Influence of mood states on information processing during decision making using fuzzy reasoning tool and neuro-fuzzy system based on Mamdani approach

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Abstract: This study provides a comparison between traditional fuzzy reasoning tools and a neuro-fuzzy system, both developed based on Mamdani approach in order to determine the influence of mood states on information processing during decision making. To begin, participants responded to questions on positive and negative prospects involving gains and losses on a health risk problem and explained the reasons for their decisions in writing. Three independent input variables, namely flexibility, originality and fluency were then derived from the participants' reasons for their choices. Four linguistic terms, such as low, medium, high and very high were used to represent each of the input variables. Using Mamdani's approach, both traditional fuzzy reasoning tool and a neuro-fuzzy system were designed for a three-input, one-output process. The neuro-fuzzy system was trained using a back-propagation algorithm. Compared to the traditional fuzzy reasoning tool, the neuro-fuzzy system could provide better results.

Keywords: information processing; fuzzy logic; neuro-fuzzy system; flexibility; fluency; originality.

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1 Introduction

Decision making (DM) is the process of choosing from a set of options. It is a fundamental aspect of everyday mental processes. Decisions are often made under conditions of uncertainty, when the payoffs are probabilistic and unknown. The study of DM has been approached from different perspectives, including philosophical, behavioural, biological, mathematical and computational, yet a large number of challenges remain in understanding this important function of higher cognition.

A cognitive process, such as thinking, understanding, language recognition, attention, memory, and DM could not be accurately understood without including emotional influences on these processes. Emotions are action-oriented in nature and are elicited in response to certain objects, persons or situations. On the contrary, moods are used to describe pervasive emotions, are less intense than emotions, lack a contextual stimulus, and fluctuate regularly from moment to moment, hour to hour, and day to day (George, 1989). Moods do not interrupt cognitive processes and behaviours; instead they tend to gently redirect ongoing thinking and behaviour (Watson and Pennebaker, 1989). People experiencing a positive mood state tends to recall positive words, evaluations, personal experiences and events. The reverse is true, when people are in a negative mood state (Clore and Huntsinger, 2009).

The term 'affect' and 'emotion' are used interchangeably (Gray and Watson, 2007). Emotions, characterised as the positive and the negative affect, are based on their nature and functions. Positive affect associated with certainty (less risk) would result in heuristic information processing, and negative affect associated with uncertainty (more risk) would result in systematic information processing. Evidence suggests that a negative affect leads to labour-intensive, focused, and systematic information processing, and less error in decision-making, and a positive affect does the reverse (Baron et al., 1994).

Two main decision-making processes are identified: first the generation of alternatives, which represent the most creativity-oriented process, and second, the evaluation of alternatives, which represent the analytical dimension of decision-making. The most recent cognitive/affectivity theories and research demonstrate that moods have a considerable impact on memory, evaluative judgments, and cognitive processing style (Forgas, 2006).

An individual evaluating available information from his/her memory is called local information processing and it is top-down information processing. An individual collects the information from surroundings, stores the information in memory, and compiles the information and finally makes the decision. This is called global information processing and is the bottom-up processing. Promotive focus is linked to global processing and preventive focus is linked to local processing. As mentioned above, heuristic processing requires less effort and involves the use of shortcuts to arrive at a decision (Chaiken et al., 1989). Decisions formed on the basis of heuristic processing reflect easily processed heuristic cue information, rather than particularistic information (Higgins, 1996) and can be equated with local processing. Contrarily, systematic processing is comprehensive, involves greater cognitive effort to reach a decision, and results in greater comprehension and memory formation (Petty and Cacioppo, 1986). This can be equated with global processing.

Human beings make decisions or solve problems having complex, imprecise, large-scale objects; fuzzy set theory (FST) is effective for creating approximate models for carrying out intelligent information processing for DM. Fuzzy logic has been applied to many fields, from control theory to computational intelligence. Variables in mathematics usually take numerical values, while in fuzzy logic applications the non-numeric linguistic variables (Zadeh, 1975) are used. These linguistic variables facilitate the expression of rules and facts (Zadeh, 1996a). In day-to-day lives' language interaction, no sharp concepts are used and the boundaries of concepts are vague. Fuzzy logic (Zadeh, 1996b) provides a tool to model this vagueness and it is possible to analyse and describe complex systems of linguistic terms in numerical values (Yager and Zadeh, 1992).

Fuzzy concepts together with cognition which is expressed in the form of rules suggest the use of a fuzzy logic rule base system for the modelling of cognition. Actually, it has been shown in FLAME (EI-Naser 2000) that cognitive processes can be expressed perfectly in this way, as concepts as well as the appraisal rules expressed using fuzzy logic and fuzzy rules, respectively, to map events and expectations to mood states because mood states influence DM and information processing. Fuzzy logic can provide an elegant way to model the information that makes up a choice in a DM task.

The choice made up from information arising from human thought and cognitive processes has been an important aspect in the information processing literature since the inception of fuzzy logic/FST by Zadeh (1965). Making decisions is a part of our daily lives, one major concern is that many of the DM problems in the real-world take place in an environment, in which the goals and/or criteria are usually in conflict with each other and are not stated precisely. The ability to make the best possible output (decision) based on past and present information and input (future prediction) is a difficult task. A tool that can assist this task will be of great help for decision makers (Malakooti and Zhou, 1994).

Research that attempts to model uncertainty into DM is basically done through probability theory and/or FST. The former presents the stochastic nature of DM, while the latter captures the subjectivity of human information processing. It is suggested by

Wang and Mendel (1992), Gupta (1991) and Dubois (1985) that a stochastic decision method, such as statistical DM does not measure the imprecision in human behaviour, rather, this method is a way to model incomplete knowledge about the external environment surrounding human beings. On the other hand, FST is a perfect means for modelling uncertainty or imprecision arising from mental phenomena, which are neither random nor stochastic. Human beings are heavily involved in the process of DM. A rational approach toward DM takes into account human subjectivity, rather than employing only objective probability measures. FST provides both an adequate conceptual framework as well as a mathematical tool to account for imprecision, such as ambiguity and vagueness. In DM, FST can place a possibility restriction on the class of events, which satisfies a statement. This restriction is then represented through a set with a graded membership, such that any event has a degree of membership in the set defining the extent to which it is consistent with the possibility restriction.

In this paper, FST is applied to quantify the linguistic variable in terms of imprecise information for DM under uncertainty having

a fuzzy input variables like flexibility, fluency, and originality

b linguistic terms like low (L), medium (M), high (H) and very high (VH).

It was found that fuzzy logic controller (FLC) is robust in the presence of perturbations, easy to design and implement. An FLC may be developed through a systematic approach for determining the knowledge base, which consists of membership function distributions of the variables (that is, data base) and rule base. Numerous methods have been suggested for developing fuzzy reasoning tool like Mamdani approach (Mamdani and Assilian, 1975), Takagi and Sugeno's (1983) approach. Gradient descent method was also used for fuzzy rule generation (Nomura et al., 1992). Reinforcement learning technique had been utilised for determining a good rule base (Fukuda et al., 1995). Moreover, many researchers had attempted to generate the rule base for fuzzy reasoning tool by using neural networks (Nauck et al., 1993; Takagi and Hayashi, 1991). In this study, conventional fuzzy reasoning tool and neuro-fuzzy approach (both designed according to Mamdani approach) had been developed to build the desired mapping between the perception of human knowledge and the decision influenced by mood state.

The paper is organised as follows: in Section 2, participants' profile, questionnaire, and dependent variable used in the experiment are explained. In Section 3, we describe the fuzzy rule-based system (FRBS). In Section 4, we mentioned the working principle of traditional FLC. In Section 5, we computed information processing with neuro-fuzzy system, finally in Section 6, conclusions and suggestions for future research are provided.

2 Method

2.1 Participants

With the permission of the class teacher, undergraduate engineering and postgraduate engineering and management students from the Indian Institute of Technology, Kharagpur, India, were contacted in the classroom. The students were informed about the purpose of the experiment. The 200 individuals, who agreed to participate and who signed the informed consent form were randomly allocated to one of two groups: the positive mood-induced group and negative mood-induced group. The positive and negative moods were induced showing comedy and tragedy movie clips respectively. Each group of 100 participants contained an almost equal number of males and females. The experiment was carried out over eight sessions. About 20 to 30 students participated in each session and each session lasted for 1 hour and 15 minutes.

2.2 Decision under uncertainty

Five problems in the questionnaire assessed a choice under uncertainty. These questions contained two positive and one negative hypothetical prospects, and two health risk situations. Every situation had two alternatives: A and B. The participants were asked to choose one alternative in each situation indicating their preferences (Table 1).

Table 1 Questionnaire

1 Positive prospect (Tversky and Kahneman, 1976)	
A: You can win Rs.25,000 with probability .33	B: You can win Rs.20,000 with certainty
Rs.24,000 with probability .66	
0 with probability .01	
2 Positive prospect (Tversky and Kahneman, 1976)	
A: You can win Rs.25,000 with probability .33	B: You can win Rs.24,000 with probability .34 0 with probability .66
0 with probability .67	
3 Negative prospect (Tversky and Kahneman, 1976)	
A: You can lose Rs.40,000 with probability .80	B: You can lose Rs.30,000 with certainty
0 with probability .20	
4 Health situation (Tversky and Kahneman, 1976)	
Consider the following two frames (survival and mortality) in each frame two alternative treatments exist. Please indicate the frame as well as treatment you would prefer.	
Survival frame	
Surgery (A): Of 100 people having surgery, 90 live through the post-operative period, 58 are alive at the end of the first year, and 32 are alive at the end of five years.	Radiation therapy (B): Of 100 people having radiation therapy all live through the treatment, 77 are alive at the end of one year, and 23 are alive at the end of five years.
Mortality frame	
Surgery (A): Of 100 people having surgery, 10 die during surgery of the post-operative period; 30 die by the end of the first year and 60 die by the end of five years.	Radiation therapy (B): Of 100 people having radiation therapy, none dies during treatment, 22 die by the end of one year and 78 die by the end of five years.

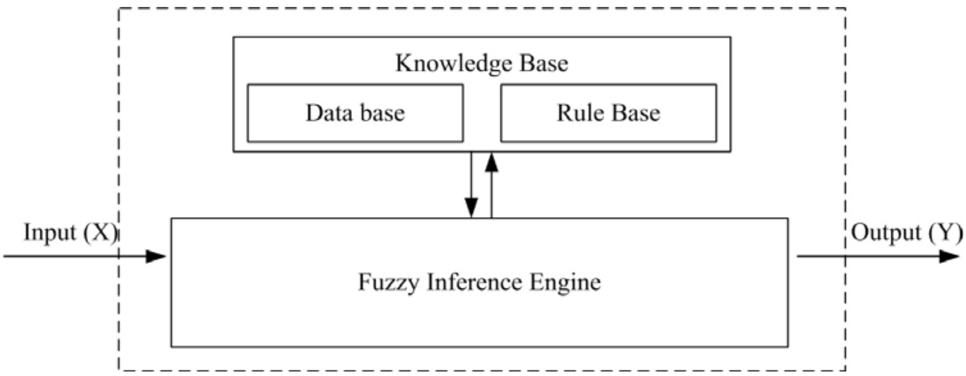
2.3 Measuring the variables: flexibility, fluency and originality

For each problem, the participants were asked to describe and explain up to 100 words, why they preferred that choice, using the space provided after each problem. After collecting the questionnaires, one expert in communication and another in management evaluated the participants' written explanations to each problem for the dimensions of fluency (production of ideas), originality (uniqueness of ideas), and flexibility (variety of ideas) on the basis of the number of arguments provided, the confidence in writing, and divergent thinking. Each dimension was measured on a ten-point scale, '0' representing an absence of the dimension and '10' indicating a complete presence of the dimension. Each expert evaluated the written statements of 100 participants.

3 Fuzzy rule-based systems

A knowledge base (KB) and inference engine (IE) are two main components of 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 inference engine 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.

3.1 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.

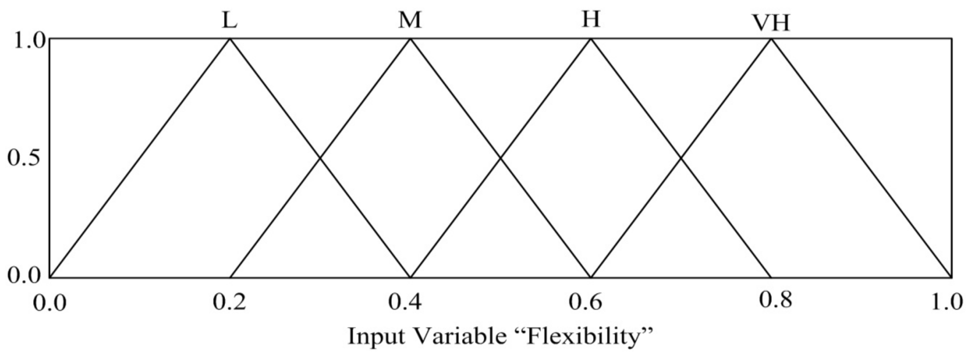
$$\alpha = \{(x, \mu_\alpha(x)) : x \in X\}.$$

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.

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{m-a}, & a < x \le m \\ \dfrac{b-x}{b-m}, & m < x < b \\ 0, & x \ge b \end{cases} \tag{1}$$

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.

Figure 2 Membership function distributions for the variables: V_1 = {flexibility}, V_2 = {fluency}, V_3 = {originality}



3.2 *Description of fuzzy input variables*

The input fuzzy variables were V_1 = {flexibility}, V_2 = {fluency} and V_3 = {originality}, and each of them was represented using four linguistic terms, such as *low* (*L*), *medium* (*M*), *high* (*H*) and *very high* (*VH*) (refer to Figure 2). The linguistic terms and their ranges are shown in Table 2.

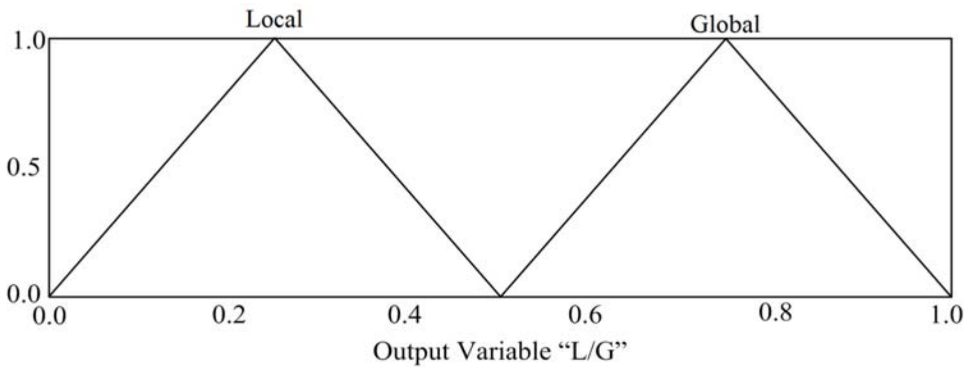
Table 2 Linguistic terms and their ranges for the variables: V_1 = {flexibility}, V_2 = {fluency}, V_3 = {originality}

Linguistic terms	*Membership function*	*Range of the parameter*
Low (L)	Trimf	[0.0, 0.4]
Medium (M)	Trimf	[0.2, 0.6]
High (H)	Trimf	[0.4, 0.8]
Very high (VH)	Trimf	[0.6, 1.0]

3.3 *Description of fuzzy output variable*

Two linguistic terms, namely local and global were used to represent the output variable: V_4 = {output} (refer to Figure 3). The Mamdani min-operator was utilised for aggregation and defuzzification was done using the centre of sums (COS) method (Pratihar, 2008).

Figure 3 Membership function distributions for output fuzzy variable: V_4 = {local/global}



3.4 *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, three input variables were considered and each of them was represented using four linguistic terms. Thus, there could be a maximum of rules in the FRBS.

For instance, the first and rules were as follows:

If V_1 is *L* AND V_2 is *L AND* V_3 is *L THEN output* is Local

and

If V_1 is *VH* AND V_2 is *VH AND* V_3 is *VH THEN output* is Global.

3.5 *Fuzzy rule encoding*

Three input variables and each having four linguistic terms constitute 64 rules. Linguistic terms are represented with their index values, as given in Table 2.

4 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, 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 label of fuzzy sets.

The rule base comprises of knowledge of the application domain by using the information of data base. Thus, the data base 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 inference engine of an FLC has the capability of simulating human decision-making 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, which is given below.

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

where $U'_{f'}$ is the output of the controller, $A(\alpha_j)$ 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.

5 Design and development of 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 knowledge base. 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:* Three variables, namely flexibility (v_1), fluency (v_2), and originality (v_3), 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, and v_3) was expressed using four linguistic terms (L: *low*, M: *medium*, H: *high*, and VH: *very 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 three inputs, the membership function distributions were assumed to be triangular.

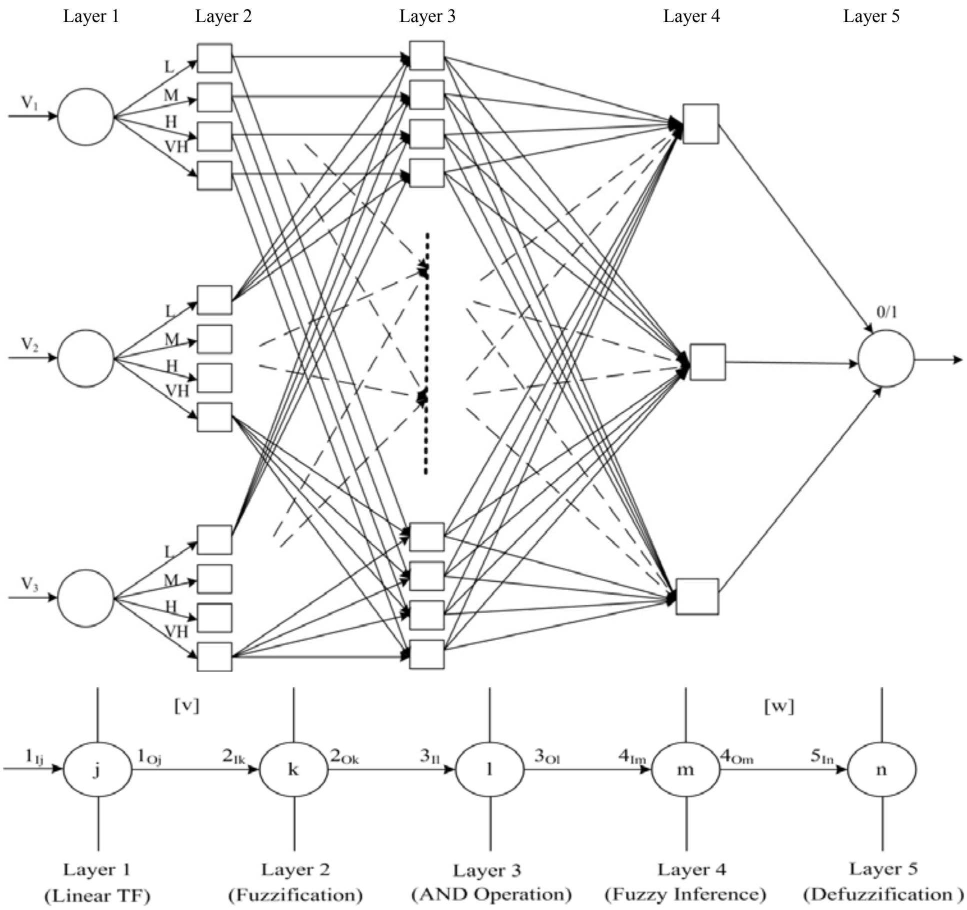
- *AND implementing layer:* This layer computes the task of original AND operation. Each neuron lying in this layer is connected to three neurons of the previous layer, as shown in Figure 4. Membership function values calculated in the previous layer were considered as the inputs of a particular neuron (say n^{th}) lying in this layer. These three membership function values were compared and the minimum of these three 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 three input variables, each having four 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 firth layers (refer to Figure 4) 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 in this study.

In this study, a neural network toolbox of Matlab 9 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 4 A schematic view of the neuro-fuzzy system based on Mamdani approach



Source: Pratihar (2008)

6 Results and discussion

The performances of traditional fuzzy reasoning tool and neuro-fuzzy system (both developed based on Mamdani approach) were measured using root mean square error and R^2 value. Results of both the methods are stated and discussed below.

6.1 Results of traditional fuzzy reasoning tools

Traditional fuzzy reasoning tool was developed using three inputs, namely flexibility, originality, and fluency, and each having four different responses (that is, low, medium, high, and very high). A set of 4 × 4 × 4 = 64 rules were designed manually, as shown in

Appendix. This method could identify 44 good rules (represented without using *) from a total of 64 rules for determining the output (refer to Appendix). The results of this approach are shown in Table 3 and graphically in Figure 5(a). The performance of this approach was tested on 64 cases.

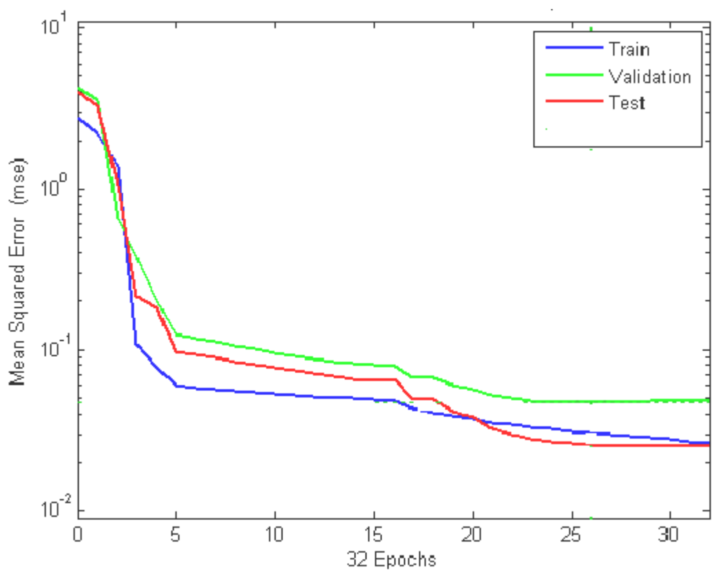
6.2 *Results of neuro-fuzzy approach*

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 on-line (that is, incremental) mode of training had been adopted. Out of a total of 64 data, 44, 10 and 10 were utilised for the training, validation and testing, respectively. The results of this approach are shown in Table 4 and graphically in Figure 5(b). It yielded better and more accurate results than the traditional fuzzy reasoning tool.

Table 3 Description of fuzzy linguistic terms

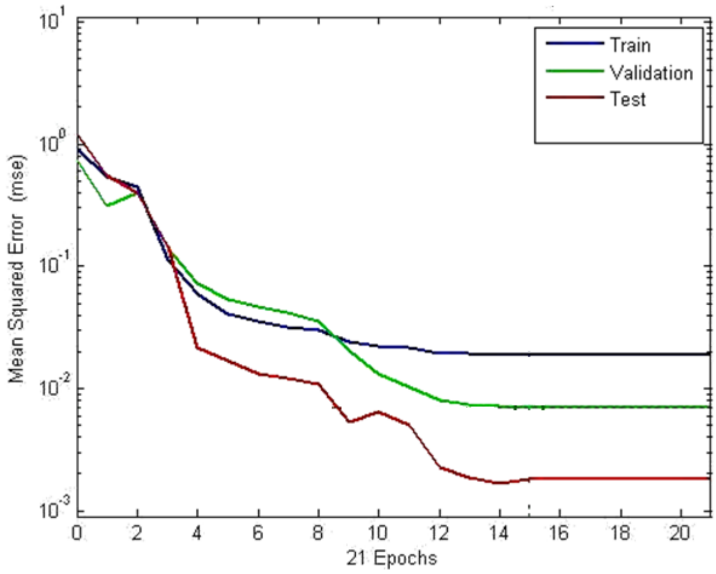
Abbreviation	*Expression*	*Index representation*
L	Low	0.2
M	Medium	0.4
H	High	0.6
VH	Very high	0.8

Figure 5 (a) Performance of traditional fuzzy logic (b) performance of neuro-fuzzy system (see online version for colours)



(a)

Figure 5 (a) Performance of traditional fuzzy logic (b) performance of neuro-fuzzy system (continued) (see online version for colours)



(b)

6.3 Accuracy in prediction of results by two 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 (Juang and Lin, 1998; George et al., 1976; Subramanian and Suresh, 2012) and regression coefficient (R^2). It is to be noted that RMSE was calculated as RMSE = $\sqrt{\frac{E^2(t)}{N}}$, where N indicates the total number of samples, $E(t)$ is the prediction error of t^{th} sample.

Results showed the advantages of using neuro-fuzzy system over traditional fuzzy reasoning tool, in terms of RMSE and R^2 values (refer to Table 4). The neuro-fuzzy approach was able to yield better results compared to the other approach, which is evident from Figures 5(a) and 5(b). It might have happened due to the reason that in the neuro-fuzzy system, the KB was tuned further with the help of some training scenarios.

Table 4 Comparison between fuzzy reasoning approach and neuro-fuzzy

Architectures	*Process*	*Sample*	*RMSE*	*R^2*
Neuro-fuzzy using Mamdani approach	Training set	44	0.0018	0.9220
	Testing set	10	0.0008	0.9920
	Validation	10	0.0070	0.9840
Fuzzy reasoning tool using Mamdani approach	Testing set	64	0.0046	0.8479

6.4 Influence of mood state on information processing during the DM

It was also observed during this study that the participants in a negative mood state retrieved and processed information in favour of their choices with more fluency, originality and flexibility than those in a positive mood. It suggests that a negative mood state facilitates systematic processing and a positive mood state promotes heuristic processing.

7 Discussion and conclusions

In this paper, we have analysed the influences of mood states 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 two approaches on ten test, 10 validation and 44 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 due to the reason that the neuro-fuzzy-based approach was able to optimise its knowledge base 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 three input variables were considered as independent variables, but in future, more than three 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 of mood states was studied on information processing during DM. Thus, uncertainty in DM was modeled using the concept of fuzzy sets. Three inputs and one output fuzzy reasoning tool was developed using Mamdani approach. This study would help to understand the mapping between the perception of human knowledge and the decision influenced by mood states.

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Appendix

Rule base used by traditional fuzzy reasoning tool for predicting outputs

Input parameters			*Output*	*Input parameters*			*Output*
Flexibility	*Originality*	*Fluency*	*Local/global*	*Flexibility*	*Originality*	*Fluency*	*Local/global*
L	L	L	L*	H	L	L	L*
L	L	M	L*	H	L	M	L*
L	L	H	L	H	L	H	G
L	L	VH	L	H	L	VH	G
L	M	L	L*	H	M	L	L*
L	M	M	L	H	M	M	G
L	M	H	L	H	M	M	G
L	M	VH	G	H	M	VH	G
L	H	L	L*	H	H	L	G*
L	H	M	L	H	H	M	G
L	H	H	G	H	H	H	G
L	H	VH	G	H	H	VH	G
L	VH	L	L*	H	VH	L	G*
L	VH	M	G	H	VH	M	G
L	VH	H	G	H	VH	H	G
L	VH	VH	G	H	VH	VH	G
M	L	L	L*	H	L	L	L*
M	L	M	L	VH	L	M	G
M	L	H	L	VH	L	H	G*
M	L	VH	G	VH	L	VH	G*
M	M	L	L*	VH	M	L	G*
M	M	M	G	VH	M	M	G
M	M	H	G	VH	M	H	G
M	M	VH	G	VH	M	VH	G
M	H	L	L*	VH	H	L	G*
M	H	M	G	VH	H	M	G
M	H	H	G	VH	H	H	G
M	H	VH	G	VH	H	VH	G
M	VH	L	G*	VH	VH	L	G*
M	VH	M	G	VH	VH	M	G
M	VH	H	G	VH	VH	H	G
M	VH	VH	G	VH	VH	VH	G

Note: *Indicating non-fired rule.