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SHORT COMMUNICATION

Expert Fuzzy Model for Avalanche Prediction

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ABSTRACT

It is imperative that the time required for the analysis and prediction of an extremely volatile event like avalanche needs to be reduced to the minimum. This is particularly critical because of the extremely fast and highly uncertain nature of the event itself. Another peculiar nature of such predictions is that these have to be based almost entirely on the long and intermediate-term data/information available, since there would hardly be any short-term warnings (unlike as in the case of a storm) that could point towards an imminent prediction. Both the above-mentioned factors favour adoption of such techniques of automated analysis, which are fast, accurate, and employable even under uncertain voids of information. Apart from empirical and statistical methods, one of the highly promising techniques for developing a practical model for prediction of avalanche is that based on rule-based expert systems. However, development of a realistic rule-based expert system based on conventional logic would imply that one has to firstly define the natural phenomenon being modelled at an extremely high resolution and accuracy. The process of defining a highly uncertain phenomenon like the avalanche at such high resolution, and thereafter, framing extensive rules for all the possibilities is likely to make the system extremely complex, and therefore, unmanageable in many ways. This study attempts to simplify this problem by proposing a simpler and better technique using an algorithm based on fuzzy logic. This algorithm has the potential to handle even highly complex phenomenon, like that of an avalanche in a fundamentally simple manner. Such potential makes it capable of handling the higher levels of details and still contains the complexity within the manageable limits. Additional details would also make the system more accurate and realistic.

Keywords: Avalanche prediction, fuzzification graph, expert system, expert fuzzy model, algorithm, avalanche prediction model, fuzzy logic

1. INTRODUCTION

Prediction of any natural event entails arriving at a conclusion regarding its time of occurrence as well as nature, based on logical analysis of all the information available on the circumstances leading to that event. Any organisation involved in the task of predicting the uncertain vagaries of nature would be faced with the task of making such conclusions out of an environment of high uncertainty. Apart from the same, of late, it has become feasible to acquire a vast databank of information from a variety of sensors as well as visual observations on a near real-time basis. It may be almost impossible to carry out manual assimilation of such a vast amount of data being continuously acquired by the automatic sensors. Manual analysis may also generate further inconsistencies due to factors, such as fatigue, contradiction of personal perceptions, etc. At the same time, prediction of a natural event would be most effective and accurate only if it is timely and based on the complete information available for analysis at any paint of time.

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2. AUTOMATED PREDICTIONS OF NATURAL SYSTEMS

2.1 Prediction of Natural Systems

All the predictions that one makes on a day-to-day basis are more or less derived from the various input factors regarding the environment that are known at that particular point of time. To analyse the predictability of an event based on a set of factors, one needs to figure out the relationship between such factors and the event itself. However, the vagaries of nature and the unpredictability of its events could, at times, seem highly intriguing. As is well known, the nature of all environmental systems is highly complex, which is one of the reasons why their prediction has, so far, remained more of an art and not entirely definable within a programmable set of logical rules. To organise an understandable sense out of the concept of natural systems, one may attempt to classify these into the following systems:

(a) Simple systems

(b) Feedback systems

(c) Random systems

2.1.1 *Simple Systems*

In simple systems, the outcome of an event is directly related to the known factors influencing that event. It is, therefore, possible to mathematically or empirically (based on data from the past events) relate the outcome with the input factors. In such cases, the outcomes are fairly predictable so long as the mathematical or empirical algorithm or formulae being used are realistic and correct.

2.1.2 *Feedback Systems*

In such systems the outcome of an event, though connected to a set of input factors, their relationship itself is far less predictable and unstable compared to simple systems. Feedback systems can be further divided into the following subsystems:

2.1.2.1 *Negative Feedback Systems*

In the negative feedback systems, the feedback of an input factor acts in such a way as to stabilise the system, i.e., in other words, it attempts to attain status quo. Therefore, even if an input event is highly significant in its apparent effect on the system, the transience introduced to the system due to the event tends to eventually taper off. This is similar to the way gravity acts upon a ripple created on the surface of water to ultimately cancel out the same.

2.1.2.2 *Positive Feedback Systems*

In the positive feedback, an apparently insignificant event may have a cascading effect on a set of events with a correspondingly unpredictable outcome, far more out of proportion, to the input event. Such systems are characteristically highly unstable and unpredictable. The transience setup by an event tends to feed on itself to blow totally out of proportion. This is similar to the way a slight shifting of a few ice crystals may lead to an avalanche. Positive feedback systems are extremely difficult to model due to their unpredictability. One of the intriguing positive feedback systems explainable through chaos theory is the butterfly effect. In this concept, it is believed that it may be possible through positive feedback of a series of events that an apparently insignificant transience in the atmosphere created by the flutter of a butterfly could snowball itself into a huge storm at a distant location.

2.1.3 *Random Systems*

In random systems, an event and its corresponding outcome are absolutely unrelated. The outcome may or may not be connected to the happening of the event, and if so, only in a random or unpredictable manner. Such systems are impossible to model by any means available and also ascribable to words like luck, grace of God, etc.

To automate a prediction system through mathematical modelling, it may be necessary that one takes all of the above-mentioned systems into consideration. Most of the present systems of modelling used in prediction of natural events are based on simple systems using empirical relationship1 algorithms. By introducing highly flexible concepts like fuzzy logic and neural network, one may attempt to model very few aspects of feedback systems also. Modelling random systems would still remain an impossible task to do. The attempt, therefore, would mean going a step further towards more realistic translation of the highly complex system of natural phenomenon. Some of the advantages of such automated prediction models are:

- It would help handle huge volume of sensor information on an almost real-time basis
- Speedy and timely predictions of avalanche dangers
- It would eliminate human errors in assessment of the situation
- A large number of factors, that would have been neglected otherwise, could be considered
- Collective experience, knowledge of expert committee, and historical analysis is used to carry out the gradation of factors and formulation of the rules. This would reduce the adverse effects of inexperience or poor knowledge of the avalanche expert committee to a great extent.

3. PROPOSED ALGORITHM FOR AVALANCHE PREDICTION MODEL

The basic structure of the algorithm based on fuzzy logic, attempts to explain the basic feasibility and logical flow of the proposed algorithm. Even though there is no limit to the number of input variables that could be considered by a computerised model, here, for the ease of explanation, the algorithm addresses only three most important input variables used for avalanche prediction. To use the algorithm in a realistic case, suitable weightage values have to be assigned to various membership functions of the input factors as well as rules thereafter, as per their importance. However, the weightages have also been disregarded for ease of explanation in the following example and all three factors and rules have been assumed to have equal weightage towards the outcome. The general block diagram of the algorithm is given in Fig. 1.

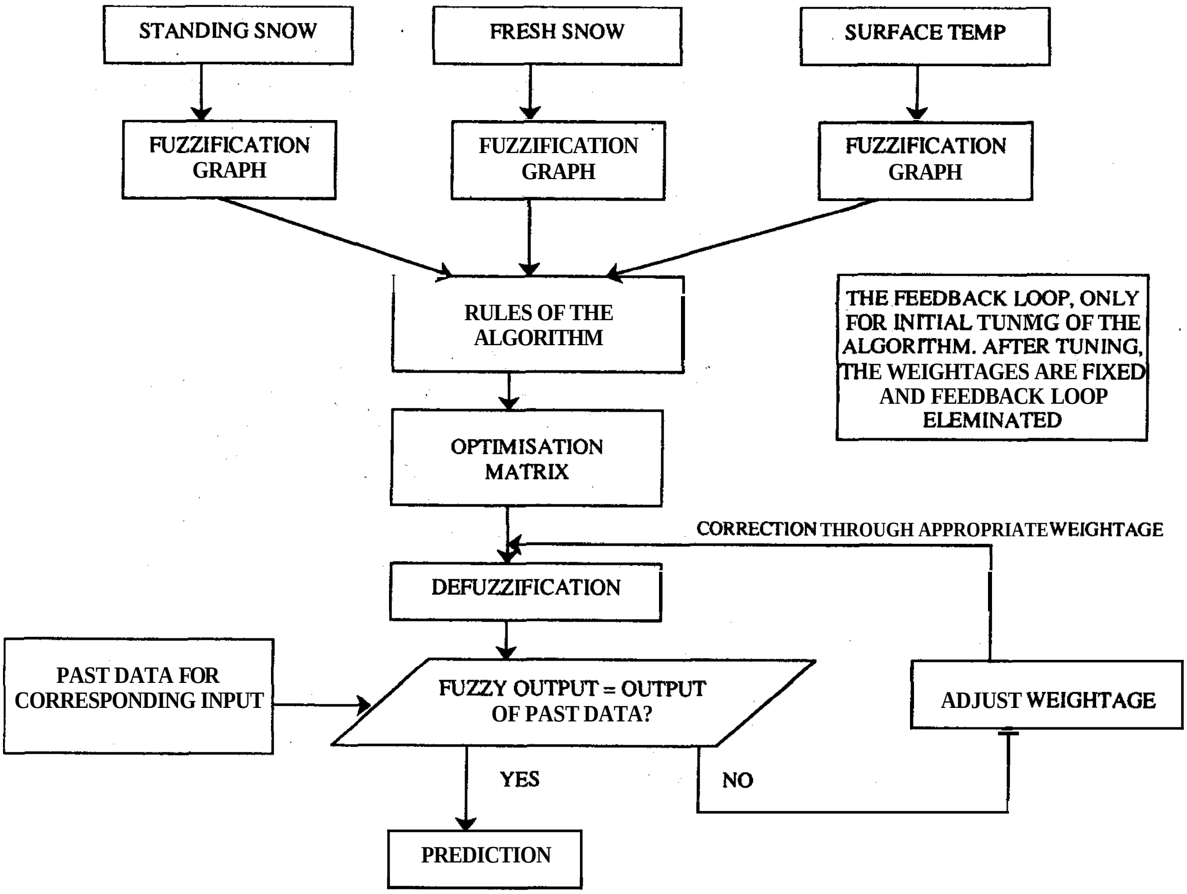

Figure 1. General block diagram of the algorithm for the prediction of an avalanche

4. FUZZIFICATION GRAPHS

The fuzzification graphs have to be made in consultation with the expert committee, since this actually translates the relationship between the variables and the membership values which would be used further in the rules. In the subject example, the complete fuzzification graph has been drawn keeping in mind the range of operation of the input variables as well as other values extrapolated from the two general points, **i.e.,** the point of low avalanche danger and the point of all-round avalanche danger.

4.1 Fuzzification Graph of Standing Snow

The points at which a given input variable (in this case standing snow) initiates low avalanche danger condition and all-round avalanche danger condition has to be arrived at, considering the influence of other two variables (in this case fresh snow and surface temperature) as negligible towards these conditions (Fig. 2).

4.2 Fuzzification Graph of Fresh Snow

The points at which a given input variable (in this case fresh snow) initiates low avalanche danger condition and all-round avalanche danger condition has to be arrived at, considering the influence of other two variables (in this case standing snow and surface temperature) as negligible towards these conditions (Fig. 3).

4.3 Fuzzification Graph of Snow Surface Temperature

The points at which a given input variable (in this case surface temperature) initiates low avalanche danger condition and all-round avalanche danger condition has to be arrived at, considering the influence of other two variables (in this case standing snow and fresh snow) as negligible towards these conditions (Fig. 4).

5. EXPERT RULES FOR PREDICTION

The rules have been developed using the fuzzy operator AND between various membership values obtained as a result of fuzzification. For example, standing snow (very high) is a membership value (between 0 and 1) of an input variable value of standing snow in the fuzzy range of very high in the graph. In this case, the fuzzy operator AND would return values, which are the minima within the set of membership values being considered in each rule as its output. These output are given as a numerical value (eg a,). The rule sets have been formulated as conditions under which a given event

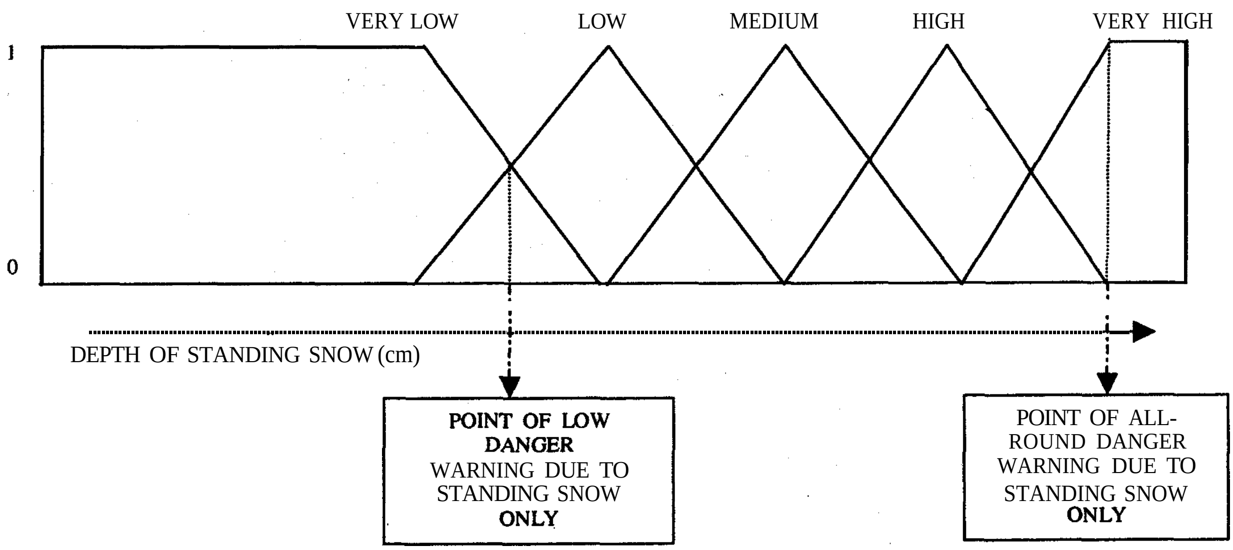

Figure 2. Fuzzification graph of the standing snow

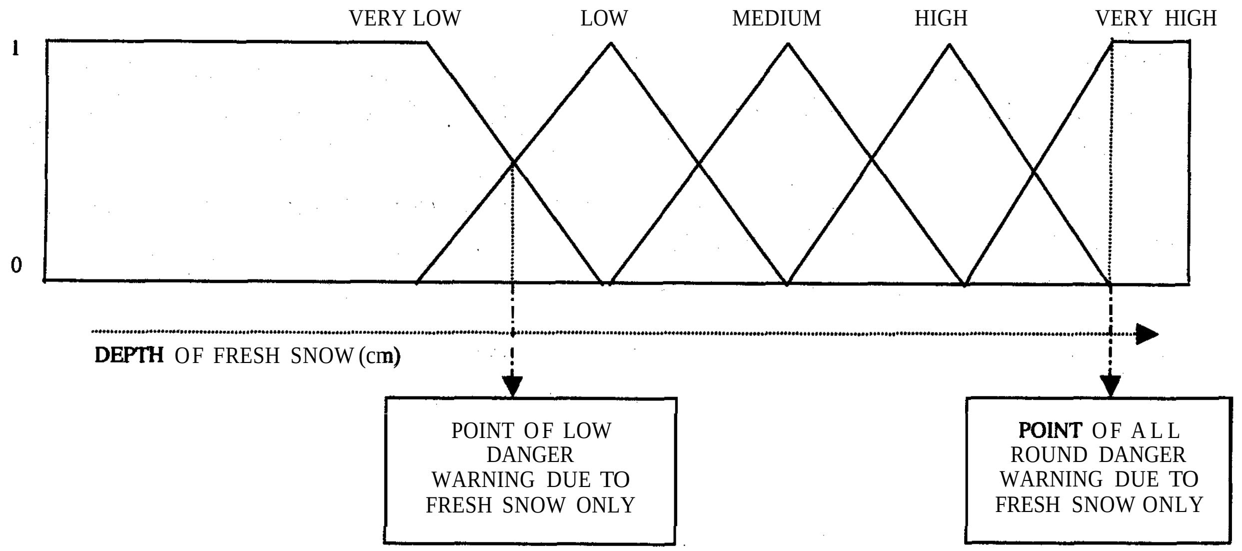

Figure 3. Fuzzification graph of fresh snow

may occur. Since, one wants the prediction in the form of five likely events, the complete set of rules has been classified into the following five groups, with each event being designated as a group:

(a) All-round avalanche danger
(b) High avalanche danger
(c) Medium avalanche danger
(d) Low avalanche danger
(e) No avalanche danger

5.1 Classification of Rules

5.1.1 Rules for All-round Avalanche Danger

- Standing snow (very high) = ***a*,**
- Fresh snow (very high) = ***a*,**
- Surface temperature (very high) = a,
- Standing snow (high) AND fresh snow (high) = a,

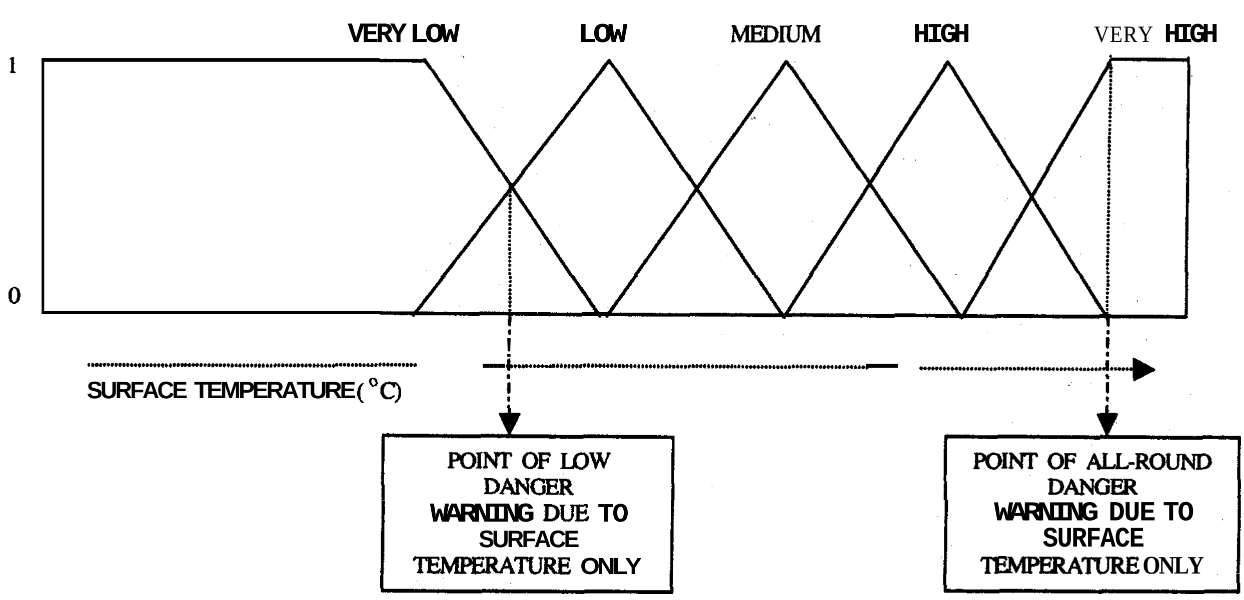

Figure 4. Fuzzification graph of snow surface temperature

- Standing snow (high) **AND** surface temperature (high) = *a*,
- Fresh snow (high) **AND** surface temperature (high) = *a*,
- Standing snow (high) **AND** fresh snow (medium) **AND** surface temperature (medium) = *a*,
- Standing snow (medium) **AND** fresh snow (high) **AND** surface temperature (medium) = *a*,

Standing snow (medium) **AND** fresh snow (medium) **AND** surface temperature (high) = *a*,

- Standing snow (medium) **AND** fresh snow (medium) **AND** surface temperature (medium) = *a*,,

5.1.1.1 Rule Set for All-round Avalanche Danger

Rule set for all-round avalanche danger = {*R*,,, R_{a2}, ..., R_{a10}}, where $R_{ai} = a_i$ if $a_i \neq 0$ or $R_{ai} = 1$, if $a_i = 0$ with $i = 1$ to 10.

5.1.2 Rules for High Avalanche Danger

- Standing snow (high) = *b*,
- Fresh snow (high) = b_2
- Surface temperature (high) = b_3
- Standing snow (medium) AND fresh snow (medium) = b_4
- Standing snow (medium) **AND** surface temperature (medium) = b_5
- Fresh snow (medium) AND surface temperature (medium) = b_6
- Standing snow (medium) **AND** fresh snow (low) **AND** surface temperature (low) = b_7
- Standing snow (low) AND fresh snow (medium) **AND** surface temperature (low) = b_8
- Standing snow (low) **AND** fresh snow (low) **AND** surface temperature (medium) = *b*,
- Standing snow (low) **AND** fresh snow (low) **AND** surface temperature (low) = b_{10}

5.1.2.1 Rule Set for High Avalanche Danger

Rule set for high avalanche danger {*R*,,, R_{b2}, ..., R_{b10}}, where $R_{bi} = b_i$, if $b_i \neq 0$ or $R_{bi} = 1$, if $b_i = 0$ with $i = 1$ to 10.

5.1.3 Rules for Medium Avalanche Danger

- Standing snow (medium) = *c*,
- Fresh snow (medium) = c_2
- Surface temperature (medium) = c_3
- Standing snow (low) **AND** fresh snow (low) = c_4
- Standing snow (low) **AND** surface temperature (low) = c,
- Fresh snow (low) **AND** surface temperature (low) = c_6

5.1.3.1 Rule Set for Medium Avalanche Danger

Rule set for medium avalanche danger = {R_{c1}, *R*, ..., *R*,), where $R_{ci} = c_i$ if $c_i \neq 0$ or $R_{ci} = 1$, if $c_i = 0$ with $i = 1$ to 6.

5.1.4 Rules for Low Avalanche Danger

- Standing snow (low) = d,
- Fresh snow (low) = d_2
- Surface temperature (low) = d_3

5.1.4.1 Rule Set for Low Avalanche Danger

Rule set for low avalanche danger = {R_{d1}, R_{d2}, ..., R_{d3}}, where $R_{di} = d_i$, if $d_i \neq 0$ or $R_{di} = 1$, if $d_i = 0$ with $i = 1$ to 3.

5.1.5 Rule for No Avalanche Danger

Standing snow (very low) **AND** fresh snow (very low) **AND** surface temperature (very low) = e_1

5.1.5.1 Rule for No Avalanche Danger

Rule for no avalanche danger = R_{e1}, where $R_{e1} = e_1$.

6. OPTIMISATION MATRIX

The optimisation matrix will be utilised for arriving at the optimum rule value (ORV) from within the five sets of rules.

(a) R_{a1} AND R_{a2} AND ...... AND R_{a10} = R_{O1}

(b) R„ AND R_{b2} AND ...... AND R„„ = R_{O2}

(c) R_{c1} AND R_{c2} AND ...... AND R_{c6} = R_{O3}

(d) R_{d1} AND R_{d2} AND R_{d3} = R_{O4}

(e) R_{e1} = R_{O5}

Optimum rule set = {O_1, O_2, ..., 0,)

where

O, = R_{O1} if $R_{O1} \neq 1$ or $O_1 = 0$ if $R_{O1} = 1$

$O_2 = R_{O2}$ if $R_{O2} \neq 1$ or $O_2 = 0$ if $R_{O2} = 1$

O, = R_{O3} if $R_{O3} \neq 1$ or $O_3 = 0$ if $R_{O3} = 1$

O, = R_{O4} if $R_{O4} \neq 1$ or $O_4 = 0$ if $R_{O4} = 1$

$O_5 = R_{O5}$

6.1 Optimum Rule Value

The ORV is obtained using the fuzzy operator OR between the various members of the optimum rule set. Therefore, ORV = Max {0,, O_2, O_3, O_4, O_5}. In case of two or more factors having same max value, the rule corresponding to the higher degree of rule set will be selected (eg, if Max {0,, O_2, O_3, O_4, O,) = Both O, and O_2, then ORV = 0,). In case for a particular set of input, all the values, viz., 0,, O_2, O_3, O_4, O, are equal to zero, ORV is also to be considered equal to zero. Such a situation may only happen when the rules framed in the algorithm are insufficient to cater for the particular input set and the result in none of the rules being fired.

7. DEFUZZIFICATION

Optimum prediction would be the one designating a particular set of rules which generates the optimum rule value. In other words, that classification group from which a rule value survives to become the ORV after having passed through the optimisation matrix, is the one selected as the prediction output.

(a) If ORV = O_1, then prediction = All-round avalanche danger

(b) If ORV = O_2, then prediction = High avalanche danger

(c) If ORV = O_3, then prediction = Medium avalanche danger

(d) If ORV = 0,, then prediction = Low avalanche danger

(f) If ORV = 0,, then prediction = No avalanche danger

(g) If ORV = 0, then output = Prediction indeterminate.

8. LEARNING MECHANISM

At this stage, it may also be suitable to introduce a learning mechanism onto the algorithm. The learning of the algorithm would be conducted using a set of test data. In this case, the optimum rule set would be defined as

Optimum rule set = {0,, O_2, ..., O,)

where

O, = $(R_{O1})^{1+w}$ if $R_{O1} \neq 1$ or $O_1 = 0$ if $R_{O1} = 1$

$O_2 = (R_{O2})^{1+w}$ if $R_{O2} \neq 1$ or $O_2 = 0$ if $R_{O2} = 1$

O, = $(R_{O3})^{1+w}$ if $R_{O3} \neq 1$ or $O_3 = 0$ if $R_{O3} = 1$

O, = $(R_{O4})^{1+w}$ if $R_{O4} \neq 1$ or $O_4 = 0$ if $R_{O4} = 1$

$O_5 = (R_{O5})^{1+w}$

The value of w in the above equations is defined as the weightage, whch is to be assigned every time the output of the algorithm tends to vary from that of the test data. The weightage could either be in the form of punishment value, in which case it would be positive, or it could be a reward, in which case it would be a negative value. The value of the weightage to be assigned for each iteration of the learning cycle could be set as 0.01. A simultaneous award and punishment is awarded each time the output of the algorithm differs from the test data. A reward would be allotted to that group of classification which ought to have been the output as per the test data and a simultaneous punishment is awarded to that classification which has been wrongly given by the algorithm. The classifications, which are neither the output of the algorithm nor that of the test data, would be assigned with zero weightage. For example, let one assumes a case when the output of the algorithm predicts all-round avalanche danger but as per the test data, the prediction ought to have been high avalanche danger. In such a case, the optimum rule values would be defined as under

where

$O_1 = (R_{O1})^{1+0.01}$ if $R_{O1} \neq 1$ or $O_1 = 0$ if $R_{O1} = 1$

$O_2 = (R_{O2})^{1-0.01}$ if $R_{O2} \neq 1$ or $O_2 = 0$ if $R_{O2} = 1$

$O_3 = (R_{O3})^{1+0}$ if $R_{O3} \neq 1$ or $O_3 = 0$ if $R_{O3} = 1$

$O_4 = (R_{O4})^{1+0}$ if $R_{O4} \neq 1$ or $O_4 = 0$ if $R_{O4} = 1$

$O_5 = (R_{O5})^{1+0}$

The algorithm would be put through as many number of iterations/learning cycles till the output of the algorithm stabilises in consonance with the output of the test data. Thereafter, the weightage values are fixed for further prediction routines.

9. CONCLUSION

Accurate prediction of an avalanche, both in terms of its likelihood as well of the likely period of occurrence, remains an extremely difficult task. In the environment of automated real-time data collection, high quantum of information may be available for rigorous analysis on a real-time basis. Such real-time analysis and selection of one outcome from among the multitudes of possibilities, is likely to be possible only through the assistance by some sort of automated prediction system.

Fuzzy logic system offers some suitable techniques since the system provides sufficient room for realistic natural input and output. It encompasses graded form of input as well as output, which is in stark contrast to the present system that can take input or give output in a form with sharp contrast at the points of transition from one range of values to another.

Fuzzy logic systems have proven to be of great advantage, especially in day-to-day life, were the definition of the phenomenon being modelled is based on a multitude of interdependent variables as manifested in case of natural environmental phenomenon. Crisp logic systems demand breakdown of such gradual transition into definite data with stark boundaries, which can be processed by a computer. This can make the phenomenon loose its original profile. To avoid this, the system has to be made complex, and therefore, unmanageable in many ways. Fuzzy logic system gives a fundamentally simple way to handle such complex situations without making the system itself exceedingly complex. The fuzzy set theory has already been extensively used throughout the world in linear regression and its application to forecasting in uncertain (almost a universal see) environment. The fuzzy logic medel system may also prove to be the most suitable in developing an automated real-time avalanche prediction system.

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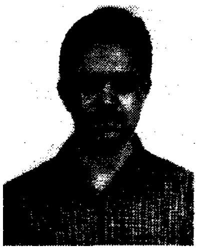

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