Simulation based Avalanche Prediction Model using Adaptive Neuro Fuzzy Inference System

Thesis
submitted in partial fulfillment of the requirements
for the award of degree of

Master of Engineering
in
Software Engineering

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Certificate

I hereby certify that the work which is being presented in the thesis entitled, **"Simulation based Avalanche Prediction Model using Adaptive Neuro Fuzzy Inference System"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in Software Engineering submitted to Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. R.K. Sharma* and *Mr. Karun Verma* and refers other researcher's works which are duly listed in the reference section.

The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university.

Chetan Jain

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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Acknowledgement

"Ideals are like stars: you will not succeed in touching them with your hands, but like the seafaring man on the ocean desert of waters, you choose them as your guides, and following them, you reach your destiny."

-Carl Schurz (1829 - 1906)

First and foremost, I would like to express my sincere gratitude to my supervisor **Dr. R.K. Sharma**, Dean of Academic Affairs and Professor, School of Mathematics and computer applications, Thapar University, Patiala for his immense help, guidance, stimulating suggestions and encouragement all the time. He always provide a motivating and enthusiastic atmosphere to work with, it is a great pleasure and honor to do work under his supervision.

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Chetan Jain

Abstract

The main aim of this study is to develop an avalanche prediction method, based on the adaptive neural-based fuzzy inference system (ANFIS). An ANFIS methodology is applied to the sample weather data inputted in the Matlab through Microsoft's excel sheets. Application is given for atmospherically time series modeling, and then the sample data is used for training data sets of the ANFIS. It is seen that the extension of input and output data sets in the training stage improves the accuracy of forecasting by using ANFIS.

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. 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 rules. 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. The present study attempts to simplify this problem by proposing a simpler and better technique using an algorithm based on fuzzy logic [10].

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Abbreviations

ANIFS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
FIS	Fuzzy Inference System
FTV	Fuzzy Truth Value
HN	Fresh snowfall (cm)
HNF	24 h fresh snowfall (cm)
HNS	72 h fresh snow (cm)
HS	Standing snow (cm)
NN	Neural Network
PS	Free penetration (cm)
SI	Snowfall intensity (cm)

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Chapter 1

Introduction

Prediction of any natural event requires information regarding its time of occurrence as well as nature, based on logical analysis. 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.

Soft Computing is an emerging field and its main constituents are fuzzy logic, neural computing, evolutionary computation, machine learning and probabilistic reasoning. Strong learning, cognitive ability and good tolerance of uncertainty and imprecision of these constituents make them best suited for wide applications.

Resemblance to human reasoning is the striking property of soft computing techniques than traditional techniques which were largely based on conventional logical systems, such as sentential logic and predicate logic, or rely heavily on the mathematical capabilities of a computer.

1.1 Fuzzy Logic

The term "fuzzy logic" emerged in the development of the theory of fuzzy sets by Lotfi Zadeh in the mid-1960s. A fuzzy expert system [3] is an expert system that uses fuzzy logic instead of Boolean logic. In other words, a fuzzy expert system is a collection of membership functions and rules that are used to reason about data. It provides an approximate but effective means of describing the behaviour of systems that are too complex, ill-defined, or not easily analyzed mathematically. Fuzzy variables are processed using a system called a fuzzy logic controller. It involves fuzzification, fuzzy inference, and defuzzification. The fuzzification [10] process converts a crisp input value to a fuzzy value. The fuzzy inference is responsible for drawing conclusions from the knowledge base. The defuzzification process converts the fuzzy control actions into a crisp control action. Fuzzy logic uses graded statements rather than ones that are strictly true or false. Thus, fuzzy logic provides an approximate but effective way of describing the behaviour of systems that are not easy to describe precisely. Fuzzy logic controllers, for example, are extensions of the common expert systems that use production rules like “if-then”.

1.2 Fuzzy Sets

Fuzzy sets [2] have membership properties defined between 0 and 1. This means that if we take an attribute say 'red' we can express the colour of any particular apple as a position in this fuzzy set. We may say for example that it is 30% red and thus has a fuzzy truth value (FTV) or membership function of 0.3. The relation of FTV to actual values depends upon the desired mapping from the real world to the normalized range 0 to 1, and this is arbitrary. The membership function is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs, and ultimately determines an output response. The fuzzy rules [4] use the input membership values as weighting factors to determine their influence on the fuzzy output sets [5] of the final output conclusion. Once the functions are inferred, scaled, and combined, they are defuzzified into a crisp output which drives the system. There are different membership functions associated with each input and output response. The commonly used shape to describe the membership function is triangular, but bell, trapezoidal and exponential can also be used. More complex functions are possible but require greater computing overhead to implement. Fig. 1.1 illustrates the different shapes of membership functions commonly in use.

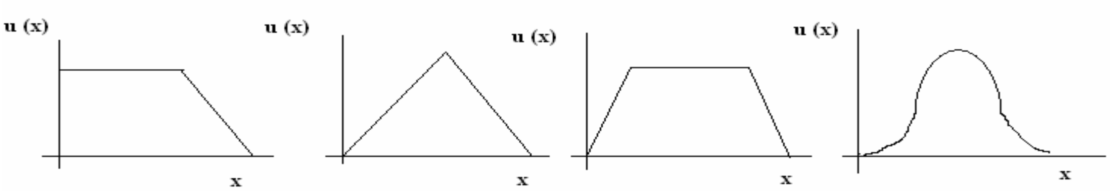


Fig 1.1: Different Shapes of Commonly Used Membership Functions

1.3 Neural Network

In general, the human nervous system is a very complex neural network. Each neuron in the brain is composed of a body, one axon and multitude of dendrites. The neuron model shown in Figure1.2 serves as the basis for the artificial neuron. The dendrites receive signals from other neurons. The axon can be considered as a long tube, which divides into branches terminating in little end bulbs. The small gap between an end bulb and a dendrite is called a synapse. The axon of a single neuron forms synaptic connections with many other neurons. The cell body of a neuron sums the incoming signals from dendrites as well as the signals from numerous synapses on its surface. A particular neuron will send an impulse to its axon if sufficient input signals are received to stimulate the neuron to its threshold level. The interest in neural networks comes from the networks' ability to mimic human brain as well as its ability to learn and respond.

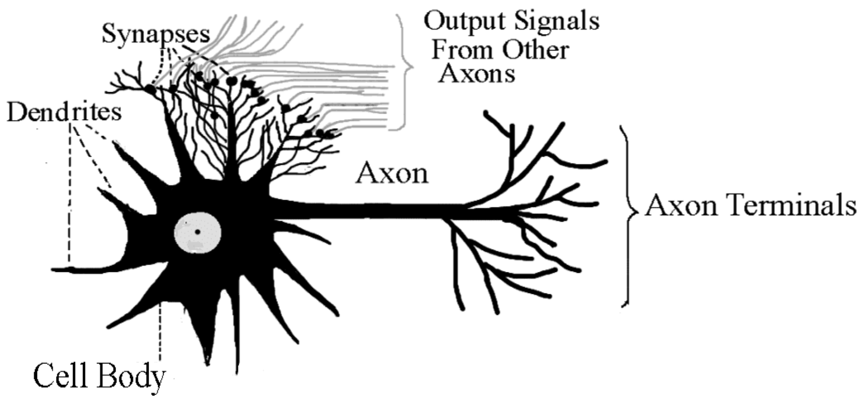


Figure 1.2: A Biological Neuron

As a result, neural networks have been used in a large number of applications and have proven to be effective in performing complex functions in a variety of fields. These include pattern recognition, classification, vision, control systems, and prediction. Adaptation or learning is a major focus of neural net research that provides a degree of robustness to the NN model. In predictive modeling, the goal is to map a set of input patterns onto a set of output patterns. NN accomplishes this task by learning from a series of input/output data sets presented to the network. The trained network is then used to apply has been learned to approximate or predict the corresponding output.

1.4 Artificial Neural Networks (ANNs)

An artificial neural network (ANN) is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. A neural network is a system of interconnecting neurons in a network working together to produce an output function. The output of a neural network relies on the cooperation of the individual neurons within the network to operate. Processing of information by neural networks is often done in parallel rather than in series (or sequentially). Since it relies on its member neurons collectively to perform its function, a unique property of a neural network is that it can still perform its overall function even if some of the neurons are not functioning. That is, they are very robust to error or failure (i.e., fault tolerant). Well-designed neural networks are trainable systems that can often "learn" to solve complex problems from a set of exemplars and generalize the "acquired knowledge" to solve unforeseen problems, i.e., they are self-adaptive systems. A neural network is used to refer to a network of biological neurons initially but its terminology in the modern usage is artificial neural networks, which are composed of artificial neurons.

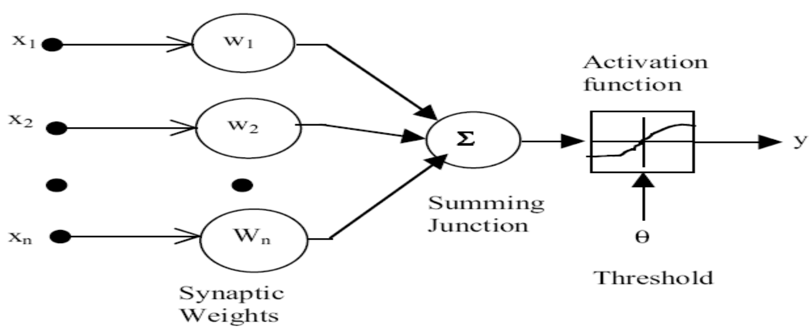


Figure 1.3: Artificial Neural Network

Thus the term 'Neural Network' has two distinct connotations:

- Biological Neural Networks**: -** are made up of real biological neurons that are connected or functionally-related in the peripheral nervous system or the central nervous system. In the field of neuroscience, they are often identified as groups of neurons that perform a specific physiological function in laboratory analysis.
- Artificial Neural Networks**: -** are made up of interconnecting artificial neurons (usually simplified neurons) designed to model (or mimic) some properties of biological neural networks.

Chapter 2

Literature Review

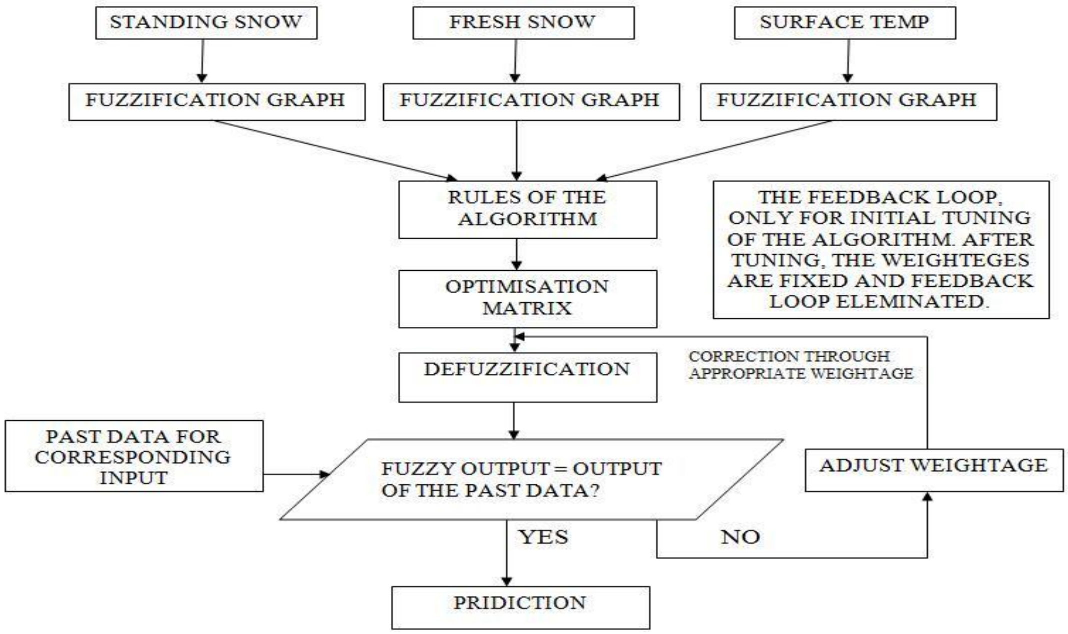
Prediction system used in the earlier stages is not of good standard and is using only observatory inferences in order to predict an event like Avalanche. There were some constraints which were removed up to some extent in the present work and still more improvements are possible in future by overcoming various constraints. The model developed is suitable for adaptive predictive control of daylight - artificial light integrated schemes incorporating dimming and window shading control. Matlab's Fuzzy logic Tool box is used for the simulations.

First a classification system for avalanche forecasts based on the weather parameters is presented. Verification of models in avalanche forecasting may consist of two stages. Often, the first stage is to ensure that the model matches the scales (space and time) and the classification of forecast and that redundant variables and parameters are eliminated. Once that is achieved, verification can proceed to the second stage, testing the model against relevant field data and situations.

2.1 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 input variables used for avalanche prediction. Fig. 2.1 [1] depicts how 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.

Fig. 2.1 The general block diagram of the algorithm [1]



Expert Fuzzy Model for Avalanche Prediction

2.2 Expert Rules for Perceptron

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 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 given in Table 2.1

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

Table 2.1 Practised avalanche danger scales and suggested precautions.

Avalanche danger scale

Degree of danger	Avalanche release probability from different types of slopes, on sequences and suggested precautions.
Low avalanche danger	Generally favourable condition. Triggering is generally possible only with high additional loads and on few extreme slopes.
Medium avalanche danger	Partly unfavourable condition. Triggering is possible from most avalanche-prone slopes with low additional loads and may reach the valley in medium size.
High avalanche danger	Unfavourable condition. Triggering possible from all possible avalanche-prone slopes even with low additional loads and reach the valley in large size. Suspend all movements. Airborne avalanches likely.
All around avalanche danger	Very unfavourable condition. Numerous large avalanches are likely from all possible avalanche slopes, even on moderately steep terrain. Suspend all movements.

2.3 Fuzzy rule-based system for prediction of direct action avalanches

Rule-based systems [7] are widely being used in decision making, control systems and forecasting. In the real world much of the knowledge is imprecise, uncertain, ambiguous and inexact in nature. Fuzzy logic offers a better way to represent complicated situations in terms of simple natural language. The condition attributes of the rule-based system are six snow-related parameters selected from the past dataset of the representative observatory 'Stage-II' in the axis. Different fuzzy sets are defined for each parameter on the basis of their distribution with four danger labels of avalanche activity. Operational avalanche forecasting based on the above methods is widely practised worldwide. For avalanche prediction, snow and meteorological parameters are categorized in three groups. The higher the class the less relevance are the data for avalanche.

a. Class I data deal with snow stability information and are the most relevant data.
b. Class II data deal with snow-pit profile which has secondary relevance, whereas
c. Class III data are snow and met parameters and bear indirect relevance to avalanche formation.

Table 2.2 Classification criteria of avalanche danger

Avalanche danger	Frequency of avalanching
Low	Less than 3 avalanche activities in the axis
Medium	Between 3 and 7 avalanche activities in the axis
High	Between 8 and 12 avalanche activities in the axis
All round	More than 12 avalanche activities in the axis

The following examples taken from research paper [1], it shows two rules for low danger (refer to Table 2.3 for nomenclature of each parameter) similarly there are rules for other types of avalanche danger too. This example is taken to understand the purpose of the problem statement.

Rule # 1:
IF [HN] IS <HEAVY> AND [HNF] IS <MODERATE>
AND [HNS] IS <LIGHT> AND [SI] IS <HIGH> AND
[HS] IS <SCATTERED> AND [PS] IS <MODERATE>
THEN [CONTRIBUTION] IS <LOW_DANGER>

Rule # 4:
IF [HN] IS <LIGHT> AND [HNF] IS <LIGHT> AND
[HNS] IS <LIGHT> AND [SI] IS <LIGHT> AND [HS]
IS <MEDIUM> AND [PS] IS <LESS> THEN [CONTRIBUTION]
IS <LOW_DANGER>

Table 2.3 Nomenclature of terms used in the rule base

Terms	Description
HN	Fresh snowfall (cm)
HNF	24 h fresh snowfall (cm)
HNS	72 h fresh snow (cm)
SI	Snowfall intensity (cm)
HS	Standing snow (cm)
PS	Free penetration (cm)
CONTRIBUTION	Contribution towards avalanche activity

Chapter 3

Problem Statement

3.1 Gaps in the present scenario

Qualitative and site-wise prediction of avalanches as well as integrated avalanche forecast models require precise weather forecast. Ideally speaking, the numerical forecast of the following weather elements up to 7 km altitude at least 24 h in advance, preferably 3 days in advance, is required for the purpose of avalanche forecasting or for the use of avalanche forecast models.

The important weather elements are:

(a) Precipitation amount and type

(b) Wind speed and direction

(c) Temperature

(d) Radiation

(e) Relative humidity (RH) and pressure.

The numerical forecast of the above parameters is possible through nested modelling approach of mesoscale modelling. Though presently aiming at a resolution of 10 or 20 km scale, avalanche forecasting demands weather forecast at a much finer resolution, preferably on a better than 2 km grid scale. Fuzzy logic [6] 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 boundaries, which can be processed by a computer. Fuzzy logic system [8] 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 model [9] system may also prove to be the most suitable in developing an automated real-time avalanche prediction system.

Chapter 4

Implementation and Results

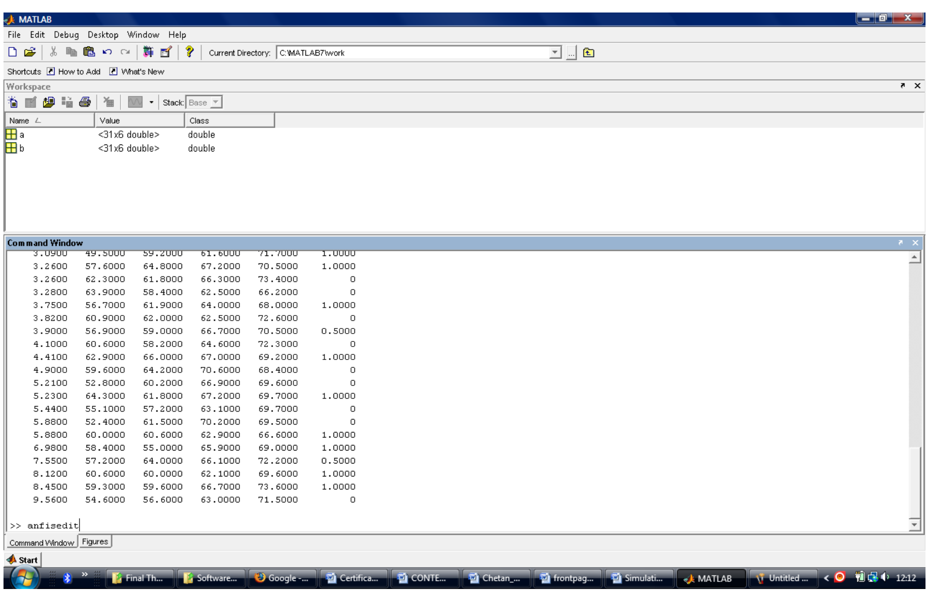
4.1 Work Domain

Before any implementation some tools are used in order to check that every thin that is being implemented is up-to-date and working properly. Here in the earlier stages many different tools were studied and out of them Matlab V.7 was short listed to give the final implementation to the initiated idea for the this work carried out in order to get an insight of the ongoing various research on the similar grounds.

Learning process took step by step implementation and learning of various inbuilt toolbox in Matlab like FIS (Fuzzy Inference System), ANFIS (Adaptive Neuro Fuzzy Inference System) and nntool for neural network helped a lot in order to get the final results provided herein in the following pages. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

a=xlsread (‘Jan.xls’), b=xlsread (‘Jan2.xls’)

Figure 4.1 Snapshots of Data Inputted in the Matlab



Temp	RH	Pressure	Wind Speed	Visibility	Climate Remarks if any
0.9	49.5	59.2	61.6	71.7	1
1.26	53.1	65.1	64.2	70	0
1.61	60.6	58.2	64.6	72.3	0
1.8	52.4	61.5	70.2	69.5	0
1.82	60	60.6	62.9	66.6	1
1.84	64.3	61.8	67.2	69.7	1
1.85	57.4	57.8	65.5	69.7	0.5
1.89	52.8	60.2	66.9	69.6	0
1.96	55.6	59.6	63.3	68.3	0
2.13	62.9	66	67	69.2	1
2.26	56.9	59.4	65.8	67.5	1
2.37	58.9	60.6	67	68.2	0.5
2.59	61.3	58	66.2	68.2	0.5
2.7	57.6	64.8	67.2	70.5	1
2.95	58.1	62.9	64.4	69.2	0.5
3.07	59.3	59.6	66.7	73.6	1
3.14	59.6	64.2	70.6	68.4	0
3.39	56.9	59	66.7	70.5	0.5
3.57	56.6	58.7	60.4	67.8	1
3.65	56.7	61.9	64	68	1
3.91	58.4	55	65.9	69	1
4.01	60.9	62	62.5	72.6	0
4.02	55.4	58	61.3	66.2	0
4.02	55.1	57.2	63.1	69.7	0
4.27	57	63.2	63.6	67.6	0.5
4.64	56.5	59.9	64.3	65.1	0.5
4.66	60.6	60	62.1	69.6	1
5.83	57.2	64	66.1	72.2	0.5
6.36	63.9	58.4	62.5	66.2	0
6.55	54.6	56.6	63	71.5	0
8.36	62.3	61.8	66.3	73.4	0

Temp	RH	Pressure	Wind Speed	Visibility	Climate	Remarks if any
1.46	61.3	58	66.2	68.2	0.5	
1.71	57.4	57.8	65.5	69.7	0.5	
1.71	56.5	59.9	64.3	65.1	0.5	
1.75	55.6	59.6	63.3	68.3	0	
1.94	58.1	62.9	64.4	69.2	0.5	
2.27	57	63.2	63.6	67.6	0.5	
2.52	55.4	58	61.3	66.2	0	
2.68	56.9	59.4	65.8	67.5	1	
2.72	56.6	58.7	60.4	67.8	1	
2.9	58.9	60.6	67	68.2	0.5	
2.96	53.1	65.1	64.2	70	0	
3.09	49.5	59.2	61.6	71.7	1	
3.26	57.6	64.8	67.2	70.5	1	
3.26	62.3	61.8	66.3	73.4	0	
3.28	63.9	58.4	62.5	66.2	0	
3.75	56.7	61.9	64	68	1	
3.82	60.9	62	62.5	72.6	0	
3.9	56.9	59	66.7	70.5	0.5	
4.1	60.6	58.2	64.6	72.3	0	
4.41	62.9	66	67	69.2	1	
4.9	59.6	64.2	70.6	68.4	0	
5.21	52.8	60.2	66.9	69.6	0	
5.23	64.3	61.8	67.2	69.7	1	
5.44	55.1	57.2	63.1	69.7	0	
5.88	52.4	61.5	70.2	69.5	0	
5.88	60	60.6	62.9	66.6	1	
6.98	58.4	55	65.9	69	1	
7.55	57.2	64	66.1	72.2	0.5	
8.12	60.6	60	62.1	69.6	1	
8.45	59.3	59.6	66.7	73.6	1	
9.56	54.6	56.6	63	71.5	0	

[System]

Name='Climate13'

Type='sugeno' (Sugeno-Type Fuzzy Inference)

Version=2.0

NumInputs=5

NumOutputs=1

NumRules=3

AndMethod='prod' (Product of array elements)

OrMethod='probor' (Probabilistic OR)

ImpMethod='prod' (Product of array elements)

AggMethod='sum' (Sum of array elements)

DefuzzMethod='wtaver' (weighted average)

[Input1]

Name='Temperature'

Range= [0 10]

NumMFs=3

MF1='Low':'trimf', [0 2 3] (Triangular-shaped membership function)

MF2='Medium':'trimf', [2.5 5.5 7.5] (Triangular-shaped membership function)

MF3='High':'trimf', [7 8 10] (Triangular-shaped membership function)

[Input2]

Name='Relative Humidity'

Range= [45 65]

NumMFs=3

MF1='Low':'trimf', [45 50 54] (Triangular-shaped membership function)

MF2='Medium':'trimf', [52 55 57] (Triangular-shaped membership function)

MF3='High':'trimf ‘, [56 62 65] (Triangular-shaped membership function)

[Input3]

Name='Pressure'

Range= [50 70]

NumMFs=3

MF1='Low':'trimf', [50 55 59] (Triangular-shaped membership function)

MF2='Medium':'trimf', [57 60 64] (Triangular-shaped membership function)

MF3='High':'trimf', [62 67 70] (Triangular-shaped membership function)

[Input4]

Name='Wind_Speed'

Range= [50 75]

NumMFs=3

MF1='No_Wind':'trimf', [50 54 59] (Triangular-shaped membership function)

MF2='Moderate':'trimf', [57 62.5 67] (Triangular-shaped membership function)

MF3='Windy':'trimf', [65 69 75] (Triangular-shaped membership function)

[Input5]

Name='Visibility'

Range= [60 75]

NumMFs=3

MF1='Low':'trimf', [60 63 66] (Triangular-shaped membership function)

MF2='Normal':'trimf', [65 68 70] (Triangular-shaped membership function)

MF3='Clear':'trimf', [69 73 75] (Triangular-shaped membership function)

[Output1]

Name='Climate'

Range= [0 1]

NumMFs=3

MF1='Harsh':' constant', [0]

MF2='Moderate':' constant', [0.5]

MF3='Good':' constant', [1]

[Rules]

1. If (Temperature is Low) and (Relative_Humidity is Low) and (Pressure is Low) and (Wind_Speed is No_Wind) and (Visibility is Low) then (Climate is Harsh) (1)

2. If (Temperature is Medium) and (Relative_Humidity is High) and (Pressure is Medium) and (Wind_Speed is Moderate) and (Visibility is Normal) then (Climate is Moderate) (1)

3. If (Temperature is Medium) and (Relative_Humidity is Medium) and (Pressure is Medium) and (Wind_Speed is Moderate) and (Visibility is Normal) then (Climate is Good) (1)

Figure 4.2 ANIFS Model Structure after loading climate13.fis from the disk

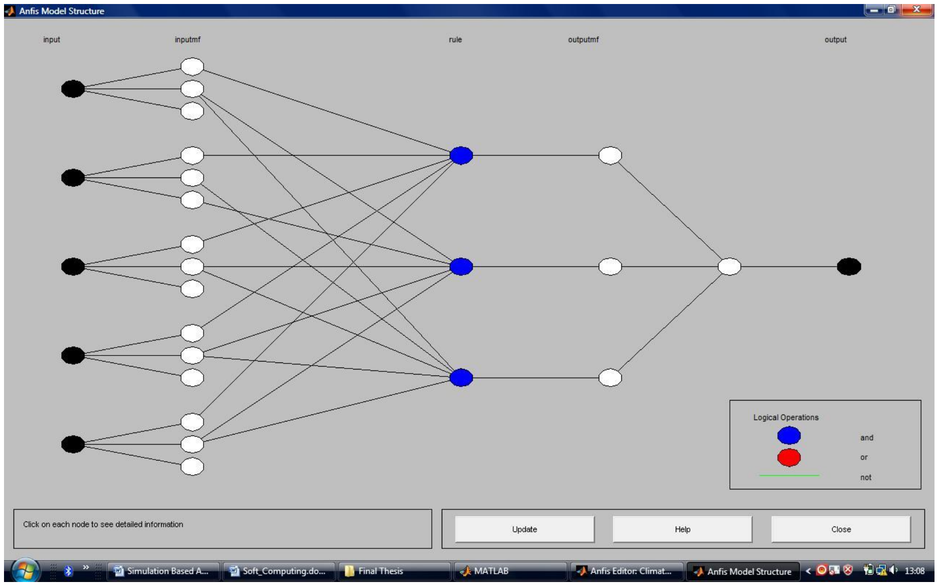


Figure 4.3 Fuzzy Inference System

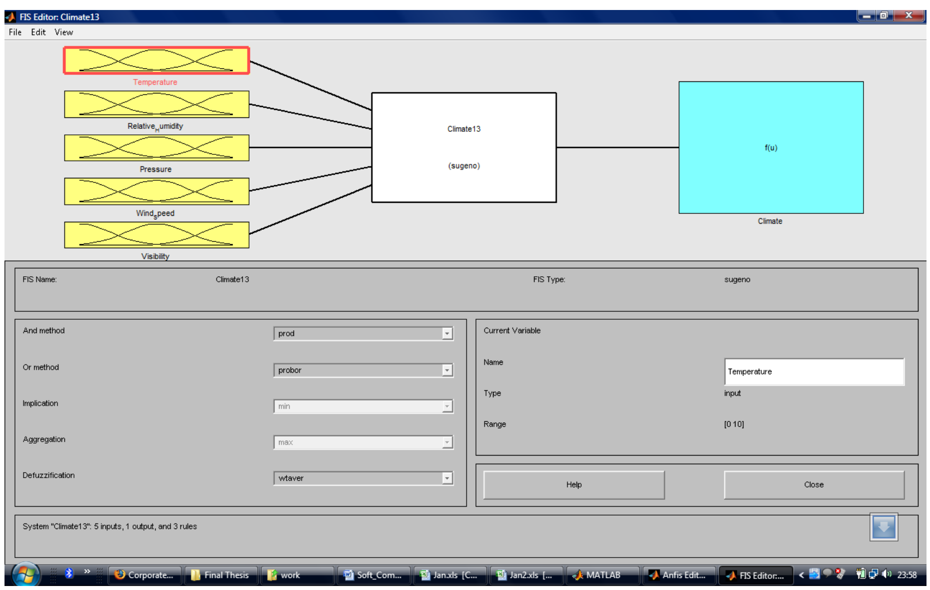
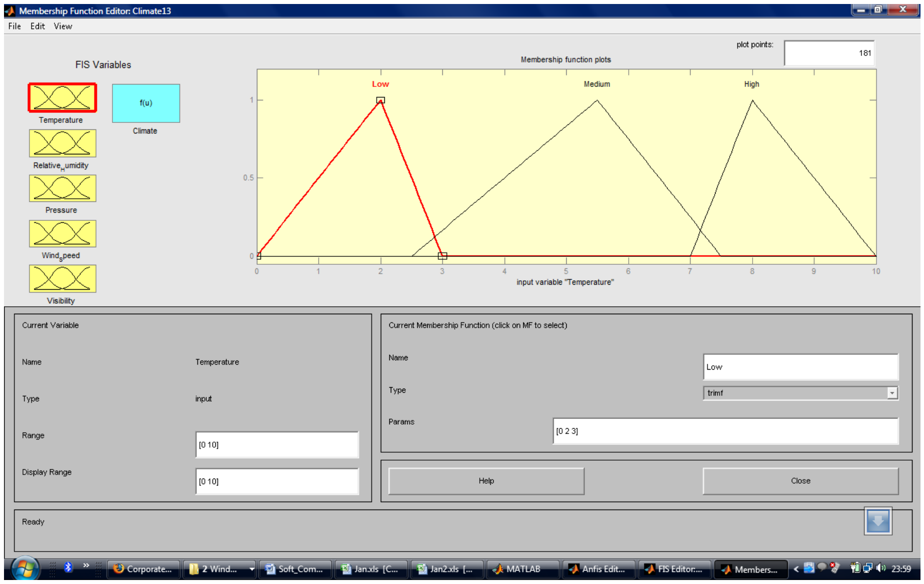


Figure 4.4 Membership functions first parameter that is Temperature

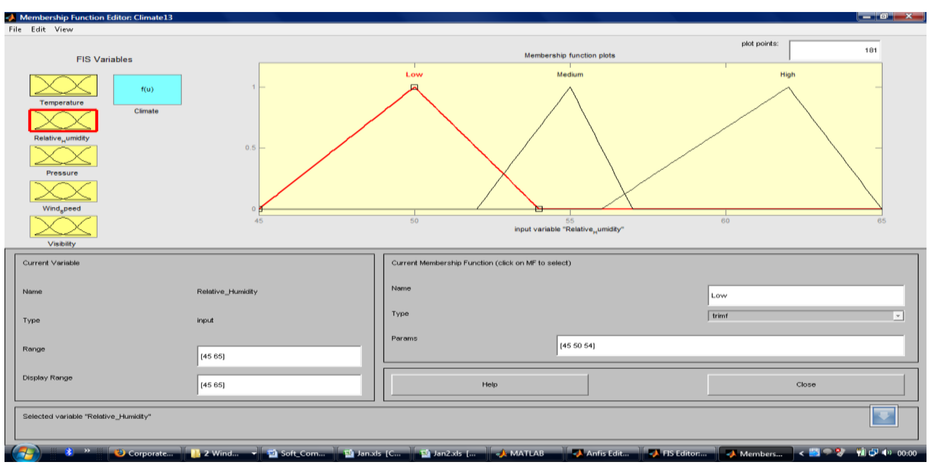


MF1='Low':'trimf', [0 2 3] (Triangular-shaped membership function)

MF2='Medium':'trimf', [2.5 5.5 7.5] (Triangular-shaped membership function)

MF3='High':'trimf', [7 8 10] (Triangular-shaped membership function)

Figure 4.5 Membership functions of second parameter that is Relative Humidity

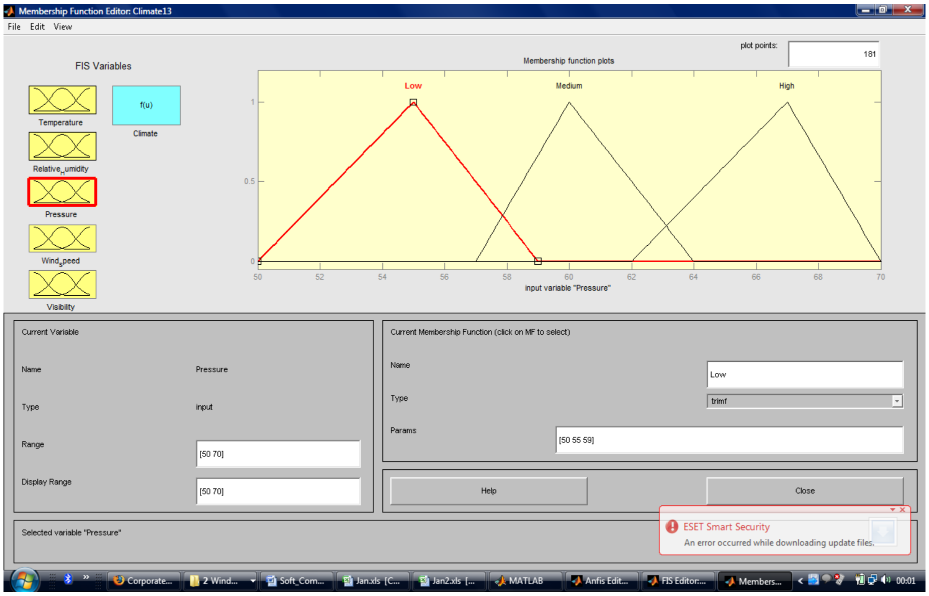


MF1='Low':'trimf', [45 50 54] (Triangular-shaped membership function)

MF2='Medium':'trimf', [52 55 57] (Triangular-shaped membership function)

MF3='High':'trimf ', [56 62 65] (Triangular-shaped membership function)

Figure 4.6 Membership functions of third parameter that is Pressure

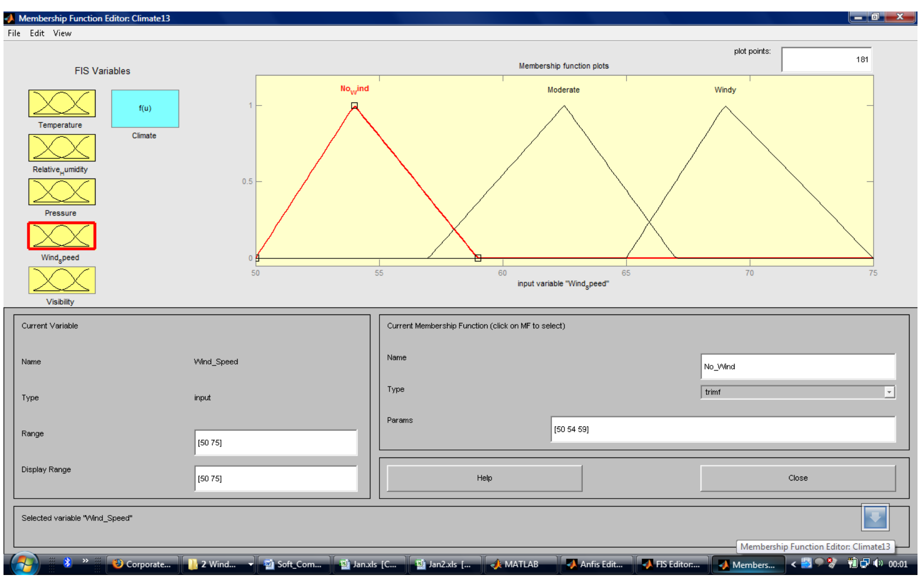


MF1='Low':'trimf', [50 55 59] (Triangular-shaped membership function)

MF2='Medium':'trimf', [57 60 64] (Triangular-shaped membership function)

MF3='High':'trimf', [62 67 70] (Triangular-shaped membership function)

Figure 4.7 Member ship functions of fourth parameter that is Wind Speed

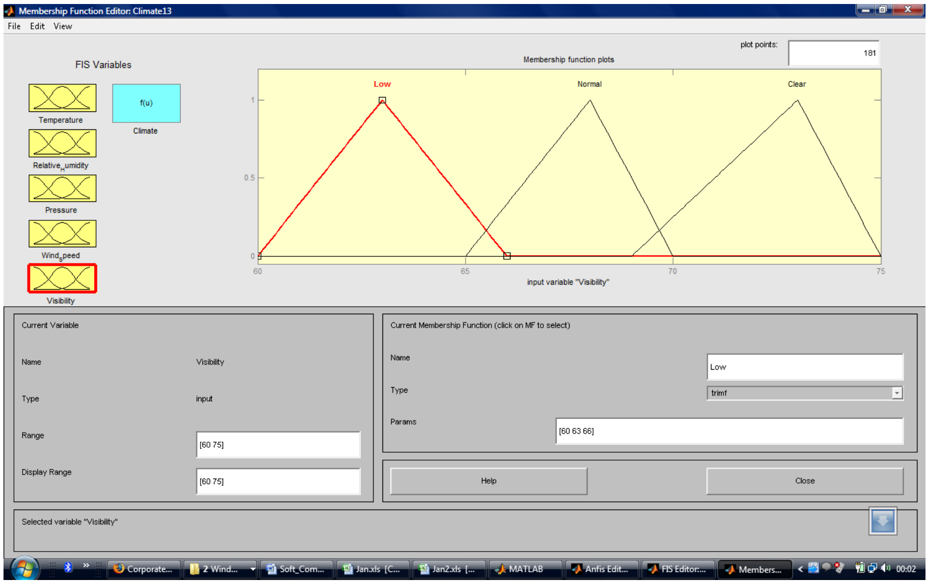


MF1='No_Wind':'trimf', [50 54 59] (Triangular-shaped membership function)

MF2='Moderate':'trimf', [57 62.5 67] (Triangular-shaped membership function)

MF3='Windy':'trimf', [65 69 75] (Triangular-shaped membership function)

Figure 4.8 Member ship functions of fifth parameter that is Visibility



MF1='Low':'trimf', [60 63 66] (Triangular-shaped membership function)

MF2='Normal':'trimf', [65 68 70] (Triangular-shaped membership function)

MF3='Clear':'trimf', [69 73 75] (Triangular-shaped membership function)

Figure 4.9 Snapshot of Training data and FIS output

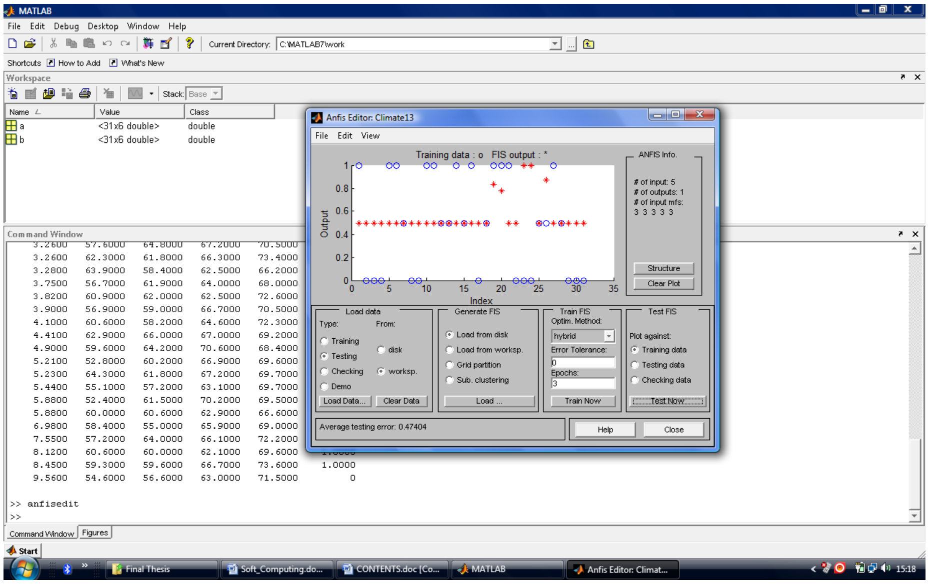


Figure 4.10 Snapshot of Testing Data and FIS output

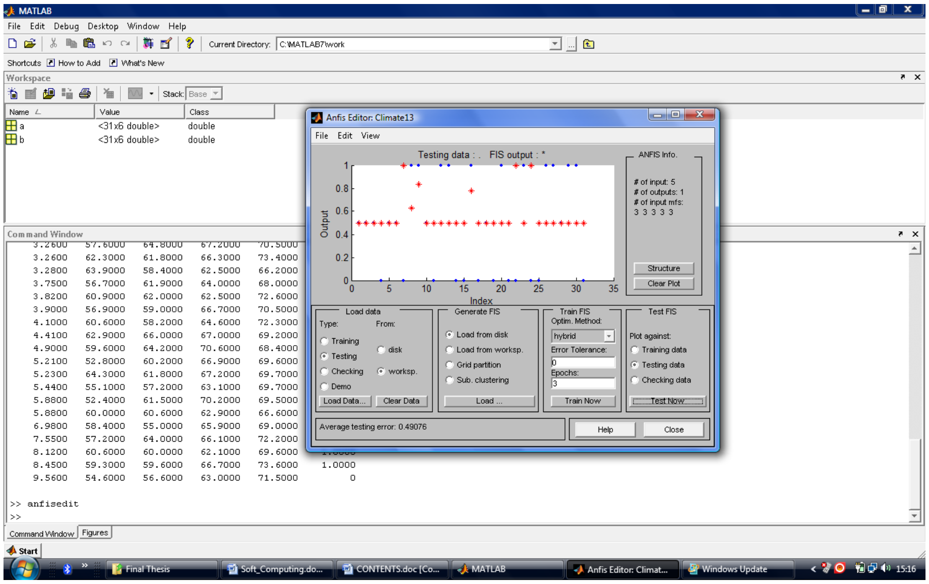
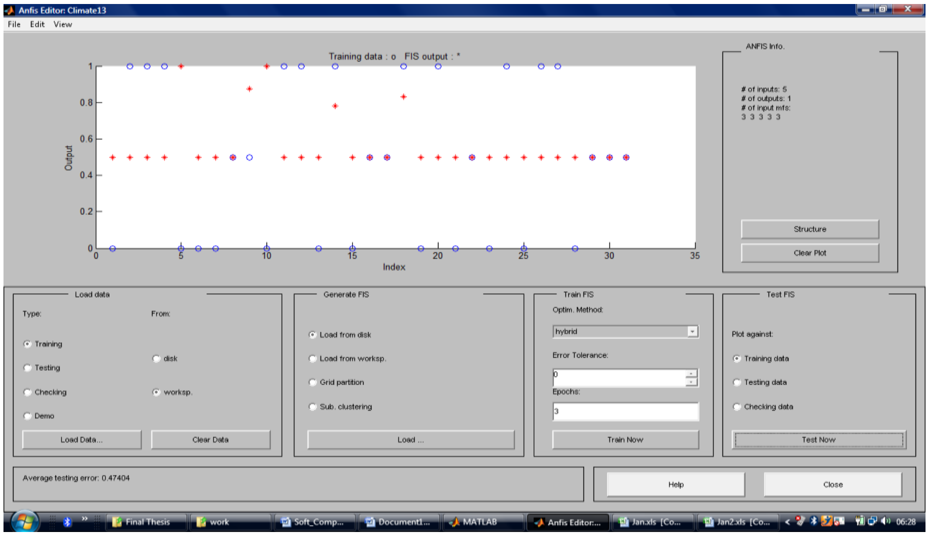


Figure 4.11 Final Result of the training test data



Final results of the sample weather data which is used for simulation tests was working properly and producing the desired output for the prediction of avalanches. Due to some constraints the actual data was not available but the motive of the research is accomplished which can be used on the real time specific applications such as avalanche forecasting and prediction of weather in order to know the favorable and unfavorable conditions of the weather for the troops and civilians in order to save precious lives.

Chapter 5

Conclusion and Future Scope

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. Presently only three rules are used for the system in future more membership functions can be defined to generate the corresponding neuro fuzzy rules.

The learning duration of ANFIS is very short than neural network case. It implies that ANFIS reaches to the target faster than neural network. When a more sophisticated system with a huge data is imagined, the use of ANFIS instead of neural network would be more useful to overcome faster the complexity of the problem. In training of the data, ANFIS gives results with the minimum total error compared to other methods. This shows that the best learning method is ANFIS among the others. However, when the trained parameters were applied to checking data, total error of neural network is smaller than that of ANFIS. Although it looks like a contradiction, the reason of this situation is due to the amount of short data, which is not enough to good learning. Fuzzy logic method seems to be the worst in contrast to others at a first look. But of course there are a lot of reasons of getting such results. First of all, the rule size was limited to only three rules while the membership variables are restricted by just three variables. Secondly, rules and the number of membership functions of fuzzy sets were chosen according to the intuitions of the expert. If more membership variables and more rules had been used, a better result would have been available. The restriction of fuzzy rules and fuzzy sets is due to the ANFIS constraint.

Future Scope:

The expert system can be developed which could correctly predict more accurately with both types of avalanche occurrence information. The performance of the expert system could be fairly good for the prediction of avalanche days along the road axis with the available information. It may perform poorly for identification of avalanche danger with the actual avalanche occurrence reports. However, it can improve with the inclusion of the expert forecaster's assessment of the situation. This could be mainly due to the lack of complete avalanche occurrence reports. The situation-based rules can be developed according to time of winter and the expert system can be calibrated accordingly to propose decision. Further, it is necessary to integrate the latest avalanche occurrence reports in any avalanche prediction model for better assessment of the avalanche danger situation, which has not been included yet. The expert system needs to be tested on a large dataset with accurate avalanche occurrence information.

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