Predicting Ice Jams With Neural Networks

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Breakup ice jams and related flooding occur suddenly. Prediction methods are desirable to provide early warning and allow rapid, effective ice jam mitigation. Due to the lack of an analytical description of the complex physical processes involved, ice jam prediction models have historically been limited to empirical, stochastic or deterministic models. Existing ice jam prediction methods range from empirical single-variable threshold-type analyses to statistical methods such as logistic regression and discriminant function analysis. In this study, a neural network method is used to predict breakup ice jams at Oil City, PA, the site of frequent damaging ice jams. A statistical screening is used to check the reliability of data that were collected over a 60-year period. Discussion of how the neural network input vector was determined and the methods used to appropriately account for the relatively low occurrence of jams are addressed. The neural network prediction proved to be more accurate than other methods attempted at this site.

1. Introduction

Ice jams are a common occurrence throughout the United States and Europe. There are two major categories of ice jams. Freeze-up jams are composed primarily of frazil ice (small particles of ice formed in turbulent, supercooled water) and occur primarily during periods of intense cold during early winter. Large concentrations of frazil ice can exceed the transport capacity of a river, generally due to surface obstruction by a competent ice cover, a significant reduction in slope, a narrowing or sharp bend in the channel. The ice movement ceases, causing a stoppage and subsequent accumulation of frazil. As more ice amasses, the flow becomes significantly obstructed, causing backwater that can result in flooding. Freezeup jam formation can be predicted by sophisticated models such as DynaRice (Lu 1999, Shen 2000), and progression has been modeled using empirical meteorological relationships combined with simplified hydraulic modeling (e.g., Zufelt and Bilello 1992).

In general, breakup jams occur during periods of thaw when increased discharge due to snowmelt and/or precipitation increases the forces on an ice cover until its strength is exceeded, causing breakup. The broken ice is transported down river until transport capacity is exceeded, forming an accumulation that obstructs flow and causes backwater. The formation and progression of breakup ice jams result from a complex interaction between hydrologic, hydraulic, and meteorological processes. The physical phenomena associated with breakup ice jam formation are far more complex and less well understood than for freezeup ice jam formation and progression or even for ice cover breakup. Due to the complexity of these interactions, an analytical model has not yet been formulated to describe the formation of breakup ice jams beginning with ice breakup and including ice transport and accumulation resulting from the breakup of river ice covers. The lack of such a model prevents the use of models based on dynamic analyses or other deterministic methods, which theoretically could be transferred fairly easily between locations. Thus, the small number of ice jam prediction models that have been developed are limited to highly site-specific empirical or stochastic models (White in prep). In addition, because of the lack of an analytical model of breakup jam processes, the selection of variables used in ice jam prediction models can be arbitrary and may be highly variable from site to site.

The confluence of the Allegheny River and Oil Creek at Oil City, PA is a location where breakup ice jams have frequently formed in the past. This area has a number of characteristics that predispose it towards serious jam events. Downstream of the confluence with Oil Creek, the Allegheny River significantly slows due to dredging that deepened the channel. Because of the sudden reduction in slope, freezeup jams often occur in this portion of the river. Deck and Gooch (1981) reviewed historic ice jam events and concluded that the most damaging ice jam floods occurred when transport of a broken ice cover on Oil Creek is halted by the presence of a the freezeup jam on the Allegheny River (Figure 1). Oil Creek, being a very flashy waterway with a quick response to rainfall events, is likely to experience a break-up of the ice cover before the ice cover and jam on the Allegheny River begin to break up and move. If the freeze-up jam on the Allegheny River is severe enough to restrict the confluence of the two rivers, then movement of the ice cover as a result of high flows in the Oil Creek is stopped and a break-up jam inevitably occurs.

In order to reduce ice jam flood damages, the US Army Corps of Engineers Pittsburgh District, with design assistance from CRREL, constructed two ice control structures. The first ice structure, a floating ice boom, was installed in 1982 on the Allegheny River just upstream from the confluence with Oil Creek. The second structure, completed in winter 1988-89, is a low, gated, overflow weir located on Oil Creek about 5.3 miles upstream from its confluence with the Allegheny River. During many winters, there is sufficient ice volume between the Oil Creek ice control structure and the Allegheny River confluence to form breakup ice jams. Although flooding since the construction of the two projects has not been significant, a method to predict the likelihood of jam occurrence is considered necessary in order to further reduce damages. Because of its frequent jam history and the need for a workable jam prediction model, this site was selected for development and testing of a breakup jam prediction model.

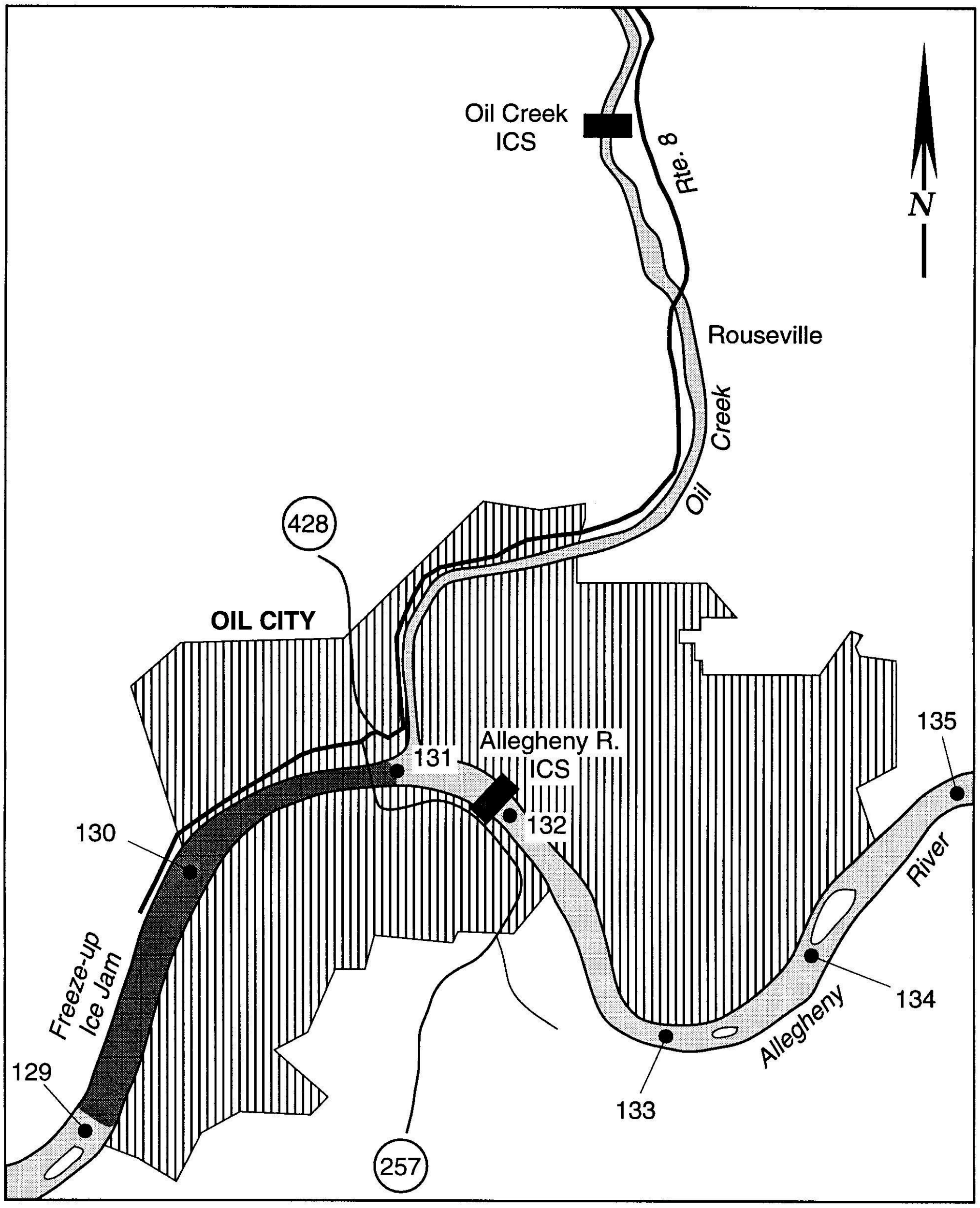

Figure 1. Location Map of Oil City, Pennsylvania.

2. General Approach

Advances in computational methods and equipment have allowed the development and growth of artificial intelligence systems. One of these techniques, the artificial neural network, has shown potential for modeling the behavior of complex nonlinear processes such as those associated with breakup jam formation. Neural networks are computer algorithms that are trained to map an input vector to an output vector such that error is minimized (e.g., Bishop 1995, Massie 2000). In terms of ice jam prediction, this can be described as a classification system that maps the values in the input vector into either a jam or a no-jam category. This is accomplished by mapping the relationship between an input vector and an output vector where each output is given a class label. Neural networks are particularly well suited for these problems since they are easily configured to map several input variables to multiple output variables. When a neural network is trained for classification, each output is assigned a class label and the probability of an output result into that class can be determined. Since neural networks can establish non-linear decision boundaries, they are capable of outperforming standard statistical classification methods. Figure 2 graphically depicts how a non-linear boundary can better determine class labels when classes are tightly intertwined.

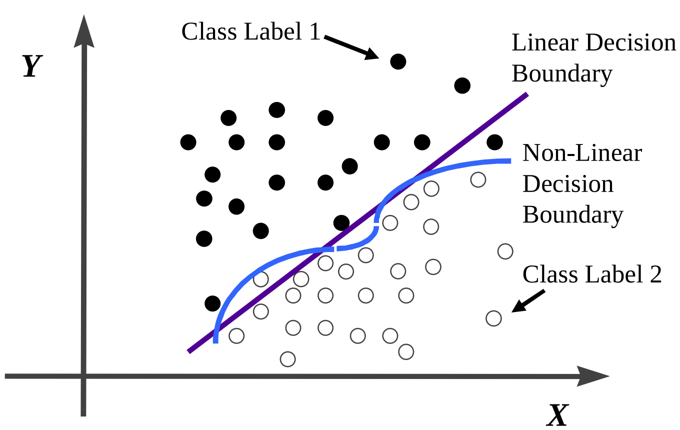

Figure 2. Linear and non-linear decision boundaries for establishing classes.

There are two types of errors we seek to minimize. False positive errors predict a jam when one does not occur. Unfortunately, a high frequency of these false positive errors can lead to the "cry wolf" syndrome, in which warnings for actual jams are ignored and a generally low confidence in the model prediction results. For example, the multivariable threshold approach utilized by Tuthill et al. (1996) identified six of eight known jams at Montpelier, VT along with an additional 22 events not known to be actual jams. Slightly better performance was achieved in a two-variable method proposed by White and Kay (1996) that identified 26 of 27 known jams on the Platte River at North Bend, NE, but also predicted jams in nine years for which jams were not reported. False negative errors predict that a jam will not occur, but in actuality, one does. False negative errors are highly undesirable since a jam could lead to significant damage with no warning or preparation for the event, again leading to low confidence in the model prediction results.

2.1. Variable Selection

Selection of input variables is perhaps the most critical decision that will impact on mapping accuracy in a neural network. The data set for Oil City contained a list of variables measured daily from the months of December through March for the period 1933 to 2000. The measured values included average temperature and volumetric flow rate of the Allegheny River and Oil Creek. The data set also indicated whether or not an ice jam had occurred on a given day. In the 67 years of observed data, 17 ice jams were recorded. Using a statistical analysis, any data that were in obvious error and could cause skewed results, were removed. An independent statistical analysis confirmed that a change in *AFDD* values and increased flow in both Oil Creek and the Allegheny River make the most significant contributions to ice jams. The change in average daily ambient temperature, over the 68-year period, was found to increase by less than 0.01^{o}F per year and assumed insignificant for this study.

An investigation of the ice, hydraulic, and meteorological conditions that lead to the formation of ice jams in Oil City (Daly et al. 1996) did not reveal a clear relationship between any of the available hydraulic and meteorological variables and the severity of ice jams at Oil City. However, inspection of the historical records revealed that ice jams could be expected when periods of intense cold are followed by sudden increases in flow in Oil Creek. After numerical experiment, they found that examining the change in AFDD throughout the winter could be used to identify periods of intense cold. They selected $\Delta_{15}AFDD$, or difference between the *AFDD* on each day of the winter season and the *AFDD* accumulated during the previous 15 days. Graphical analysis indicated that this value was found to increase continuously during intense cold periods, reaching a peak when the cold period ended. The magnitude of the peak varied with the intensity and duration of the cold. Sudden increases in the discharge in Oil Creek were identified by determining, on each day of the winter season, the difference between the daily average discharge in Oil Creek and the daily average discharge on the previous day. Final variable selection included ambient air temperature, one through fifteen-day change in *AFDD*, flow rates from both the Allegheny River and Oil Creek, as well as a one-day change in the volumetric flow rates for both rivers.

2.2. Data Pre-Processing

Data preprocessing for neural networks involves normalizing the input data and reducing its dimensionality. Each value of input and output is normalized so that no one set of values dominates the solution. Without normalization, input variables with something as simple as a change in units could produce significantly different results. One of the simplest and most common methods to normalize data is through a simple linear rescaling. This normalizing process involves subtracting the mean, $\bar{x}_i$, of each feature, x_i and dividing by the standard deviation σ_i as shown:

$$\tilde{x}_i = \frac{x_i - \bar{x}_i}{\sigma_i} \tag{1}$$

This simple linear normalization technique results in an input space with zero mean and unit standard deviation. Other data transformations, such as power functions, tangent, logarithm, were also applied to input variables. The transformation that gave the smallest misclassification rate was used in the final network.

2.3. Network Architecture

The network consisted of a feed-forward architecture without the use of recursion. 23 fields were used as input and the output value was made into categorical variables, which do not presuppose natural ordering. In this case, since there are only two categories of output, jam or no-jam, output values were represented by values of (1,0) and (0,1) respectively.

2.4. Low Occurrence of Ice Jams

As in many statistical methods, imbalance in the size of the data sets representing the populations to be classified results in difficulty in application. In the 67 years of observed data, only 17 ice jams were observed and recorded out of over 7,700 records. The low probability of occurrence of jams $P(x|C_J)$ can cause a neural network to draw a hyperplane that does not represent a general solution.. An example of this would be to classify every occurrence as a no jam $P(x|C_N)$, and in this case will only misclassify 17 dates. While the misclassification of no jams $P(x|C_N)$ is small, the error rate of jam predictions is unacceptably high. To overcome this, an equal number of jam and no-jam occurrences was used in the training and testing set. With such a few number of no-jam days used for training, it is important to insure that the training set includes the features needed to predict a jam. This was accomplished by observing that a jam always occurs when there is an increase in ambient air temperature and flow in Oil Creek. All data that did not fit these criteria were removed, thus reducing the number of no-jam events to 2,700 occurrences. In this case, only six jam days were included in the training set and 11 jam days were used for testing. Using a clustering technique, fifty no-jam days were selected for training and testing the neural network.

When this was done, the neural network training set correctly classified five of six jams and correctly classified all 11 jams in the testing set. The entire database was then fed to the trained neural network to check for a generalized solution. 93% of all no-jam events were correctly classified.

3. Results and discussion

Overall, the neural network-based classifier functioned with an accuracy of 93%. With all the original data, the network produced 94.1% jam accuracy and 92.6% no jam accuracy. These results can be compared with previous studies conducted at Oil City. A statistical discriminant functional analysis is described in White and Daly (in prep) and the empirical results are described in Daly et al (1996). As Table 1 illustrates, the neural network solution provides an improvement over alternative methods.

The neural network classifier only predicts whether a jam will or will not occur on a given day. To obtain reliable future predictions, however, ambient temperatures and stream flow rates must be determined. Temperature predictions are readily available from the National Weather Service. Stream flow rates, however, cannot be predicted so readily. To obtain these, stream flow must be determined from anticipated precipitation amounts and ground conditions. Current work includes the refinement and calibration of a WMS model for Oil Creek and use of an existing WMS model for the Allegany River. With this information, a future prediction, with an associated error rate, can be made. The final product will consist of an easy-to-use internet-based program, that allows for predictions up to five days in the future.

Table 1. Comparison of predicting ice jams at Oil City using various techniques.

Error Type	Empirical	Statistical	Neural Network
% False Positive Errors	11.8% (2/17)	35.3% (6/17)	5.9% (1/17)
% False Negative Errors	40.0%	18.0%	7.4%

4. Conclusion

This study demonstrates, at least for one location, that a neural network-based ice jam predictor is capable of providing improved accuracy over statistical and empirical methods in obtaining a solution to a complex and elusive problem. The complex physical processes involved in the formation of breakup ice jams makes them difficult to predict. However, the sudden nature of occurrence and high stages makes jam prediction desirable. As is the case with empirical methods, neural network classifiers will most likely be site specific. However, since neural networks learn patterns with no modification of the algorithm, it is likely that they can be transported to other locations with minimal modifications. Further investigation must be made into this area.

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