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Knowledge-Based System for Forecasting Snow Avalanches of Chowkibal-Tangdhar Axis (J&K)

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ABSTRACT

In this paper an attempt has been made to use artificial intelligence in avalanche forecasting and to develop a rule-based expert system for predicting direct action avalanches of Chowkibal-Tangdhar axis (J&K). Using C-language integrated production system (CLIPS), procedural knowledge is represented in the form of rules. The condition attributes of the rule-based system are 28 variables selected from 1 154 samples of snow-met and snow profile data.The relative contribution of each variable on avalanche days and non-avalanche days and their influence on sitewise release of avalanche was studied to formulate 358 rules. These rules, which include 173 decision rules, were finally implemented and validated for running the model. Sixty-three samples of snow-met data and pit profile data attributing to avalanche days and 54 samples of non-avalanche days were run on the model. The results show that the knowledge-based model can predict avalanche days with 76 per cent efficiency. The misclassified results accounted for 28.2 per cent of 117 test samples.

NOMENCLATURE

tx	Maximum temperature (°C)
dtx	Twenty-four hour maximum temperature departure (°C)
dmtx	Maximum temperature departure from mean value (°C)
tn	Minimum temperature (°C)
dtn	Twenty-four hour minimum temperature departure (°C)
dmtn	Minimum temperature departure from mean value (°C)
ta	Ambient temperature (°C)
dta	Twenty-four hour ambient temperature departure (°C)
*t*1	*tx-tn* (°C)
*t*2	*tx-ta* (°C)
*t*3	*tn-ta* (°C)
u	Zonal component of wind (km hr^{-1})
v	Meridional component of wind (km hr^{-1})
hn	Fresh snowfall (cm)

Revised 23 August 1999

hnf	Twenty-four hour fresh snowfall (cm)
hns	Seventy-four hour fresh snowfall (cm)
si	Snowfall intensity (cm hr^{-1})
dn	Fresh snow density (g cc^{-1})
hs	Standing snow (cm)
ts	Snow surface temperature (°C)
dts	Twenty-four hour *ts* departure (°C)
dmts	*ts* departure from mean value (°C)
ct	Snow crust thickness (cm)
ps	Penetration below crust (cm)
*th*1	Thickness of the weakest layer (cm)
*th*2	Thickness of snow beneath the weakest layer (cm)
*th*3	Thickness of snow above the weakest layer (cm)
dec	December

1. INTRODUCTION

The two predominantly used methods for forecasting of avalanche hazards are conventional knowledge-based assessment of avalanche hazard, and statistical methods, such as discriminant analysis and the nearest neighbourhood techniques[1, 2]. Operational avalanche forecasting based on the above methods is widely practised in India and in several other countries[3-5]. Nevertheless, the efficiency of the models based on these approaches is weighed upon how snow-met and pit profile data is represented in the model. McClung and Schaerer[1] extended the work of La Chapelle[2] and categorised the snow-met and snow profile data into three classes. The higher the class numbers, the less directly relevant is the data, and therefore, its significance for avalanche prediction is not conclusive. Class I data, such as stability of snowpack estimated by stability tests bears direct relevance to avalanche formation. Class II factors, such as snowpack parameters obtained through pit profile tests (or stratigraphy) have secondary relevance to avalanche formation, whereas class III data, such as meteorological and snow variables measured at or above snow surface bear indirect relevance. Any model, which incorporates all the above data, of which some are symbolic in nature, may be relatively successful in avalanche prediction. This, however, is not possible in the case of numerical models where solutions are obtained in a systematic procedure. The demand for the representation of both symbolic and numerical data has attracted use of artificial intelligence techniques in addition to the existing statistical approaches[6]. The present work is a step forward to develop a knowledge-based avalanche forecasting system. This work is oriented towards extracting rules from historical data set of stage II (J&K) observatory and implement these in an expert shell.

The study area of present work is Chowkibal-Tangdhar axis which is the only road connecting the district of Tithwal with Kupwara of J&K. It negotiates and crosses the Pir Panjal range at Nastachun pass (3120 m). Icing at the onset of winter and the snow and avalanche problems during winter affect the trafficability between Chowkibal and Tangdhar. A stretch of 36.18 km is characterised by 26 registered avalanche sites (Fig. 1). It is on account of heavy pedestrian traffic (approx. 3000 personnel per month) and their unavoidable interaction with avalanches, this work gains importance. Seventeen avalanche sites, CT1 to CT17, were chosen for the model development. The Snow & Avalanche Study Establishment (SASE), Manali, has undertaken extensive studies on the formation of avalanches in the Himalayas. The work of Ganju[3], *et al*. gives an understanding of the terrain, snow and meteorological characteristics for avalanching over the above sites.

This paper describes the data analysis, the expert shell and representation of knowledge used in the shell, the implementation and validation of the rules, performance of the model and its usefulness for sitewise avalanche prediction, and possible future improvements of the model.

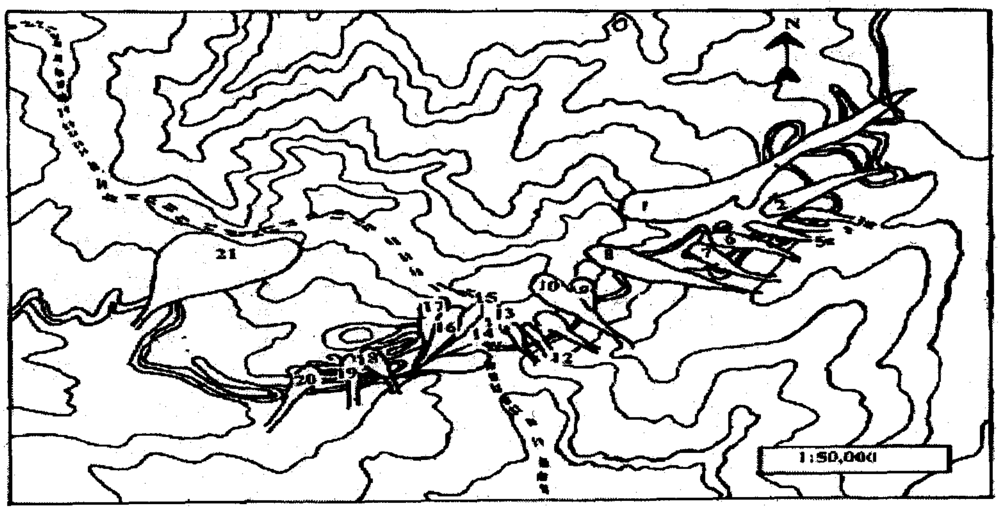


Figure 1. Avalanche sites of Chowkibal-Tangdhar axis

2. DATA ANALYSIS

The data used for the study is of snow-met and snow profile data of stage II observatory situated between Chowkibal and Nastachun Pass. The data for seven years starting from the winter (1991-92 to 1997-98) has been selected and after deleting the missing data, the final set containing a sample of 1154 observations (both 0830 hr and 1730 hr, of a day) has been considered for the study.

Extensive analysis of data available at SASE has provided evidence that either snow loading or warming up of snowpack or combined action of both are the principal causes of release of most of the avalanches in the Chowkibal-Thangdhar axis. Moreover, since the gullies of avalanche sites are affected by snowdrift loading by the wind, the wind speed and direction modified rapidly by the mountains and applied in the model may yield insignificant contribution to the decision-making system, such as rule-based system*. An alternate to the problem is the representation of wind speed and direction in the form of zonal and meridional components. These components can provide a decisive presence as variables in the numerical models[7].

Twenty-eight variables are selected for the development of the model. These consist of both directly observed and derived variables. The data is separated into avalanche days and non-avalanche days and later categorised monthwise to identify each variable's range (minimum, maximum) and mean value using a FORTRAN program. The data is further classified for each avalanche site and categorised monthwise to identify the range wrt magnitude of the variables. Percentage of avalanche triggered, over a site wrt magnitude of a variable falling above and below mean value was determined. This classification allows formulation of rules based on the influence of each variable, considered for the study on sitewise release of avalanches. Figures 2 and 3 show the relative contribution of variables for the formation of avalanches over the avalanche sites (CT1 to CT17).

3. REPRESENTATION OF KNOWLEDGE USING RULES

The main elements of a rule-based system are global database, a set of production rules, and a control system. The global database is the central data structure used by a rule-based system. The production rules operate on the global database. Each rule has a precondition that is either satisfied,

* A knowledge-based system which uses knowledge encoded in the form of production rules, that is, if .... then rules.

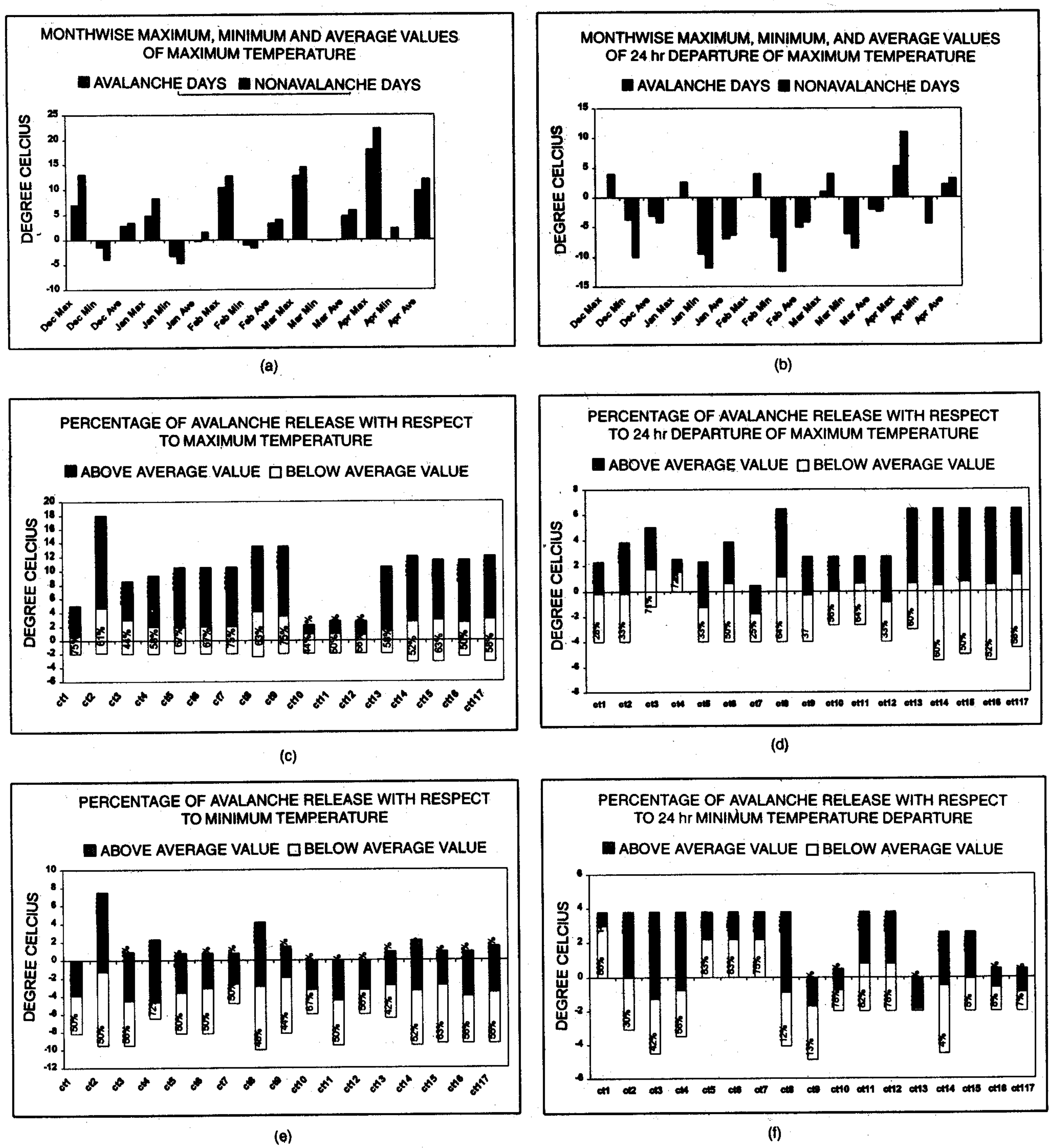
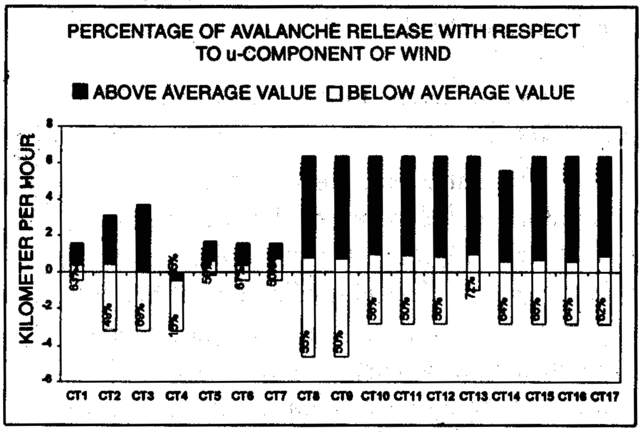


Figure 2. The maximum, minimum, and average values of temperature variables determined from six years data are shown in Figs (a) and (b). Figures (c), (d), (e) and (f) show the influence of temperature variables on avalanche release. Shaded (dark) bar shows the range of the variable above its mean value and nonshaded portion shows the range below mean value. Percentage of avalanche release for both above and below mean values is given in respective portions.



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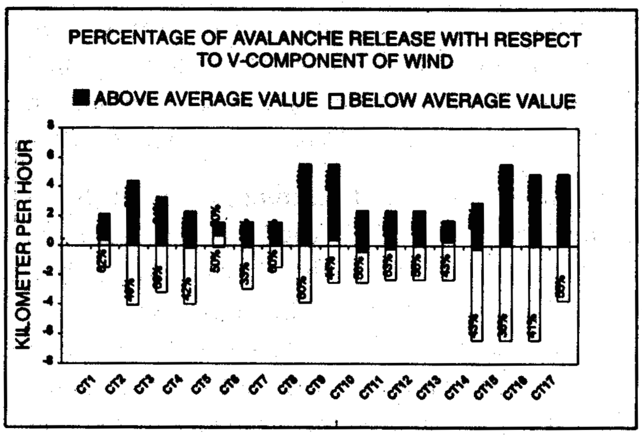

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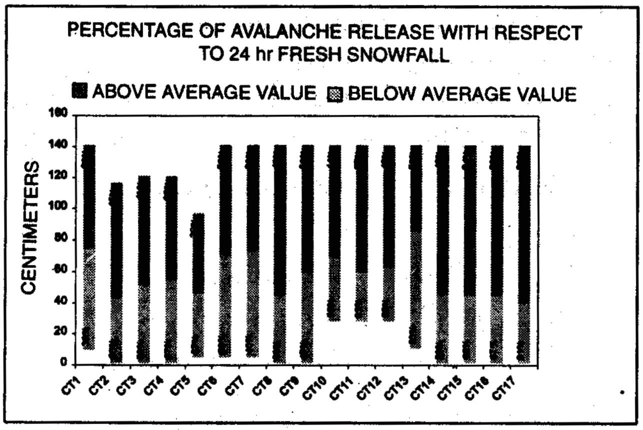

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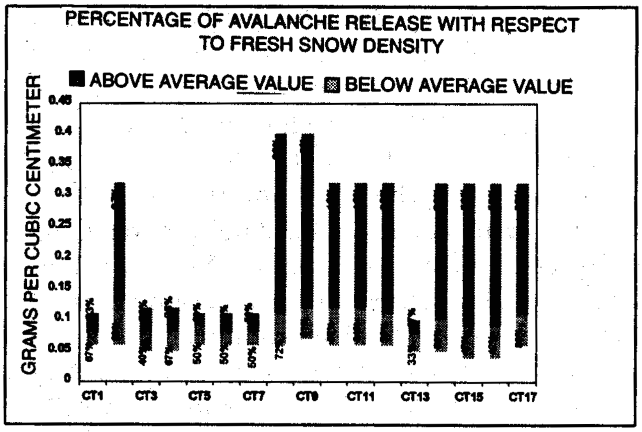

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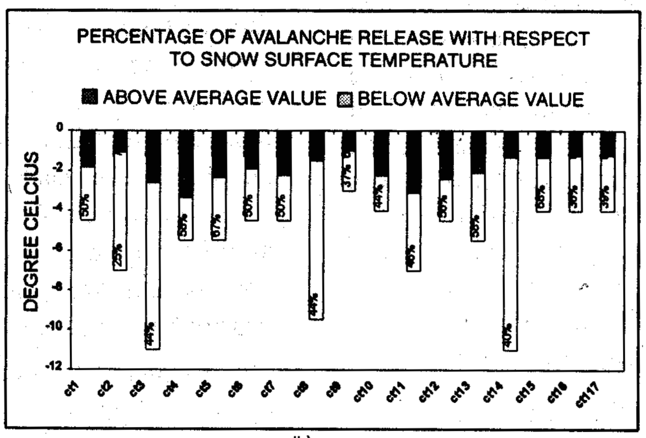

(k)

Figure 3. Zonal and meridional components of wind, snow variables and their influence on avalanche release

or not by the global database. If the precondition is satisfied, the rule can be applied. Application of the rule changes the database. The control system chooses that applicable rule which has to be applied and ceases computation when a termination condition on the global database is satisfied.

Selecting rules and keeping track of those sequences of rules already tried and the databases they produced, constitute the control strategy for the rule-based system. The operation of a rule-based system can be characterised as a search process in which rules are tried until some sequence of them is found that produces a database satisfying the termination condition.

The C-language integrated production system (CLIPS) is a tool used for the development of expert systems. Originally, the primary representation methodology in CLIPS was a forward chaining rule language based on the Rete algorithm[8]. Later versions of CLIPS introduced the new programming paradigms: procedural programming and object-oriented programming. Version 6.1 of CLIPS, provides support for the development of modular programs and tight integration between the object-oriented and rule-based programming capabilities of CLIPS**. The versatility of CLIPS allows knowledge engineers to integrate numerical models with knowledge base. It has the capability of function calls from knowledge base to numerical models and vice versa. Originally, it was decided to develop models by integrating numerical avalanche forecasting models based on neural networks and discriminant analysis with the knowledge base[7]. This work being too ambitious to begin with, it was later decided to reduce the complexity of the problem by concentrating only on designing the knowledge base for avalanche forecasting. The knowledge base was designed (Fig. 4) after studying functions of the expert forecaster.

Section 2 describes the relative contribution of each variable on avalanche days and non-avalanche days, and their influence on sitewise release of avalanches. The sitewise release of avalanches can be termed as a sub-set of conditions favourable for avalanche days and therefore, the first priority is to formulate rules for avalanche days and non-avalanche days.

3.1 Rules for Avalanche & Non-avalanche Days

The rules are formulated after an understanding of the type of winter that persists during avalanche periods, for example, normal, peak or lean winter[3]. The classification of winter directly refers to the variation of snow and meteorological conditions from early to late winter. This has led to the categorisation of data monthwise and to check the range wrt magnitude of each condition attribute as shown in Figs 2 and 3. The next step to formulate the rules is the combination of condition attributes required to trigger sub-actions necessary for the achievement of the goal. The following examples show the combination of temperature attributes:

Rule 1 If : *tx*(-1.5,7.0) & *dtx*(-5.5,6.2) & *dec*

Then : Avalanche 1

Rule 2 If : *tx* (-4.0, 13.0) & *dtx* (-6.5, 5.5) & *dec*

Then : Non-avalanche 1

The rule 1 shows the combination of condition attributes required for triggering and asserting the fact avalanche 1. The fact avalanche 1 is one of the sub-actions necessary to trigger a goal related to avalanche day. Similarly, rule 2 holds for non-avalanche day. In this manner, rules have been developed for each month (December, January, February, March, April) of a winter period. Like the above temperature rules, rules relating to the wind components, fresh snow, standing snow and snow profile have also been formulated.

An examination of the rules cited in the above examples shows that certain ranges, such as (-1.5, 7.0) of maximum temperature is applicable to both goals of avalanche days and non-avalanche days. This is, however, not going to affect the decision-making system since many other rules are

** More details of CLIPS expert shell can be obtained from CLIPS web page http://www.ghg.net/clips/CLIPS.html.

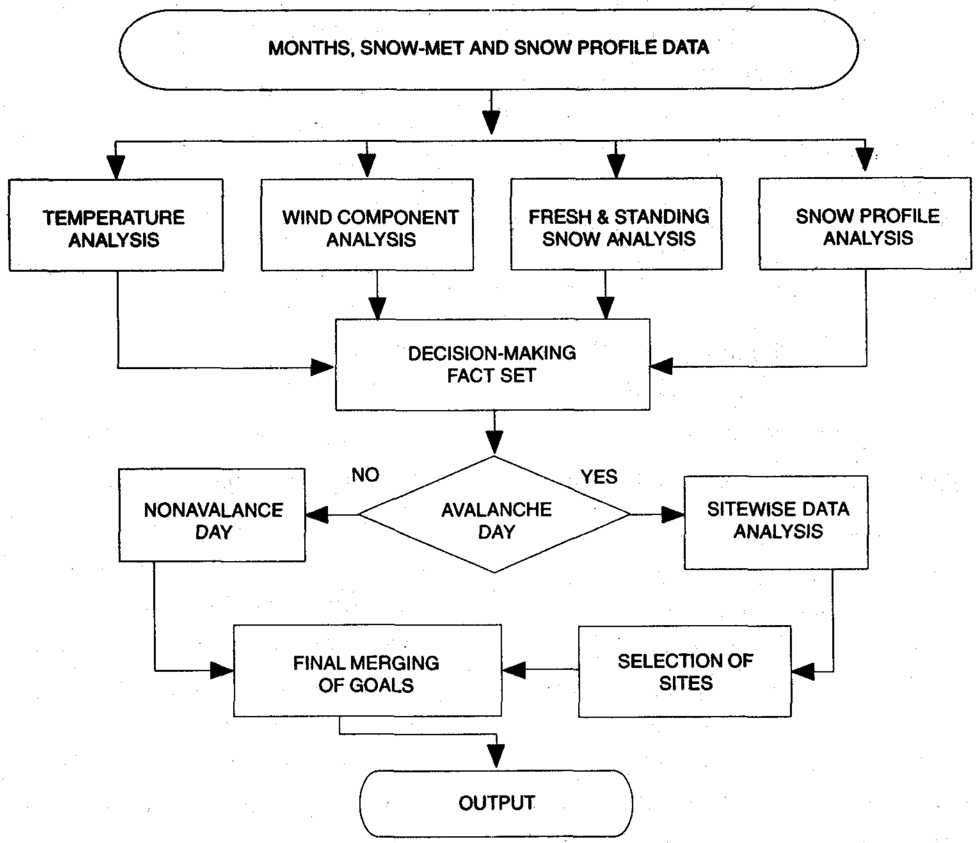

Figure 4. Structure of the knowledge-based avalanche forecasting model

also required to trigger a goal of avalanche day or non-avalanche day. As the number of rules increases, the variable range of the condition attributes decided by the day-to-day observation helps in identifying a suitable goal.

3.2 Rules for Avalanche Sites

If a goal avalanche day is triggerred by the knowledge-based system, the next requirement is to predict the avalanche sites ready for release of an avalanche. Here, it is necessary to decide the condition attributes and its magnitude range holding true for avalanche release wrt to each avalanche site. One way of doing this is by separating the magnitude range of variables into two groups: below mean value group and above mean value group, and determining the percentage of avalanche release wrt each group. The mean value of a condition attribute is the monthly mean value determined from the seven years' data used in the study. The group representing 60 per cent or more release of avalanche is considered as an effective magnitude range of condition attribute holding true for the sitewise release of an avalanche. The following example shows the rule required for predicting an avalanche over site CT1:

Rule 99 If : *tx* (-2.0, 0.6) & *ta* (-8.2, -2.0)
Then : *tmp* 11

Rule100 If : *dtx* (-0.2, 2.3) & *dtn* (0.0, 3.8)
Then : *tmp* 12

Rule101 If : *ts*(-4.5,0.0) & *dmts*(0.0,4.3)
Then : *tmp* 13

Rule169 If : *u*(-0.48, 0.39) & *v* (-1.48, 0.35)
Then : *uvc* 1

Rule200 If : *hnf* (75, 141) & *dn* (0.06, 0.08)
Then : *hndn* 1

The assertion *tmp* 11, *tmp* 12, *tmp* 13, *uvc* 1, and *hndn* 1 form the antecedents along with assertion avalanche day. The values given in brackets are the effective magnitude range of the condition attribute considered as true for triggering the goal. When the combination of all these facts are true then the goal avalanche over CT 1 will be true as shown in the following rule:

Rule 274 If : Avalanche day (0.75 OR 0.50) & *tmp*11 & *tmp*12 & *tmp*13 & *uvc*1 & *hndn* 1

Then : Goal CT 1 avalanche 100

The above rule treats six antecedents to trigger the goal avalanche over CT 1 with a confidence level of 100. The first antecedent avalanche day (0.75 or 0.50) is added to the fact list when general rules related to avalanche days hold true. The values (0.75 or 0.50) are the two confidence levels attributed to the fact avalanche day. These values are determined by the experts after assessing the individual contribution of variables to release an avalanche. A value of 0.75 gives 75 per cent or more chance to declare the day as an avalanche day, whereas, a value of 0.50 gives only 50 per cent chance. Similarly, the confidence level for each site is 50, 75, and 100. If a rule triggers a goal attributed to confidence level 100, then the chance of avalanche over the concerned site is 100 per cent. The antecedents holding true for release of avalanche over CT 1 will not necessarily hold true for other sites. Therefore, in a similar manner different rules are formulated for different sites by considering the effective range in magnitude of those condition attributes holding true for a particular avalanche site.

4. RESULTS & DISCUSSION

Using CLIPS expert shell, 358 rules were implemented. Out of 358 rules, 173 rules are decision rules. Table 1 shows the number of rules of various categories of variables. The implemented rules were subjected to consistency check using the CLIPS tool. These rules were modified and finally validated for running the model.

Table 1. Description of rules used in the model

Category	Condition rules	Decision rules
Temperature	98	40
Snow profile	20	16
u.v.	16	32
Fresh snow and standing snow	51	(both combined)
Sitewise rules	-	81
Selection rules	-	2
Goal-satisfaction rules	-	2

The knowledge-based system is now required to give answers, such as whether today's data corresponds to an avalanche day or a non-avalanche day. And if avalanche day, what is the chance of formation of avalanche over sites CT 1 to CT 17? If all avalanche sites are not yet ready for the formation of avalanche, then the model should only give the names of those sites ready for release. Sixty-three samples of snow-met and pit profile data attributing to avalanche days and 54 samples of non-avalanche days were run on the model. These samples were randomly selected from the entire database of stage II observatory. Table 2 shows the efficiency of the model by declaring avalanche days and non-avalanche days.

Table 2. Efficiency of the model

Category	Samples	Predicted	Misclassified
Avalanche days	63	48.0	15.0
Non-avalanche days	54	36.0	18.0
Percentage	100	71.8	28.2

The result shows that this expert system could predict with a reasonable accuracy of 76 per cent for avalanche days and 66 per cent for non-avalanche days. A considerable per cent of days were misclassified. This attributes to limitation in decision-making process due to insufficient number of rules. More rules are needed to make the inference engine of the knowledge-based system to trigger a goal correctly.

A sample of the model prediction day is reproduced below:

Result 1: *Non-avalanche day*

Date	*tx*	*dtx*	*tn*	*dtn*	*ta*	*dta*	*t*1	*t*2	*t*3
250398F	8.0	3.0	-4.0	2.5	1.0	3.5	4.0	-1.0	-5.0
	u	*v*	*hn*	*hnf*	*hns*	*si*	*dn*	*hs*	*ts*
	0.00	1.30	3	3	3	1.20	0.06	39	-5.0
	dts	*dmts*	*dmtx*	*dntn*	*dmta*	*ps*	*ct*		
	-1.5	-3.9	-7.7	2.7	-0.8	3	0		

Stratigraphy data: *th*1 = 60 *th*2 = 147 *th* 3 = 0

No avalanche danger on 250398F; chance(0.5)

Assert the prognostic weather.

Result 2: *Avalanche day*

Date	*tx*	*dtx*	*tn*	*dtn*	*ta*	*dta*	*t*1	*t*2	*t*3
300393F	1.2	0.0	-4.4	-3.4	1.8	1.6	5.6	-0.6	-6.2
	u	*v*	*hn*	*hnf*	*hns*	*si*	*dn*	*hs*	*ts*
	0.00	0.30	21	40	65	2.33	0.06	105	-2.5
	dts	*dmts*	*dmtx*	*dntn*	*dmta*	*ps*	*ct*		
	-2.0	-1.3	-3.7	-2.0	1.2	40	0		

Stratigraphy data: *th* 1 = 1 *th* 2 = 44 *th* 3 = 60

Avalanche condition may develop in next 24 hr wef 300393F

Verify for any avalanche activity during past 48 hrs.

(CT2) is unstable; Chance (50)

(CT8) is unstable; Chance (50)

(CT9) is unstable; Chance (50)

(CT4) is unstable; Chance (75)

(CT15) is unstable; Chance (50)

The above sample result shows the avalanche day on 30 March 1993. On this day, avalanche sites CT2, CT14, CT15 and CT16 were reported for release of avalanches. Three days before this avalanche day, the weather condition was fair-to-partly cloudy with an odd event of trace precipitation. An experienced avalanche forecaster might have been puzzled since there were snow spells reported up to 26 March 1993 and most of the avalanche sites got triggered by the evening of 26 March. Moreover, there was no adequate sunshine from 26-30 March so as to give adequate radiation input to the snowpack and activate re-crystallisation or melt-freeze processes. The knowledge-based system examined the data and activated the rule necessary for release of an avalanche. The sample result shows CT2, CT4, CT15, CT8, and CT9 are unstable with a confidence level of 50 to 75. The sample result, when compared to actual occurrence of the avalanche, shows two sites predicted correctly out of five. The results are satisfactory as regards the sitewise prediction of avalanche days is concerned. A further modification of rules or addition of rules may make the knowledge-based system more efficient. Moreover, it is difficult to say at this stage whether addition of rules makes the knowledge-based system highly efficient. This is because one has to closely examine the processes of formation of avalanches over the sites with data observed at each site and implement rules in the knowledge base accordingly. This is a limitation in operational avalanche forecasting since data is by far available only from the observatories situated at an average distance of 10 to 15 km and one always finds that the data observed at the observatory is not a true representation of the snow-met conditions over the sites due to spatial and temporal variation in snow-met conditions. It has been found for the axis under study that the knowledge-based system could predict six out of 17 sites very reasonably. These were CT2, CT4, CT6, CT14, CT15 and CT16. The remaining sites' activities of avalanche formation were not predicted with reasonable efficiency. A re-examination of the rules and implementation of more rules may yield better results. This step can be taken after further data analysis and selection of more variables.

5. CONCLUSION

Numerical avalanche forecasting methods statistically analyse only meteorological parameters. The efficiency of forecasting can be increased if all the information regarding snowpack characteristics and snow-met parameters are considered. Avalanche takes place when all thesevariables offer a tricky combination. For incorporating qualitative and quantitative information, an attempt has been made to develop a knowledge-based system for avalanche forecasting. Since parameteric situations are ever changing so rules are developed monthwise. A total of 358 rules have been developed, out of which 185 rules relate to condition attributes, which analyse the database and assert facts of avalanche and non-avalanche days. Rest of the rules relates to decision attribute, which analyse facts asserted by condition attribute rules and decide the goal. When a day is declared as avalanche day only then the model invokes sitewise prediction.

The model is found suitable for predicting avalanche days. The results discussed in Section 4, show that an overall accuracy of 76 per cent is achieved for predicting avalanche days. However, misclassified results account for 28.2 per cent. The development of a sitewise avalanche prediction model is a first step taken at SASE. An in-depth data analysis is required to build rules for incorporating sitewise prediction. The snow profile data will be further studied to know more about the process of avalanche initiation for each site. Once this is understood, accuracy level of sitewise prediction with the help of modified snow-met rules, can be increased. In addition to this, it is also felt that the knowledge base should be integrated with numerical avalanche forecasting and numerical weather prediction models. This will lead to the development of a short range (1 to 3 days) avalanche prediction model.

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