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BREAKUP ICE JAM FORECASTING BASED ON NEURAL NETWORK THEORY AND FORMATION FACTOR

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ABSTRACT

Cold regions suffer from severe ice jam flooding in the spring. Forecasting of ice jam and its break-up is crucial to prevent or reduce flooding risk in cold region. This paper analyzes the formation factors governing the formation of breakup jams. A neural network model based on formation factors has been developed with air temperatures and precipitation as inputs and applied for ice jam forecasting in a given year in the upper reaches of the Heilongjiang River (Amur River), where ice flooding occurs frequently during spring. The model based on the neural network clustering method had an accuracy rate of 85%, which was significantly higher than the 62% accuracy rate of the conventional statistical method for breakup ice jam forecasting. The model had a forecast period of 10 days with a maximum error of 2 days and forecast qualified rate of 100% for breakup date forecasting. The forecast on the breakup ice jam, which was released 24 days ahead, provides the accurate results for the breakup date and the occurrence of breakup ice jams in the spring of 2017.

Keywords: River ice; breakup; ice jam; formation factor; forecast; neural network

1 BACKGROUND

Ice jams occurring in rivers of cold region can cause severe ice flooding problems. According to the definition of ice jam suggested by Shen et al. (1995), the surface ice jams will be formed as a large amount of floating ice pieces are blocked by ice covers in the downstream river reach, and consequently the free surface level of the river is elevated. The surface ice jams can be generated during freezeup or breakup period. Further, the frazil ice jams can be formed when enough frail-ice particles are built-up under ice cover before and during freezeup. As for the two types of the ice jams during freezeup, much efforts has been devoted to understand its physical mechanism and to develop a rational theoretical model accordingly. Shen et al. (1991, 1995) suggested a one-dimensional model which simulates frazil ice accumulation and transportation process. Yet the impact of real three dimensional flow characteristics beneath ice cover and complex geometry boundary cannot be incorporated in such simplified model. Shen et al. (1993, 2010) further presented a two-dimensional model, which is applied to simulate ice transport and ice jam formation during Clair River freezeup (Kolersk and Shen 2015). Fu et al. (2015, 2017) studied the correlation between safe discharge and water level of an inverted siphon for preventing ice jam formation with a physical model using real ice.

Artificial neural network models are also developed to predict ice condition in field as there are not enough field data and boundary information available for theoretical modelling. For instance, the Heilongjiang River, the border river of China and Russia, locates in the northern part of China. Only limited data of the geometry of the river and its flow condition can be obtained in China territory. Moreover, for meandering river, such as Yellow River, its natural flow passage is flexible to some extent due to erosion and scouring. So it is difficult to apply and verify the rigid mathematical model in the situations above. It is well known that neural network theory is an alternative for modelling complex nonlinear physical process without directly solving governing partial equations. In addition the noise present in input and output of the network is processed without pronounced loss of accuracy due to distributed processing feature of the network. Therefore with advantage of the neural network, there are many practical application of neural network theory in recent years. ASCE (2000a, b) presented a set of practical applications related in hydrological forecasting, including forecasting of water levels, sedimentation, flooding, rainfall, and surface runoff (Chau 2006; Dawson et al. 2006; Riad et al. 2004). With the advancement of river ice research, the artificial neural network has shown the potentiality for modeling the behavior of complex nonlinear processes of ice jam formation for its advantage of overcoming the limitations of conventional forecasting methods. Chen et al. (2004) used conventional BP neural network to predict ice-run and freezeup during winter. Wang et al. (2012, 2014) developed neural fuzzy model for forecasting ice-run and freezeup dates, which has been used in the Yellow River and South-North Water Transfer Projects.

In general, breakup ice jams occurring during periods of thaw can be classified into thermal breakup and mechanical breakup. During the thermal breakup process, the ice cover gradually deteriorates and melts in region with insignificant movement by natural thermal effects. The river flow remains relatively steady during the spring breakup period. No ice jams can be produced by accumulation of large floating ice blocks. Mechanical breakup is produced by hydraulic forces caused by changes of river flow and its surface level. Ice blocks are transported downstream of the river until transport capacity of the river is exceeded. After the blocks are obstructed by the ice covers, the ice jams will be produced. Consequently, the river flow is backed up and its surface can be raised rapidly causing risk of downstream flooding. The ice jams can break up in short time, say several hours. When ice jams break suddenly, severe flooding can also happen downstream. Therefore, ice jam forecasting for river breakup is critical in preventing or alleviating ice jam and flooding hazards. Roughly, the formation and development of ice jams during breakup can be affected by multiple factors including air and water temperature, wind speed and direction, river flow feature, and weather condition, etc.

Currently there are few established mathematical models for simulating and forecasting breakup ice jams process. Beltos (1984, 2008, 1993, 1995) described and analyzed the physical process of ice accumulation, ice jam formation, and ice jam breach during breakup. Beltos (1990) also defined the onset of the breakup as the time when sustained ice movement occurs in a particular site, and formulated an empirical method for forecasting the breakup occurring based on the boundary constraints of the river plane geometry. Dai et al. (2010) performed ice jam forecasting on the Heilongjiang River using statistical methods and empirical equations. The conventional artificial neural network is also applied for forecasting onset of breakup. Wang et al. (2008, 2009, and 2013) performed the forecast of the Yellow River breakup date and water temperature change during winter based on the neural network theory. Mahabir et al. (2006, 2007) applied the neural network theory to predict breakup and flooding after ice jam release on the Athabasca River. As the mechanical breakup is still not well understood and limitation of field information, the breakup forecasting techniques are much empirical and site-specific.

This paper reports a neural network model using Back Propagation (BP) to simulate ice jam occurrence based on of the mechanism of the ice jam evaluations. The model has been applied to forecast breakup ice jam occurrence and breakup date in the Mohe County reach of the Heilongjiang River, where the frequent damaging ice jams occur.

2 FORMATION FACTORS FOR BREAKUP JAM FORMATION ON HEILONGJIANG RIVER

Ice covers of Heilongjiang River are typically very thick and strong with heavy snow on the top. Based on the records since the 1950s, ice jams occur on almost yearly basis in certain reaches of the Heilongjiang River. On average, significant ice jam events occur every 3 years. The ice jam phenomenon in the Heilongjiang River are so prominent that it is crucial to conduct detailed ice jam observation and forecasting for preventing possible flooding in this region. A reliable ice jam forecasting system of Heilongjiang River can provide an effective tool to assist with ice jam removal and flooding disaster prevention. The jams usually occurred during spring breakup period. Main reasons of breakup ice jam occurrence include the following:

(1)Geographical location and river flow direction

The river location and flow direction are the dominating factors on the reversed breakup and lead to ice jam formation in the Heilongjiang River. The Argun River and the Shilka River are two large tributaries of the Heilongjiang River, which are the headstreams of Heilongjiang River. Both rivers flow from southwest to northwest, as shown in Figure 1, and from the low latitude to the high latitude with a 700km distance difference. This condition causes breakup to occur in the upstream reach and tributaries usually breaks up before the downstream reach. The ice cover in the downstream reach becomes a natural obstacle to the ice discharge and causes jam formation.

Figure 1. River locations and flow direction of the Heilongjiang River

(2)River geometry and topography characteristics

Topography and river characteristics play an important role of ice jam formation. The upper reach of the Heilongjiang River flows through the Greater Xinggan Mountains with high mountains, valleys, and plains alternating on the river banks. Under the radiation and thermal effects of the sun, the plains receives more heat than the valleys, and the sunny reach of the mountains receives more heat than the shady one, resulting in variations in ice melting at different locations along the river, which may cause ice jam by the ice blocks. The upper reach of the Heilongjiang River is a typical mountainous river with steep channel bottom, variations in the channel width, and irregular bank lines. The river meanders like L, S, or Ω routes, and even has more than 90 degree bends, as shown in Figure 2. Some river reaches are narrow and meandering with connecting center islands, many diversions and bifurcations as shown in Figure 2 The channel width and depth change significantly along the river. All these channel characteristics and its flow capacity provide favorable hydraulic conditions for easy ice jam formation.

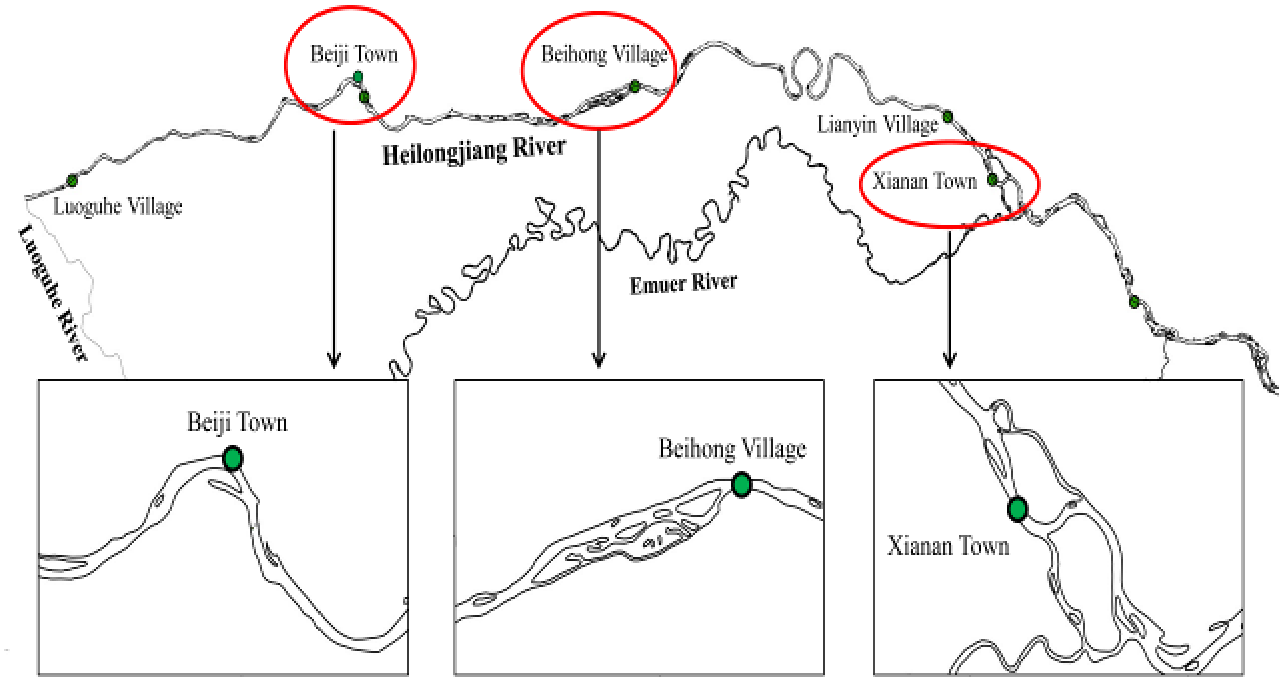

Figure 2. Location Map of Mohe reach, Heilongjiang River

(3) Hydrological and meteorological factors

Hydrometeorological factors directly influence the formation of ice jam. The main factors in the Heilongjiang River basin include the winter and spring air temperature, water storage capacity of the channel, precipitation during the freezeup period and before breakup, evaporation, snow cover thickness, and ice cover thickness. When these unfavorable hydrometeorological conditions or combinations of unfavorable hydrometeorological conditions occur, mechanical breakup of the Heilongjiang River could happen and lead to ice jam formation. For example, rapid rise of air temperature coupled with rainfall or snowfall during early spring will cause a rapid increase in river discharge due to snowmelt runoff and precipitation. This process then leads to mechanical breakup and breakup ice jam formation the Heilongjiang River.

3 NEURAL NETWORK MODEL FOR ICE JAM FORECASTING

Ice forecasting modeling based on BP neural network theory and formation factors involves two processes: learning process of historical ice conditions and forecasting process, as shown in Figure 3. The learning process of the network includes forward information transmitting procedure and backward error correction procedure. The procedure that the input information is transmitted from the input layer to the output layer through hidden layers is referred to forward information transmitting.

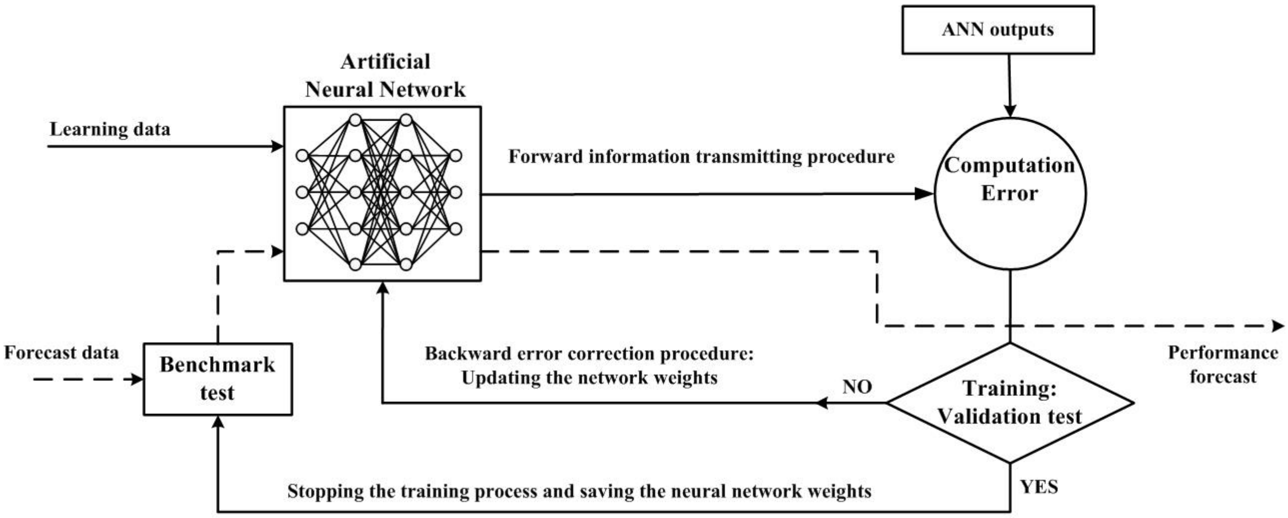

Figure 3. Forecast procedure of the Neural Network

If the actual output of the network does not meet expected errors, the error in the output is feedback from the output layer to the input layer in the reversed direction in order to correct the connection weights at the neuron nodes on each of the layers. This procedure is referred to backward error correction transmitting. These iterative procedures are performed until the output error in the model satisfies the required accuracy or maximum number of iterations has been reached and the learning process ends.

After the steps described above, the algorithm is developed and trained to map an input vector to an output vector between which the error is minimized, and then the network model using weight coefficients and thresholds based on the historical data learning process is applied to ice jam forecasting.

The majority of the artificial neural network applications in water engineering involves the application of the BP model, which is found superior over conventional statistical and stochastic methods in continuous flow series forecasting (Alp 2006). Yet the iterative procedures of the neural network are sensitive to the selected initial weight values and the networks are sometimes trapped by the local error minima during the training stage, which could prevent the network training from reaching the global minimum error in BP neural network model based on the Gradient Descent algorithm proposed by Maier (2000). The methods, such as Newtons algorithm, Levenberg-Marquardt algorithm, stochastic gradient algorithms, and simulated annealing, may overcome this problem of training a number of networks starting with different initial weights, and help the networks escape local minima.

To deal with this problem, the Levenberg-Marquardt algorithm is used to improve the BP neural network models. Wang (2008) successfully applied a BP neural network model improved by the Levenberg-Marquardt algorithm to forecast the beginning date of ice run, freeze up and break up in the Yellow River. This algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of a nonlinear real-valued function, and the minimum sum of squares error can be obtained by using the square error instead of the mean square error. Therefore, the Levenberg-Marquardt algorithm can be considered as a hybrid between the classical Newton and steepest descent algorithms. It has been proven that the Levenberg-Marquardt algorithm converges more quickly than the Gradient Descent method (Wang, 2014).

When the occurrence of an ice jam is forecasted by neural network model based on its learning process of the historical hydrological data, meteorological data and so on, the output is in the form of whether an ice jam would occur or not. This corresponds to an output value of 1 or 0. The training process of the network model is a process of network clustering. That is to say it groups the data based on similar properties. When a neural network is trained for classification or clustering, each output is assigned a class label and the probability of an output result into that class can be determined. Neural networks can establish non-linear decision map which can better determine class or clustering processes. Ice jam forecast can be performed based on the nonlinear learning and computation processes of the neural network clustering method. Since breakup ice jams often occur at the beginning period of the breakup, the form period of ice jam forecasting is known through forecasting the breakup date.

An ice jam forecast model based analyzing the formation factors is expressed as

$$D_{jam} = f\left(P_{bf}, P_{df}, P_{bb}, T_{df}, T_{bb}, Q, H_1, H_{snow}, H_{ice} \cdots\cdots V_{cs}\right) \quad [1]$$

Where D_{jam} = the occurrence condition of ice jams; P_{bf} = precipitation prior to freezeup, mm; P_{df} = precipitation during the freezeup period, mm; P_{bb} = precipitation prior to breakup, mm; T_{df} = accumulated negative air temperature during the freezeup period, ℃; T_{bb} =change of temperature prior to breakup, ℃; Q = volumetric discharge, m3/s; H_1 = water level during freezeup, m; H_{ice} =ice cover thickness, m; H_{snow} = snow depth on the ice cover, m; and V_{cs} = water channel storage, m3.

In order to eliminate the influence of the different dimensions of all the factors during the neural network training and forecasting, and to avoid the neural network unit saturating, these factors are expressed in non-dimensional form as the following:

$$y_i = \frac{z_i - z_{\min}}{z_{\max} - z_{\min}} \alpha + \beta \qquad [2]$$

Where z_i and y_i = original and standardized parameters, respectively; $z_{\max}$ and $z_{\min}$ = the maximum and minimum values of z_i, respectively; α is a coefficient in [0, 1], and $\beta = (1 \quad \alpha)/2$, so the network input units y_i is the range of [0.05 0.95].

The Heilongjiang River is located in a remote region. The number of hydrologic stations in this region is far below the national average. Since the Heilongjiang River is the border of China and Russia, the river cross sections and flow rates cannot be directly measured, which results in severely deficient field information including meteorological data, hydrographic data and river geometry. This study used neural network modeling to forecast ice jam formation in the Mohe reach. The hydrological data for the model input was obtained mainly from the Beiji Gaging Station in Mohe County. Daily average precipitation and air temperature data for Mohe County were from the China Meteorological Administration. The forecast factors included:

- Precipitation (snowfall and rainfall) before freezeup, mm;
- Precipitation (snowfall and rainfall) during freezeup, mm;
- Precipitation (snowfall and rainfall) before breakeup, mm;
- Accumulative negative temperature during freezeup, ℃;
- Air temperature change before breakeup, ℃;
- Thickness of ice cover, m; and
- Date when the air temperature goes above zero degrees, month/date.

Breakup Ice jam forecasting

The ice jam forecasting model based on the Levenberg-Marquardt BP neural network clustering method includes 3 layers, an input layer, a hidden layer, and an output layer. The Sigmoid function is used as the transfer function in the hidden layer. The Logarithm function is employed as the transfer function for the output layer, which defined the network output value to a range between 0 and 1. The adaptive learning rate, whose values change from 0 to 1, is used throughout the simulations. In this study, the Hydrological and meteorological data measured from 1957 through 2002 are used for training the networks and those from 2003 through 2015 for forecasting the ice jam.

For comparison, the forecast results of the statistical analysis model are presented to test the accuracy of the forecasting results from the neural network model. The current ice jam forecasting statistical model of the Heilongjiang River is based on the probability statistical method. The occurrence probability P is calculated based on Eq. [3] and [4] below:

$$P_{total} = P_1 + P_2 + P_3 + \cdots\cdots P_n \qquad [3]$$

$$P_{average} = P_{total} / n \qquad [4]$$

Where n = Number of forecast factors, P_n = Probability of No. nth factor, P_{total} =Sum of the probabilities, and $P_{average}$ =Average probability of the No. n impacting factors.

The occurrence probabilities of the ice jam impacting factors between 1990 and 2015, as the same as the above forecast factors, are analyzed and the average probability is about 45%. Therefore 45 percent is used as the criterion for ice jam occurrence.

Comparison with the ice jam forecast results based on the neural network clustering method and probability method is summarized in Table 1. It shows that the forecast result of the neural network model in ice jam occurrence is accurate for 11 of the 13 years from 2003 to 2015, resulting in an accuracy rates of 85%, while the statistical model was accurate for 8 years, resulting in an accuracy rate of 62%. These results suggest an obvious advantage of the neural network model over the conventional statistical model. Both models forecast shows that breakup ice jam would occur in 2015 because of the fact that the precipitation during freezeup and before breakup was 51% and 74% higher than the annual average, respectively. However, ice breaking measures with explosives before breakup were implemented in Mohe reach of the upper Heilongjiang River where potential ice jam risk would occur based on ice jam forecasting, which prevented ice jam formation and ice flooding from occurring in 2015(Liu and Wang, 2017).

Table 1. Results comparison between neural network method and statistical method

Year	Measured of Ice jams	Neural Network Method		Statistical Method	
		Forecasted Result	Pass (Y/N)	Forecasted Result	Pass (Y/N)
2003	No ice jam	No ice jam	Y	Ice jam occurrence	N
2004	Ice jam occurrence	Ice jam occurrence	Y	Ice jam occurrence	Y
2005	No ice jam	No ice jam	Y	No ice jam	Y
2006	No ice jam	Ice jam occurrence	N	No ice jam	Y
2007	No ice jam	No ice jam	Y	No ice jam	Y
2008	No ice jam	No ice jam	Y	No ice jam	Y
2009	Ice jam occurrence	Ice jam occurrence	Y	Ice jam occurrence	Y
2010	Ice jam occurrence	Ice jam occurrence	Y	No ice jam	N
2011	No ice jam	No ice jam	Y	Ice jam occurrence	N
2012	No ice jam	No ice jam	Y	No ice jam	Y
2013	Ice jam occurrence	Ice jam occurrence	Y	Ice jam occurrence	Y
2014	No ice jam	No ice jam	Y	Ice jam occurrence	N
2015	No ice jam	Ice jam occurrence	N	Ice jam occurrence	N

4 BREAKUP DATE FORECASTING

Breakup ice jams occurrence usually occur 1-2 days after the breakup. The beginning date of breakup ice jam can be estimated based on the forecasted breakup date, which provides valuable time for agencies to take preventive measures in advance to prevent and mitigate ice dam formation and potential ice flood disaster. The BP neural network model based on the Levenberg-Marquardt algorithm is used to forecast the breakup date. Data from the 49-year period from 1957 through 2003 were used as learning data, and then the model was used to forecast the breakup date from 2004 through 2015. The forecasting results are summarized in Table 2 below. The average forecast period of the model was 10 days and the maximum error was 2 days. Based on the Hydrological Forecasting Standards (GB/T 22482-2008) (see Table 3), this forecast results have high accuracy with the measured and meet the requirements of the national standards.

This forecasting model was used for ice jam forecasting of the Mohe reach in 2017. Based on long-term forecast of hydrometeorological information of the upper Heilongjiang River published by the China Meteorological Administration, the breakup ice jam condition forecast was released on April 1, 2017 ahead, that there would not be ice jams during breakup, and the breakup date was estimated to be April 28. In fact, the breakup date in the headstream Luogu villages in Mohe reach was April 28, and the breakup date was April 24 in Beiji town of Mohe reach which is 40km away from the upper Luogu Villages (Figure 3). Moreover, no ice jam or ice jam flooding occurred in this Mohe reach. The actual breakup date on the Luogu Villages reach matched the forecasting result perfectly. In the Beiji town reach, the experiments for breaking ice cover with explosives were conducted on 9-12 April (Liu and Wang, 2017), which resulted in an earlier breakup than the Luogu villages reach and the breakup date was 4 days earlier than the forecasted date. This ice jam forecast in 2017 had a forecast period of over 24 days. According to the Hydrological Forecasting Standards in China (GB/T 22482-2008), the allowed error is 7 days for a forecast period of 15 days. Therefore, the forecasting error was significantly smaller than the allowed value and the forecasting results were in good agreement with the measured values.

Table 2. Results of river breakup date forecasting

Year	Measured Date (Month-Date)	Forecasted Date (Month/Date)	Error (days)	Forecast period (days)	Pass (Y/N)
2004	04-28	04/27	-1	8	Y
2005	05-02	04/30	-2	12	Y
2006	05-01	05/01	0	11	Y
2007	04-26	04/26	0	6	Y
2008	05-02	05/02	0	12	Y
2009	04-14	04/15	1	/	Y
2010	05-02	05/02	0	12	Y
2011	04-25	04/25	0	5	Y
2012	04-30	05/01	1	10	Y
2013	05-01	04/30	-1	11	Y
2014	04-29	04/29	0	9	Y
2015	04-27	04/27	0	7	Y

Table 3. Allowed error based on Hydrological Forecasting Standards (GB/T 22482-2008)

Forecast period (days)	<2	3～5	6～10	11～13	14～15	>15
Allowed error	1	2	3	4	5	7

5 CONCLUSIONS

Cold regions suffers from severe ice flooding from ice jams in spring. Forecast of ice jam occurring are keys to ice flooding prevention and mitigation. The mechanism of breakup ice jam formation and development is very complex and not understood completely. Ice jams form and break quickly, which imposes difficulty for field observation and measurements as well as forecasting. The advantages of the neural network method include the following: (1) it has strong approximation capability for complex nonlinear mapping relations, the robustness and fault toleration; and (2) it has strong adaptive capability of handling obscure and incomplete data. Due to these reasons, the neural network method is considered to be an excellent tool for ice jam forecast, which is a complex nonlinear phenomenon and impacted by many different factors. This paper presents an ice jam neural network forecast model based on the formation factors that is developed for natural rivers in the cold regions. Conclusions from this study include the following:

(1)Based on field investigations and theoretical analyses of historical ice jam data on the Heilongjiang River, it is found that the main causes of ice jam occurrence on the upper reach of the Heilongjiang River are mechanical and thermal effects as well as hydraulic and geometric characteristics of the river. With analyzing the ice jam occurrence as well as available hydrometeorological data, it is found that important factors that affect river breakup and ice jam forecast include the precipitation before freezeup, precipitation during freezeup, precipitation before breakup, air temperature during freezeup, air temperature change before breakup, water level change before breakup, and thickness of the ice.

(2)The neural networking clustering method can forecast of ice jam for the Mohe reach of the Heilongjiang River. The model grouped the parameters related to ice jam occurrence through the neural learning procedure of the network and completed ice jam forecasting. The forecast accuracy rates are 85% for the neural network model and 62% for statistical model, respectively. It was apparent that the neural network clustering method had advantages over the conventional statistical method.

(3)The neural network model can predict the beginning date of ice jam occurrence by forecasting breakup date. The maximum error in the forecasting results for the 12-year period from 2004 to 2015 is 2 day under the condition of the 10-days average forecasting period in the Mohe reach. The forecast results are in good agreement with the measured values and meet the national standards.

(4)The neural network model accurately forecasted the breakup date and ice jam condition of the Mohe reach in 2017, which provided reliable data for agencies to implement little measures on ice disaster prevention and mitigation, and, as a result, a significant amount of economical and human resources was saved.

As a result, the critical deflection , which expresses mechanism model of ice cover structure change, can be used as the basis for the break-up.

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