USE OF NEURAL NETWORKS IN AVALANCHE HAZARD FORECASTING

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Abstract

Artificial neural networks were investigated as a tool to be used in avalanche hazard forecasting. Such forecasts are presently formulated by experts using their knowledge and experience. While the experts utilize a variety of information in their decision making process, the exact nature of the relationship between these factors and the level of avalanche hazard is unknown. The consistency and reliability with which these assessments are made may be improved, if the experts are provided with tools, such as an artificial neural network, that explicity utilize these various types of information. Trial networks were developed herein that act upon weather and snow condition data to generate an opinion on avalanche activity on a daily basis for a specific slide path. These networks were developed using historical avalanche data. Networks trained on a season by season basis issued correct predictions of avalanche activity as many as 78 to 91 percent of the evaluation cases considered. On days that avalanches were known to occur, these networks were correct for 36 to 100 percent of the cases considered. Networks trained over multiple seasons were less successful, correctly predicting avalanche activity for up to 82 percent of the days considered, but with a success rate on days avalanches were known to occur of only 40 percent. Additional work is necessary before a tool of this type will be useful to the avalanche expert. Improvements in network performance may result from modifying inputs, and/or modifying the newtwork architecture, training algorithm, or output configuration.

Introduction

Every winter, numerous avalanches occur in the mountainous regions of the United States and around the world. Many of these avalanches occur in relatively unpopulated regions, and thus have only nominal impact on man. This situation is changing, however, in response to ever increasing development of both permanent communities and recreational facilities in such areas. Use of back country areas by skiers, snowmobilers, and other outdoors people is also continuing to increase. Hazards posed by avalanches in these areas range from loss of life, to loss of property, to loss of property access (road closures). These avalanche hazards can be reduced by using control techniques (artifically triggering events) and by issuing appropriate warnings to people venturing into avalanche active areas. The effectiveness and efficiency of these hazard mitigation techniques can be most completely realized when they are used in conjunction with a reliable avalanche forecasting technique.

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At present, avalanche forecasting is performed by experts acting on their knowledge and experience with snow stability situations. These experts utilize information related to the past and present snow and weather conditions, the terrain, and the past avalanche history to issue an opinion on potential avalanche activity. While the experts generally agree on the important types of information that are used in this decision making process, the exact manner in which these various types of information influence the final decision is not well established. Precise and generally accepted models for avalanche forecasting have not been developed. The reliability and consistency with which these forecasts can be made would be improved if the experts are provided with additional tools that explicitly utilize the various types of information available in the diecison making process. An artificial neural network trained to issue avalanche forecasts may be such a tool. Artifical neural networks are analytical systems designed to mimic the biological decision making process of the human brain. The networks are trained to perform specific tasks (such as avalanche forecasting) using historical data on the problem under study. Attractive features of neural networks include that (1) several inputs of diverse types can be collectively considered in the decision making process, and (2) apriori assumptions on the form of the relationship(s) between the input variables and the network outputs are unnecessary.

The artificial neural networks experimented with in this study were trained to issue opinions on the likelihood of the occurence of avalanches along a specific slide path on any given day based on present and previous weather and snow conditions in the area. This initial work purposefully focused on developing networks for specific slide paths, to eliminate terrain and exposure related variables from the problem. Fifteen parameters related to weather and snow conditions were used as network inputs. The network output was an index whose value ranged from zero to one, with higher values corresponding to increased likelihoods of avalanche activity. Network training and evaluation was accomplished using data collected over the past several years on a slide path in south central Colorado. The resulting networks that were trained on a season by season basis correctly predicted over-all avalanche activity up to 78 to 91 percent of the evaluation cases considered. Correct prediction of avalanches on days on which they actually occurred ranged from 36 to 100 percent. Networks trained over multiple seasons realized over-all success rates in predicting avalanche activity of up to 82 percent. These networks, however, were only correct in predicting avalanches 40 percent of the time for days on which avalanches were known to occur.

These results are sufficiently encouraging to justify additional research on artificial neural networks as a tool for avalanche hazard forecasting. Steps that may lead to better network performance include adding new inputs, modifying existing inputs, revising the network outputs, and changing the network learning algorithm and parameters. Successful networks will become one more tool available to an expert faced with formulating an avalanche hazard forecast. Such networks may also be useful as part of an automatic warning system that electronically collects and processes weather and snowpack data.

Avalanche Hazard Assessment

Avalanches occur due to the failure of the snow pack to withstand the stresses placed upon it by its self weight and other imposed forces. Failure initiates at the weakest point in the snow pack with regard to applied stress and available strength. Failure then propagates throughout the mass as adjacent areas become overloaded and fail. Spatially, the properties of the snow pack can be highly variable, with regard to both the stress it is being asked to resist and the available strength. Thus, to analytically model snow pack behaviour to predict avalanche occurence would require extensive data collection and material property tests at closely spaced points throughout the potential slide area. Generally, such data collection efforts are unfeasible from life safety and/or financial resource perspectives. Even if such data were available, inadequacies still exist in the ability of current analysis tools to fully model all aspects of snow pack performance.

In light of the complexities and limitations cited above, avalanche forecasters often rely on indirect indicators of snowpack stress and strength conditions, possibly coupled with rudimentary tests of snow conditions, in formulating hazard forecasts. These indicators include such items as new snow depth, which may be known and which can be used to infer increased stress level on the snowpack, which is unknown. These various indicators of avalanche hazard can generally be grouped into the broad categories of terrain features, slope exposure, snow conditions, weather conditions, and past history. A list of specific factors that are typically used in snow stability analyses, as identified by Schaerer (1981), is presented in Table 1. Other and related parameters that may be indicative of avalanche activity include new snow water equivalency and weather trends (e.g., warming trends).

While the relationships that exist between some of these parameters have been explored (in statistical studies, for example (Thompson and McCarty, 1994)), universally accepted models (either mechanistic or empirical) that fully utilize and characterize the interrelationship between variables have not been developed. A robust approach to avalanche hazard forecasting would use all these indicators collectively in the forecasting process. An artificial neural network may offer such an approach to the problem.

Neural Networks

A strong need exists for an evaluation method that incorporates all the various factors related to snow stability in formulating avalanche hazard forecasts. Artificial neural networks, a form of artificial intelligence, may be an appropriate tool to meet this need. Artificial neural networks are computing systems that operate on input data to obtain a related output in a fashion that simulates the action of the biological neural network of the human brain (Firebaugh, 1988). Based upon research in neurophysiology, a human brain has on the order of 100 billion neural cells interconnected in a complex manner to form a large scale network. The artificial neural network model of this system consists of layers of neurons connected by weighted paths. Network models range in complexity from a simple single neuron to multilayer nets (see Figure 1). In a typical network model, the input signals are transmitted along the indicated paths to the first layer of middle neurons. During transmission, the signals are multiplied by a weighting factor associated with each connection path. The neurons in the middle layer sum all the inputs they receive. The summed inputs are transformed by the neurons (using a sigmoidal or other function) and then output to the next layer of neurons, as shown in Figure 2. This process is repeated until the output layer is reached. The complexity of knowledge that can be represented by a network is related in part to its configuration, i.e. when complex relationships are suspected

Table 1. Factors Used in Snow Stability Analysis (adapted from Schaerer, 1981).

Category	Factor	Critical Condition	Used in Neural Network
Terrain	Terrain in starting zone	Slope greater than 25°	No*
	Surface roughness	See snow depth	No*
Exposure	Solar radiation	Slope exposed to the sun	No*
	Orientation with respect to wind	Lee side	No*
Snow Conditions	Snow depth	> 30 cm, smooth ground > 60 cm, average ground	Yes
	Depth of new snow	30 cm new snow and greater	Yes
	Snow stratification	Weak intermediate layers	Indirectly
	Settlement of new snow	Less than 15 percent per day	Indirectly
	Snow Temperature	0° C	Yes
	Slope test	Ski trigger 0° C	No
Weather Conditions	Precipitation	20 mm and greater	No
	Rate of precipitation	2 mm/hr and greater	No
	Wind speed	Greater than 4 m/s	Yes
	Wind direction	On lee slopes	Yes
	Air temperature	0° C and higher -10° C and lower	Yes
Avalanche History	Avalanche since last storm?	No avalanche in last storm, Avalanches running now	No

*Neural network developed for single slide path, eliminating the need to consider these slide path related variables between inputs and outputs, a multilayer network may be appropriate.

Key to the neural network concept is a means for establishing the connection weights. These weights are determined based on available data for which both the network inputs and actual outputs are known. The connection weights are adjusted to minimize the error between the network generated and actual outputs. A least squares error minimization scheme is frequently employed. For multilayer networks, the responsibility for the error can be back propagated through the network, resulting in correction of the weights along each connection. The weight adjustment or training process continues iteratively until the differences between the network generated and actual outputs are within an acceptable level (referred to as the training tolerance).

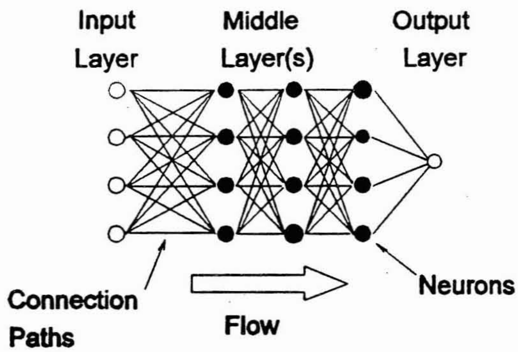

Figure 1. Typical artificial neural network configuration.

Neural networks can be programmed on computers (and possibly hand calculators, depending on network size) or constructed with electrical circuits. A neural network software package called NNICE, developed by VanLuchene and Sun (1990), was used in this investigation. Network operations were validated using a commercial software package. Both pieces of software are designed to run on personal computers.

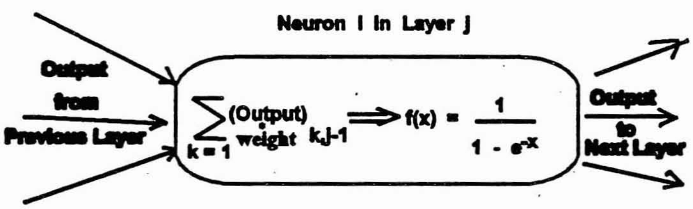

Figure 2. Typical neuron function.

Neural networks have been experimented with in a variety of applications, including character recognition (Nellis and Stonham, 1992), medical diagnostics (Wu, et.al., 1992), mine safety assessment (VanLuchene, 1993), and postearthquake structural damage assessment (Stephens, Huo and Larsson, 1994). Advantages of neural networks include that (a) many variables of diverse types can be included in the problem formulation, (b) assumption of the form of the relationship between the independent oand dependent variables is unnecessary, and (c) new data on the problem under study can easily be considered in improving the solution by retraining the network. If all the important parameters for the problem under study are identified and reasonably represented as inputs, reasonable and useful results should be obtained.

Inputs and Outputs

The fifteen inputs listed in Table 2 were selected for consideration in the avalanche forecast network. To simplify the problem under study, the decision was made to focus on developing separate networks to forecast avalanches along individual slide paths. Thus, factors related to terrain and exposure were constant within each problem and eliminated from network consideration. The selected inputs represent to varying degrees most of the remaining factors identified in Table 1, under the categories of snow and weather conditions, as being often used in snow stability forecasts. Criteria used in selecting these specific inputs inluded (a) their importance to the problem, (b) the ease with which they could be obtained, and (c) the degree of subjectivity in their evaluation. An effort was made to include inputs on current snow and weather conditions for each day, as well as on trends in these conditions that might reflect very short term metamorphises within the snowpack. With regard to snow conditions, factors considered included temperature below the snow surface, change in temperature below the snow surface from previous days reading, snow depth, new snow depth, water equivalency of new snow, and change in water equivalency of new snow from previous day. Weather information included maximum air temperature, minimum air temperature, air temperature at time of observation, change in average temperature from previous day, fastest one-hour average wind speed, previous day one-hour wind speed, fastest one-hour average wind direction, and previous day fastest one-hour average wind direction.

Factors not included as network inputs that have been identified as important to the problem include the results of slope tests and avalanche history. Slope tests results were perceived to be somewhat subjective in nature and generally unavailable in the historical records. If this perception is incorrect, slope test results could be a very important input to the network. Avalanche history, perhaps measured in terms of days since last avalanche, should be added as a network input in future studies.

For this investigation, the selected network output was simply whether or not an avalanche occurred each day. Other and more specific forms of output were considered and may be used in future investigations. These output systems include the numerical size classification system used by the U.S. Forest Service or and/or a system consistent in some manner with the hazard assessment scheme used by the Colorado Avalanche Information Center in which verbal hazard levels of low, medium, high, and extreme are used (Bachman and Hogan, 1993). For slide paths above roadways, appropriate network outputs might be depth of slide snow at centerline of road and length of centerline covered with slide snow.

After much discussion, no distinction was made between artificially triggered and and naturally occurring avalanches. By following this approach, the implicit assumption was made that natural avalanches were imminent when artificial triggers were used. This treatment of natural and artificially triggered events merits further study and possible revision in future investigations. Neural networks can have multiple outputs, and separate outputs could have been assigned to each kind of event.

Table 2. Neural Network Inputs

Category	Input (for each day)	Normalization scheme
Snow Conditions and Trends	Temp. 20 cm below snow surface (°C)	$\frac{x + 20}{2}$
	Snow depth (in)	$\frac{x}{120}$
	New snow depth (1/2 in)	$\frac{\log(x + 1)}{\log(181)}$
	Water equivalency of new snow (1/100 in)	$\frac{\log(x + 1)}{\log(181)}$
	One day trend in temperature 20 cm below snow surface (today's temperature minus yesterday's temperature (°C))	$\frac{x + 7}{19}$
	Previous day new snow depth (in)	$\frac{\log(x + 1)}{\log(181)}$
Weather Conditions and Trends	Maximum air temperature (°F)	$\frac{x}{60}$
	Minimum air temperature (°F)	$\frac{x + 20}{50}$
	Air temperature at time of observation (°F)	$\frac{x + 10}{60}$
	Fastest one-hour average wind speed (mph)	$\frac{x}{60}$
	Fastest one-hour average wind direction	$\frac{x}{36}$
	Previous day average air temperature (°F)	$\frac{x + 6}{45}$
	One day trend in air temperature (today's temp. minus yesterday's temp. (°F))	$\frac{x + 38}{68}$
	Previous day fastest one-hour average wind speed (mph)	$\frac{x}{60}$
	Previous day fastest one-hour average wind direction	$\frac{x}{36}$

Training and Evaluation Data

The knowledge base of the network was established based on past experience, which in this case consisted of records on daily avalanche activity along specific slide paths and attendant weather and snow condition data in the same area over several years. This information was collected for over 50 slide paths along U.S. Route 550 in south central Colorado for the period fall of 1971 to spring of 1975. Information on avalanche activity was collected from U.S. Forest Service Avalanche and Control Occurence Charts. Weather and snow condition data was obtained from U.S. Forest Service Monthly Summary of Weather and Snow Condition data sheets. Any additional data that are available and should be used in future studies. Avalanche information has already been collected for the period of fall of 1957 to spring of 1993.

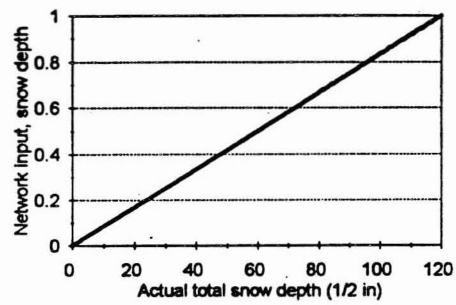

Figure 3. Typical linear normaliztion of input.

Data on the Bluepoint slide path was specifically extracted from the above described data base for use in this investigation. A significant number of the avalanches that occured in this area happened on this slide path in the three avalanche seasons between the fall of 1972 and the spring of 1975.

Neural network algorithms generally use a numeric format to represent input and output information, with all input and output values ranging from zero to one. Thus, the various inputs and outputs were normalized prior to entry into the network. The normalization schemes used in this study are summarized in Table 2. Most of the parameters were simply normalized using a linear transformation from their actual range of realizations to a range from zero to one, as is shown in Figure 3 for total snow depth. Thoughtful selection of normalization schemes can result in better utilization of all the information available from a parameter. New snow depth, for example, was normalized using a logarthmic function, as shown in Figure 4. Such an approach reflects the belief that if new snow depths are high, avalanches occur with more frequency, independent of the precise amount of new snow that has fallen. Thus, above some threshold value, all snow depths have similar influence on avalanche occurence. Consideration was given to further expanding the sensitivity of this input by limiting its influence at low new snow depths, which are known to infrequently result in avalanches. In future studies, consideration

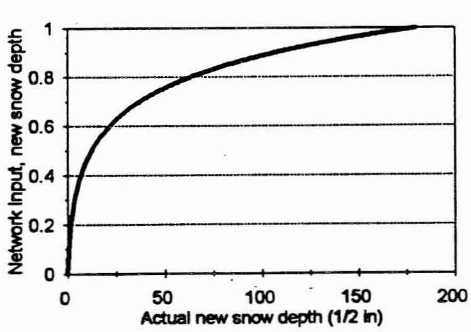

Figure 4. Logarithmic transformation of input.

will be given to normalizing new snow depth using a sigmoidal function that replicates both of these observations regarding the the effects of low and high new snow depths on avalanche activity. Relationships of this kind identified in the literature for various inputs should be utilized at every opportunity.

The network output was verbal in nature, consisting of a yes or no answer to the question of whether or not an avalanche occurred each day. Two approaches typically have been tried for representing this kind of network parameter. The verbal responses can be assigned numerical realizations. This approach is appropriate if intermediate values of the parameter have an interpretable significance. Alternatively, two separate outputs can be used and assigned values of either 0 or 1 depending on the appropriateness of the response. The former approach was used in this investigation with a value of 0.25 assigned on days without avalanches; 0.75, on days with avalances. Intermediate values generated by the network were perceived as loosely representing the likelihood of avalanche occurence (from very low, at values around 0.25; to very high, for values around 0.75).

Late in the investigation, the discovery was made that some of the input data may be in error. Notably, the reported values for the water equivalency factor for new snow appeared in a few instances to be inconsistent with the amount of new snow and total snow depth reported. The performance of neural networks is directly related to the quality of the data with which they are trained. Data errors can result in parameters known to be important to the problem under study having little influence, or more importantly, an incorrect influence, on network preformance. In this case, only a few percent of the data points appeared irregular, primarily in the 72-73 season. The decision was made to proceed without altering the data.

Training And Evaluation Process

The matched sets of input and output values assembled above were used to train and evaluate different avalanche forecasting networks for the Bluepoint slide path. Initially, independent networks were trained for each of three avalanches seasons from the fall of 1972 to the spring of 1975. Thus, interseasonal variations in avalanche activity were purposefully elimnated from consideration, in an effort to further simplify the phenomena under study for this preliminary investigation. Certainly, network training will have to be extended to include several avalanche seasons if a useful avalanche forecasting tool is to be developed. Schaerer (1981) suggests that avalanches have cycles which usually run from 12 to 20 years. Some experimentation was done with networks trained using data from all three avalanche seasons. The data sets used in creating each network were partitioned into two groups. Between 50 and 75 percent of the data was used in network training, with the remainder of the data reserved for evaluation. The only condition enforced in this process was that the training and evaluation partitions for each data set nominally contained the same ratio of avalanche to non-avalanche days. A summary of the avalanche activity for each data set is presented in Table 3. The number of avalanche events included in some of these data sets is small, and the associated characterization of the avalanche phenomena embodied in this data could be limited.

All work was done using feed forward networks, with the neurons on each layer fully connected to the neurons on the following layer (see Figure 1). Various architectures were considered with regard to number of middle layers and number of neurons per layer. During the training process, the network weights were adjusted using the delta rule (Rumelhart and McClelland, 1986). Values for other common network related parameters, whose purpose and

Table 3. Avalanche Activity in Each Data Set Used in Neural Network Development.

Data Set	Partitioning of the Data			Summary of Avalanche Activity Represented in the Data	
	Total days	Training days	Evaluation. days	Percent of days with no avalanches	Percent of days with avalanches
72-73	115	71	44	89	11
73-74	106	71	35	83	17
74-75	136	71	67	83	17
72-75	357	213	146	85	15

function is more completely described in neural network literature (e.g., Rumelhart and McClelland, 1986), included a learning rate of 0.95 and a smoothing factor of 0.9. A sigmoidal transfer function was used with both constant and trained bias. The performance of trained networks was measured using the evaluation data. The network generated outputs were judged to be correct when they fell within plus or minus 0.250 of the actual outputs (one-half of the numerical step between non-occurence and occurence) .

Network Performance

The performance of the networks trained for individual avalanche seasons was both discouraging and encouraging with regard to the potential usefulness of neural networks as a tool for avalanche forecasting. The performance of these networks is summarized in Table 4. The network structures considered ranged in architecture from a network with 1 middle layer containing 7 neurons to a 3 middle layer network containing 6 neurons per layer. Note that the range of network architectures experimented with is not exhaustive. Few guidelines are available for selecting trial architectures. The selected networks should be generally representative of levels of performance that can be expected using these inputs and the selected training algorithm. The training tolerance (permissible difference between the network generated and known output) was varied from 5 to 25 percent of full scale (1.0). Performance of the networks developed using the data from the 72-73 and 73-74 avalanche seasons was impressive in some instances. Referring to Table 4, the best overall performance for the networks for the 72-73 season was 89 percent, with a 100 percent success rate in predicting avalanches on days they were known to occur. The performance of the best network for the 73-74 season was equally remarkable. This network had an overall success rate of 91 percent and correctly predicted avalanches on 100 percent of the days they were known to occur. These networks also exhibited a possibly desireable conservativism in their behavior,in that they nominally overpredicted avalanche occurrence. The best network for the 74-75 season, however, had an overall success rate of only 78 percent, and it correctly predicted avalanches on only 45 percent of the days they were known to have occurred.

Table 4. Summary of Network Performance, Seasonal Networks.

Data Set	Nuerons per Hidden Layer	Number of Hidden Layers	Training Tolerance (fraction of range 0 to 1)	% of Correct Outputs, Overall	% of Correct Outputs, Days with Avalanches
72-73	7	1	0.05	70	40
			0.10	86	60
			0.25	82	60
	6	2	0.05	70	60
			0.10	66	40
			0.25	82	60
	5	3	0.05	did not train	did not train
			0.10	did not train	did not train
			0.25	did not train	did not train
	6	3	0.10	89	100
73-74	7	1	0.05	74	50
			0.10	77	50
			0.25	83	50
	6	2	0.05	89	25
			0.10	86	50
			0.25	74	50
	5	3	0.05	91	75
			0.10	91	100
			0.25	91	75
74-75	7	1	0.05	73	45
			0.10	33	91
			0.25	33	55
	6	2	0.05	78	45
			0.10	did not train	did not train
			0.25	73	36
	5	3	0.05	did not train	did not train
			0.10	did not train	did not train
			0.25	did not train	did not train

The behavior of the seasonal networks may have been influenced by, among other things, the size of the data sets. As previously mentioned, the data contain few avalanche events, and these events probably do not comprehensively represent all combinations of factors that would indicate avalanche occurrence. This issue can be addressed by repartitioning the data and repeating the training and evaluation process. If different results are obtained using different partitionings of the same base data, the conclusion can be made that the network is modeling behaviors particular to the specific data set being used in addition to (or, in the worst case, instead of) characterizing the under lying phenomena being studied. Additional insights can be obtained by studying the specific events for which the network is in error. Such analyses are currently underway and may indicate that better results are possible for this problem than might be expected based on the 74-75 networks. Unfortunately, these analyses will probably also reveal that the remarkable results obtained for the 72-73 and 73-74 networks represent to some degree a fortuitous partitioning of the data and/or a coincidental match of the properties of the particular data sets to specific network configurations.

The decision to treat artificially triggered avalanches as no different than naturally occuring avalanches may also have influenced the performance of the seasonal neural networks. Artifically triggered avalanches represented 16, 17, and 48 percent of the total avalanches reported in the 72-73, 73-74, and 74-75 seasons, respectively. The performances of the networks trained for the 72-73 and 73-74 seasons, which included predominantly natural events, were significantly better than that of the networks trained for the 74-75 season, which included an almost even mixture of naturally occurring and artificially triggered events. Conditions associated with the two types of events may be sufficiently different that the network is confused when forced to treat them the same. This situation requires further investigation. Consideration should be given to using separate outputs for naturally occuring and artificially triggered events.

The performance of the limited number of networks trained using the data from all three avalanche seasons is summarized in Table 5. Attempts were initially made to develop networks using the same architectures and tolerances as used above for the single season networks. These networks, however, could not be trained. These networks apparently offered insufficient capacity to model all the relationships encountered in the combined data set. This situation implies that the relationships between the various input factors and avalanche occurrence do indeed vary between seasons. Some of this variation may be related to the problem already discussed regarding the treatment of artificially triggered avalanches. Networks with two middle layers and 9 and 10 neurons per middle layer were successfully trained at a tolerance of 0.20. The best network issued correct assessments of overall avalanche activity for 82 percent of the evaluation cases considered. This same network, however, was only successful in predicting avalanches on 60 percent of the days they were known to occur.

Table 5. Summary of Network Performance, Multi-Season Network.

Data Set	Nuerons per Hidden Layer	Number of Hidden Layers	Training Tolerance (fraction of range 0 to 1)	% of Correct Outputs, Overall	% of Correct Outputs, Days with Avalanches
72-75	9	2	0.20	77	30
	10	2	0.20	82	40

A well specified problem coupled with a comprehensive data base should produce good results with a variety of network architectures and range of tolerances. The network performance obtained to-date, while promising in specific situations, does not meet this general criteria. Additional work is necessary to improve the problem formulation and increase the database.

Conclusions

Artificial neural networks are a promising tool for use avalanche forecasting. Networks experimented with in this investigation realized over all success rates in predicting avalanche activity of between 78 and 91 percent. These networks were successful between 36 and 100 percent of the time in predicting avalanches on days on which avalanches were known to occur. While these results are not dramatically encouraging, they are sufficiently promising to justify further investigation of neural networks for avalanche hazard assessment. Activities suggested by the work done in this study include:

1) Consideration of more slide paths and more avalanche seasons in the training process. This preliminary study considered a single slide path and 3 avalanche seasons.

2) Thorough review of the state-of-the-art in avalanche forecasting. This review would identify additional and/or different factors that should be considered as network inputs. This review would also reveal relationships that have been identified between specific factors and avalanche occurrence that may be useful in optimizing parameter normalizaition. The results obtained by neural network could also be compared with those obtained following other procedures.

3) Complete review of the treatments used for each input and output parameter. The lack of distinction drawn between artificially triggered and naturally occuring avalanches, for example, may be deleteriously affecting network. Careful consideration should be given to assuring temporal trends are adquately represented with the selected input parameter

4) Performance of statistical analyses of the information contained in the training and evaluation databases. Such analyses can reveal gross trends between independent and dependent variables represented in the data

5) Comprehensive reveiw of the network architecture and training algorithms used.

6) Performance of sensitivity studies on successful networks to insure network function is reasonable.

Successful networks will become an additional tool available to the avalanche forecaster. They may also be useful in issuing preliminary automatic warnings when the avalanche hazard is high.

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