (see online version for colours)



(e)

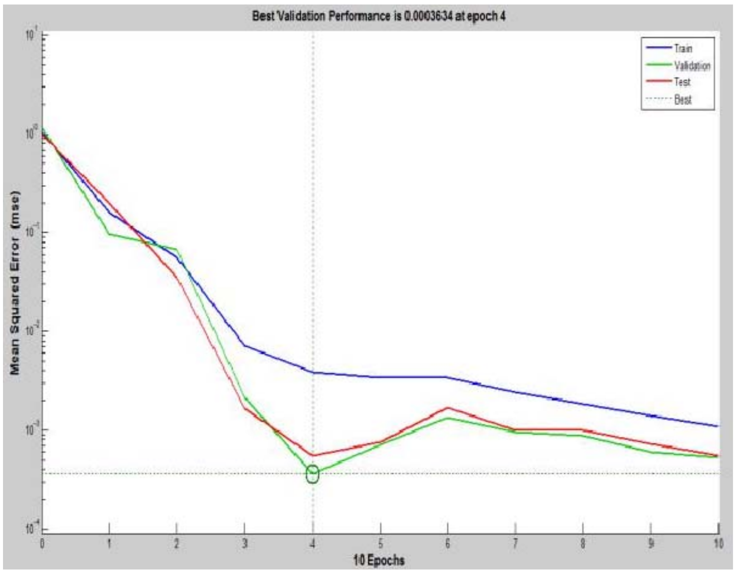


(f)

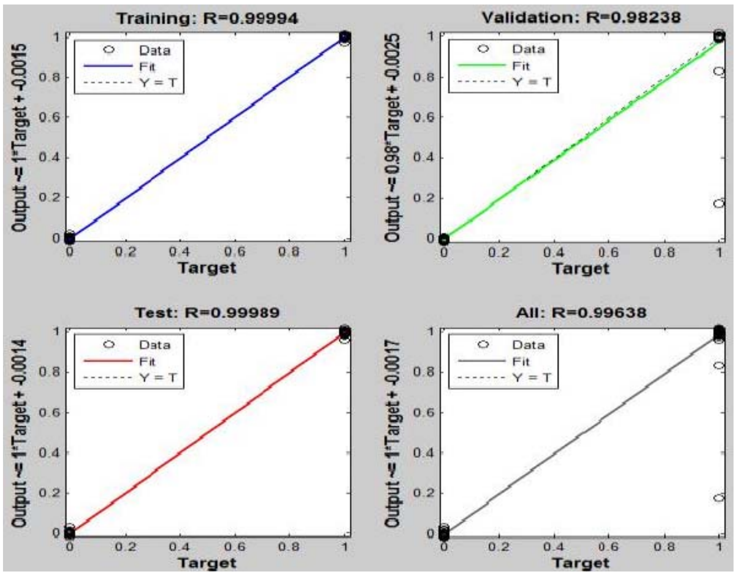
7.3 Results of ANN

In this method first, we applied the standard back-propagation algorithm to a three layer feed-forward neural network with seven input units, five hidden units and two output units. The learning was iterated 1000 times (i.e., 1,000 epochs) with the learning rate 0.25 and the momentum constant 0.9. Total network was obtained from the trained neural network by hard DM (refer Figure 8).

Figure 8 (a) Performance graph using ANN tool (b) Regression graph using ANN tool (see online version for colours)



(a)



(b)

7.4 Accuracy in prediction of results by three approaches

In this study, the performances of neuro-fuzzy system and traditional fuzzy reasoning tool were compared in terms of root mean square error (RMSE) in predictions and regression coefficient (R^2). It is to be noted that RMSE was calculated as RMSE = 0.9989, where N indicates the total number of samples, $E(t)$ is the prediction error of t^{th} sample.

The results showed the advantage of using neuro-fuzzy system over traditional fuzzy reasoning tool, in terms of RMSE and R^2 value (refer to Table 3). The neuro-fuzzy approach was able to yield better results compared to the other approach, which is evident from Figure 8(a) and Figure 8(b). It might have happened because in the neuro-fuzzy system, the KB was tuned further with the help of some training scenarios.

From the above analysis, the hybrid approach neuro-fuzzy using Mamdani (ANFIS) revealed that more accuracy with R^2 value was 0.9998. It suggests that most of the individuals generally prefer the feature of the cell-phones cost, talk-time and operating system during the purchase of the cell-phones.

8 Discussion and conclusions

In this paper, we have analysed the purchase of cell phones on information processing during DM using fuzzy reasoning tool and neuro-fuzzy system developed based on Mamdani approach. We have focused upon a new view on fuzziness in information processing; both traditional fuzzy reasoning tool and neuro-fuzzy system developed based on Mamdani approach were used in order to determine input-output relationships of this process. Comparisons were made of the above three approaches on 60 test, 20 validation and 120 training cases. An online (that is, incremental) mode of training was adopted to train the network. We conclude that neuro-fuzzy approach showed better performance in predictions compared to that of the traditional fuzzy reasoning tool. It could be because the neuro-fuzzy-based approach was able to optimise its KB during the training. On the other hand, traditional fuzzy reasoning tool was developed based on human observations and experiences.

In this paper, computational complexities of the developed approaches were not studied, which could be attempted in future. Moreover, in this study, only triangular membership function distributions were considered. Nonlinear membership functions like Gaussian or exponential could be used to have better accuracy. Apart from that, in this study, only seven input variables were considered as independent variables, but in future, more input variables could be taken into consideration. In such cases, computational complexity and size of the rule base would be increased. An attempt will be made to further improve the performance of neuro-fuzzy system by using other types of learning algorithm. In this study, the influence purchase of cell-phones on information processing during DM. Thus, uncertainty in DM was modelled using the concept of fuzzy sets. Seven inputs and one output fuzzy reasoning tool was developed using Mamdani approach. This study would help the moderator of age group individuals for purchasing of cell phones.

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Appendix A

Rule base used by traditional fuzzy reasoning for predicting outputs

Sl no.	Cost	Battery backup	Rear camera	Weight	Screen size	Memory	Operating system	Output
1	L	L	L	L	L	M	M	NSELECT
2	L	L	L	L	L	M	H	SELECT
3	L	M	L	L	L	M	M	SELECT
4	L	M	L	L	L	M	H	SELECT
5	L	H	L	L	L	M	M	SELECT
6	L	H	L	L	L	M	H	SELECT
7	L	L	M	L	L	M	M	NSELECT
8	L	L	M	L	L	M	H	SELECT
9	L	L	H	L	L	M	M	NSELECT
10	L	L	H	L	L	M	H	SELECT
11	L	L	L	M	L	M	M	NSELECT
12	L	L	L	M	L	M	H	SELECT
13	L	L	L	H	L	M	M	NSELECT
14	L	L	L	H	L	M	H	NSELECT
15	L	L	L	L	M	M	M	NSELECT
16	L	L	L	L	M	M	H	SELECT
17	L	L	L	L	H	M	M	SELECT
18	L	L	L	L	H	M	H	SELECT
19	L	L	L	L	L	M	M	SELECT
20	L	L	L	L	L	M	H	SELECT
21	M	L	L	L	L	M	M	NSELECT
22	M	L	L	L	L	M	H	SELECT
23	M	M	L	L	L	M	M	SELECT
24	M	M	L	L	L	M	H	SELECT
25	M	H	L	L	L	M	M	SELECT
26	M	H	L	L	L	M	H	SELECT
27	M	L	M	L	L	M	M	SELECT
28	M	L	M	L	L	M	H	SELECT
29	M	L	H	L	L	M	M	SELECT
30	M	L	H	L	L	M	H	SELECT
31	M	L	L	H	L	M	M	NSELECT
32	M	L	L	H	L	M	H	NSELECT
33	M	L	L	L	L	M	M	NSELECT
34	M	L	L	L	L	M	H	SELECT
35	H	L	L	L	L	M	M	NSELECT
36	H	L	L	L	L	M	H	NSELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
37	H	M	L	L	L	M	M	NSELECT
38	H	M	L	L	L	M	H	SELECT
39	H	H	L	L	L	M	M	NSELECT
40	H	H	L	L	L	M	H	SELECT
41	H	L	M	L	L	M	M	NSELECT
42	H	L	M	L	L	M	H	NSELECT
43	H	L	L	M	L	M	M	NSELECT
44	H	L	L	M	L	M	H	NSELECT
45	H	L	L	H	L	M	M	NSELECT
46	H	L	L	H	L	M	H	SELECT
47	H	L	L	L	M	M	M	NSELECT
48	H	L	L	L	M	M	H	NSELECT
49	M	L	M	M	M	M	M	NSELECT
50	M	L	M	M	M	M	H	SELECT
51	M	H	M	M	M	M	M	SELECT
52	M	H	M	M	M	M	H	SELECT
53	M	M	L	M	M	M	M	NSELECT
54	M	M	L	M	M	M	H	SELECT
55	M	M	H	M	M	M	M	NSELECT
56	M	M	H	M	M	M	H	SELECT
57	M	M	M	L	M	M	M	NSELECT
58	M	M	M	L	M	M	H	SELECT
59	M	M	M	H	M	M	M	NSELECT
60	M	M	M	H	M	M	H	NSELECT
61	M	M	M	M	L	M	M	NSELECT
62	M	M	M	M	L	M	H	SELECT
63	M	M	M	M	H	M	M	NSELECT
64	M	M	M	M	H	M	H	SELECT
65	L	M	M	M	M	M	M	SELECT
66	L	M	M	M	M	M	H	SELECT
67	M	M	M	M	M	M	M	NSELECT
68	M	M	M	M	M	M	H	SELECT
69	H	M	M	M	M	M	M	NSELECT
70	H	M	M	M	M	M	H	NSELECT
71	H	L	H	H	H	M	M	NSELECT
72	H	L	H	H	H	M	H	NSELECT
73	H	H	H	H	H	M	M	NSELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
74	H	H	H	H	H	M	H	SELECT
75	H	H	L	H	H	M	M	SELECT
76	H	H	L	H	H	M	H	SELECT
77	H	H	M	H	H	M	M	NSELECT
78	H	H	M	H	H	M	H	SELECT
79	H	H	H	L	H	M	M	NSELECT
80	H	H	H	L	H	M	H	NSELECT
81	H	H	H	M	H	M	M	NSELECT
82	H	H	H	M	H	M	H	SELECT
83	H	H	H	H	L	M	M	NSELECT
84	H	H	H	H	L	M	H	NSELECT
85	H	H	H	H	M	M	M	NSELECT
86	H	H	H	H	M	M	H	SELECT
87	L	H	H	H	H	M	M	SELECT
88	L	H	H	H	H	M	H	SELECT
89	M	H	H	H	H	M	M	SELECT
90	M	H	H	H	H	M	H	SELECT
91	H	H	H	H	H	M	M	NSELECT
92	H	H	H	H	H	M	H	SELECT
93	M	M	L	L	L	M	M	NSELECT
94	M	M	L	L	L	M	H	SELECT
95	H	H	L	L	L	M	M	NSELECT
96	H	H	L	L	L	M	H	NSELECT
97	L	L	M	M	L	M	M	NSELECT
98	L	L	M	M	L	M	H	SELECT
99	L	L	H	H	L	M	M	NSELECT
100	L	L	H	H	L	M	H	NSELECT
101	M	L	M	L	L	M	M	NSELECT
102	M	L	M	L	L	M	H	SELECT
103	H	L	H	L	L	M	M	NSELECT
104	H	L	H	L	L	M	H	NSELECT
105	M	L	L	M	L	M	M	NSELECT
106	M	L	L	M	L	M	H	SELECT
107	H	L	L	H	L	M	M	NSELECT
108	H	L	L	H	L	M	H	NSELECT
109	M	L	L	L	M	M	M	NSELECT
110	M	L	L	L	M	M	H	SELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
111	H	L	L	L	H	M	M	NSELECT
112	H	L	L	L	H	M	H	NSELECT
113	L	M	M	L	L	M	M	SELECT
114	L	M	M	L	L	M	H	SELECT
115	L	H	H	L	L	M	M	SELECT
116	L	H	H	L	L	M	H	SELECT
117	L	M	L	M	L	M	M	SELECT
118	L	M	L	M	L	M	H	SELECT
119	L	H	L	H	L	M	M	SELECT
120	L	H	L	H	L	M	H	SELECT
121	L	M	L	L	M	M	M	SELECT
122	L	M	L	L	M	M	H	SELECT
123	L	H	L	L	H	M	M	SELECT
124	L	H	L	L	H	M	H	SELECT
125	L	L	M	L	M	M	M	NSELECT
126	L	L	M	L	M	M	H	SELECT
127	L	L	H	L	H	M	M	NSELECT
128	L	L	H	L	H	M	H	SELECT
129	L	L	L	M	M	M	M	NSELECT
130	L	L	L	M	M	M	H	SELECT
131	L	L	L	H	H	M	M	NSELECT
132	L	L	L	H	H	M	H	SELECT
133	M	M	M	L	L	M	M	SELECT
134	M	M	M	L	L	M	H	SELECT
135	H	H	H	L	L	M	M	SELECT
136	H	H	H	L	L	M	H	SELECT
137	M	M	L	M	L	M	M	SELECT
138	M	M	L	M	L	M	H	SELECT
139	M	M	L	L	M	M	M	SELECT
140	M	M	L	L	M	M	H	SELECT
141	H	H	L	L	H	M	M	SELECT
142	H	H	L	L	H	M	H	SELECT
143	L	M	M	M	L	M	M	SELECT
144	L	M	M	M	L	M	H	SELECT
145	L	H	H	H	L	M	M	SELECT
146	L	H	H	H	L	M	H	SELECT
147	L	M	M	L	M	M	M	SELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
148	L	M	M	L	M	M	H	SELECT
149	L	H	H	L	H	M	M	SELECT
150	L	H	H	L	H	M	H	SELECT
151	L	H	L	H	H	M	M	SELECT
152	L	H	L	H	H	M	H	SELECT
153	L	L	M	M	M	M	M	NSELECT
154	L	L	M	M	M	M	H	SELECT
155	L	L	H	H	H	M	M	NSELECT
156	L	L	H	H	H	M	H	SELECT
157	M	L	L	M	M	M	M	NSELECT
158	M	L	L	M	M	M	H	SELECT
159	H	L	L	H	H	M	M	NSELECT
160	H	L	L	H	H	M	H	NSELECT
161	M	M	M	M	L	M	M	SELECT
162	M	M	M	M	L	M	H	SELECT
163	H	H	H	H	L	M	M	SELECT
164	H	H	H	H	L	M	H	SELECT
165	M	M	M	L	M	M	M	SELECT
166	M	M	M	L	M	M	H	SELECT
167	H	H	H	L	H	M	M	SELECT
168	H	H	H	L	H	M	H	SELECT
169	L	M	M	M	M	M	M	SELECT
170	L	M	M	M	M	M	H	SELECT
171	H	L	M	M	M	M	M	NSELECT
172	H	L	M	M	M	M	H	NSELECT
173	H	H	M	M	M	M	M	SELECT
174	H	H	M	M	M	M	H	SELECT
175	L	M	H	H	H	M	M	SELECT
176	L	M	H	H	H	M	H	SELECT
177	M	L	H	H	H	M	M	NSELECT
178	M	L	H	H	H	M	H	SELECT
179	M	M	H	H	H	M	M	SELECT
180	M	M	H	H	H	M	H	SELECT
181	L	H	L	H	M	M	M	SELECT
182	L	H	L	H	M	M	H	SELECT
183	L	M	L	M	H	M	M	SELECT
184	L	M	L	M	H	M	H	SELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
185	M	L	M	L	H	M	M	NSELECT
186	M	L	M	L	H	M	H	SELECT
187	M	L	M	L	M	M	M	NSELECT
188	M	L	M	L	M	M	H	SELECT
189	H	L	H	L	M	M	M	NSELECT
190	H	L	H	L	M	M	H	NSELECT
191	H	L	H	L	H	M	M	NSELECT
192	H	L	H	L	H	M	H	SELECT
193	H	M	H	M	L	M	M	NSELECT
194	H	M	H	M	L	M	H	SELECT
195	H	M	H	M	H	M	M	NSELECT
196	H	M	H	M	H	M	H	SELECT
197	H	M	H	M	M	M	M	SELECT
198	H	M	H	M	M	M	H	SELECT
199	M	H	L	L	L	M	M	SELECT
200	M	H	L	L	L	M	H	SELECT
201	M	H	L	L	M	M	M	SELECT
202	M	H	L	L	M	M	H	SELECT
203	M	H	L	L	H	M	M	SELECT
204	M	H	L	L	H	M	H	SELECT
205	M	H	M	M	L	M	M	SELECT
206	M	H	M	M	L	M	H	SELECT
207	M	H	M	M	H	M	M	SELECT
208	M	H	M	M	H	M	H	SELECT
209	M	H	H	H	L	M	M	SELECT
210	M	H	H	H	L	M	H	SELECT
211	M	H	H	H	M	M	M	SELECT
212	M	H	H	H	M	M	H	SELECT
213	M	H	L	M	M	M	M	SELECT
214	M	H	L	M	M	M	H	SELECT
215	M	H	L	H	H	M	M	SELECT
216	M	H	L	H	H	M	H	SELECT
217	M	H	M	L	L	M	M	SELECT
218	M	H	M	L	L	M	H	SELECT
219	M	H	M	H	H	M	M	SELECT
220	M	H	M	H	H	M	H	SELECT
221	M	H	M	H	M	M	M	SELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
222	M	H	M	H	M	M	H	SELECT
223	M	H	L	M	H	M	M	SELECT
224	M	H	L	M	H	M	H	SELECT
225	M	H	H	L	M	M	M	SELECT
226	M	H	H	L	M	M	H	SELECT
227	M	H	M	H	L	M	M	NSELECT
228	M	H	M	H	L	M	H	SELECT
229	M	H	L	H	M	M	M	NSELECT
230	M	H	L	H	M	M	H	SELECT
231	M	H	M	H	L	M	M	SELECT
232	M	H	M	H	L	M	H	SELECT
233	M	H	M	H	M	M	M	NSELECT
234	M	H	M	H	M	M	H	SELECT
235	M	H	M	H	H	M	M	NSELECT
236	M	H	M	H	H	M	H	SELECT
237	H	M	L	L	M	M	M	NSELECT
238	H	M	L	L	M	M	H	SELECT
239	H	M	L	L	H	M	M	NSELECT
240	H	M	L	L	H	M	H	SELECT
241	H	M	L	M	M	M	M	NSELECT
242	H	M	L	M	M	M	H	SELECT
243	H	M	L	H	H	M	M	NSELECT
244	H	M	L	H	H	M	H	SELECT
245	H	M	L	M	H	M	M	NSELECT
246	H	M	L	M	H	M	H	SELECT
247	H	M	L	H	M	M	M	NSELECT
248	H	M	L	H	M	M	H	NSELECT
249	H	M	M	M	L	M	M	NSELECT
250	H	M	M	M	L	M	H	NSELECT
251	H	M	M	M	H	M	M	NSELECT
252	H	M	M	M	H	M	H	SELECT
253	H	M	M	L	L	M	M	NSELECT
254	H	M	M	L	L	M	H	SELECT
255	H	M	M	H	H	M	M	NSELECT
256	H	M	M	H	H	M	H	SELECT
257	H	M	M	L	H	M	M	NSELECT
258	H	M	M	L	H	M	H	SELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
259	H	M	M	H	L	M	M	NSELECT
260	H	M	M	H	L	M	H	NSELECT
261	H	M	H	H	L	M	M	NSELECT
262	H	M	H	H	L	M	H	SELECT
263	H	M	H	H	M	M	M	NSELECT
264	H	M	H	H	M	M	H	SELECT
265	H	M	H	L	L	M	M	NSELECT
266	H	M	H	L	L	M	H	SELECT
267	H	M	H	L	M	M	M	NSELECT
268	H	M	H	L	M	M	H	SELECT
269	L	H	L	L	M	M	M	SELECT
270	L	H	L	L	M	M	H	SELECT
271	L	H	L	M	M	M	M	SELECT
272	L	H	L	M	M	M	H	SELECT
273	L	H	L	M	H	M	M	SELECT
274	L	H	L	M	H	M	H	SELECT
275	L	H	M	M	L	M	M	SELECT
276	L	H	M	M	L	M	H	SELECT
277	L	H	M	M	H	M	M	SELECT
278	L	H	M	M	H	M	H	SELECT
279	L	H	M	L	L	M	M	SELECT
280	L	H	M	L	L	M	H	SELECT
281	L	H	M	H	H	M	M	SELECT
282	L	H	M	H	H	M	H	SELECT
283	L	H	M	L	H	M	M	SELECT
284	L	H	M	L	H	M	H	SELECT
285	L	H	M	H	L	M	M	NSELECT
286	L	H	M	H	L	M	H	SELECT
287	L	H	H	H	M	M	M	SELECT
288	L	H	H	H	M	M	H	SELECT
289	L	H	H	M	M	M	M	SELECT
290	L	H	H	M	M	M	H	SELECT
291	L	H	H	L	M	M	M	SELECT
292	L	H	H	L	M	M	H	SELECT
293	L	H	H	M	L	M	M	SELECT
294	L	H	H	M	L	M	H	SELECT
295	H	M	H	L	H	M	M	NSELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
296	H	M	H	L	H	M	H	NSELECT
297	H	M	M	H	M	M	M	NSELECT
298	H	M	M	H	M	M	H	NSELECT
299	H	M	L	H	L	M	M	NSELECT
300	H	M	L	H	L	M	H	NSELECT
301	M	H	H	M	H	M	M	SELECT
302	M	H	H	M	H	M	H	SELECT
303	M	H	L	H	L	M	M	NSELECT
304	M	H	L	H	L	M	H	SELECT
305	M	H	M	H	M	M	M	SELECT
306	M	H	M	H	M	M	H	SELECT
307	M	H	H	L	H	M	M	SELECT
308	M	H	H	L	H	M	H	SELECT
309	M	L	L	M	H	M	M	NSELECT
310	M	L	L	M	H	M	H	NSELECT
311	M	L	L	H	M	M	M	NSELECT
312	M	L	L	H	M	M	H	NSELECT
313	M	L	M	M	L	M	M	SELECT
314	M	L	M	M	L	M	H	SELECT
315	M	L	M	M	H	M	M	NSELECT
316	M	L	M	M	H	M	H	SELECT
317	M	L	M	H	H	M	M	NSELECT
318	M	L	M	H	H	M	H	NSELECT
319	M	L	M	H	L	M	M	NSELECT
320	M	L	M	H	L	M	H	NSELECT
321	M	L	H	H	L	M	M	NSELECT
322	M	L	H	H	L	M	H	NSELECT
323	M	L	H	M	L	M	M	NSELECT
324	M	L	H	M	L	M	H	NSELECT
325	H	L	L	M	M	M	M	NSELECT
326	H	L	L	M	M	M	H	NSELECT
327	H	L	L	M	H	M	M	NSELECT
328	H	L	L	M	H	M	H	NSELECT
329	H	L	L	H	M	M	M	NSELECT
330	H	L	L	H	M	M	H	NSELECT
331	H	L	M	M	L	M	M	NSELECT
332	H	L	M	M	L	M	H	SELECT

Rule base used by traditional fuzzy reasoning for predicting outputs (continued)

Sl no.	*Cost*	*Battery backup*	*Rear camera*	*Weight*	*Screen size*	*Memory*	*Operating system*	*Output*
333	H	L	M	M	H	M	M	SELECT
334	H	L	M	M	H	M	H	SELECT
335	H	L	M	H	L	M	M	NSELECT
336	H	L	M	H	L	M	H	SELECT
337	H	L	H	H	L	M	M	NSELECT
338	H	L	H	H	L	M	H	SELECT
339	H	L	H	H	M	M	M	NSELECT
340	H	L	H	H	M	M	H	SELECT
341	H	L	H	M	M	M	M	NSELECT
342	H	L	H	M	M	M	H	SELECT
343	H	L	M	H	H	M	M	NSELECT
344	H	L	M	H	H	M	H	SELECT

Appendix B

Questionnaire

Please tick on the appropriate answer (range) you consider for purchasing mobile phones

1 Cost*

a) 2–5 b) 5–8 c) 8–12 d) 12–15

2 Camera

a) 2 mp b) 5 mp c) 8 mp d) 16 mp

3 Talk Time

a) 5 hr b) 10 hr c) 15 hr d) 20 hr

4 Size

a) 4 inch b) 4.5 inch c) 5 inch d) 5.5 inch

5 Weight

a) Very low b) Low c) Medium d) High

6 Memory

a) 2 gb b) 4 gb c) 8 gb d) 16 gb

7 Operating system

a) Jelly bean b) Kitkat c) Lollipop d) Marshmallow

Note: *All ranges are in thousands.