MACHINE LEARNING ON THE CORRELATION BETWEEN WEATHER CONDITION AND SEEPAGE RATE: A CASE STUDY ON 20 YEARS MONITORING DATA FROM A WASTE ROCK DUMP

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ABSTRACT

Reliable prediction of seepage flow rate is important to flood controls and contaminant treatment for waste rock dumps. In this paper, a machine learning algorithm is developed to automatically study the correlations between seepage flow rate and mine site weather condition. Compared with traditional water balance approach, the advances of this study lie in all processes in the hydrological cycle require no simplification and assumption. Furthermore, a computer tool from the proposed approach is developed by Matlab and further applied to investigate a specific case on the full-scale waste rock dump of the Equity Silver mine. Seepage flow rates and weather conditions (precipitation and temperature) during 1998-2017 are used to train the tool accordingly. To validate this approach, the seepage flow rate predicted by the trained tool is compared with the real site monitoring data for that 20 years, which shows high agreement. It is also found that all full-scale peak flow scenarios in the field are fully captured and predicted by the developed computer tool. Overall, seepage flow rate was impacted mainly by long term weather conditions in the field, best represented in this case study by average weekly total precipitation and mean temperature of the preceding eight weeks.

KEYWORDS: artificial neural network, Equity Silver mine, full-scale, Matlab

INTRODUCTIONS

Acid rock drainage and metal leaching (ARD-ML) from sulphide bearing waste rock dumps and its environmental impact are becoming critical issues to the mining industry and regulators. In terms of full-scale mine site managements, flood controls and contaminant treatment strategies rely on quality predictions of seepage flow rate in field conditions. If seepage is not contaminated, the flow still often has to be re-directed and managed so that other areas of the mine sites and the downstream environment are not adversely affected by additional water. Therefore, in most cases, understanding the dynamic natures of full-scale seepage flows is important for optimum water management and environmental protection at mine sites.

Although various predictive models have been developed over the last several decades, a comprehensive and confident predictive model does not exist at the current stage. For example, a state-of-the-art numerical approach (Molson *et al*. 2005; Lahmira *et al*. 2017) can simulate the groundwater flow through unsaturated beds or layers of earth coupled with geochemical reactions. Also, water balance approach (Isabel *et al*. 1994) calculates the conservation of mass in a closed system based on breaking down the whole hydrological cycle into independent components. However, both of the approaches require intensive physical and hydrogeological characterizations on-site. As the real conditions at real mine sites are usually much more complicated than theoretical simplifications and assumptions, it is always challenging to precisely predict the full-scale seepage flow rate in the field.

For this study, a new methodology based on artificial neural network (ANN) is proposed and developed to automatically correlate measured seepage flow rate with weather condition data collected from real full-scale waste rock mine sites. The advantages of this approach lie in all processes and mechanisms in the hydrological cycle can be automatically captured by computational data interactions used for advanced machine learning algorithms.

Generally, the proposed ANN approach considers the impacts of all hydrological processes that are determined by on-site environmental conditions, which includes but not limited to precipitation, snow melt, runoff, evapotranspiration, infiltration, percolation, subsurface flow, etc. Compared with state-of-the-art water balance approach, the proposed ANN approach requires no simplifications and assumptions in advance. For example, the principle of snow melting process does not have to be pre-defined, instead it can be gradually figured out by the ANN implicitly based on step-by-step machine learning from historical site monitoring data.

In addition, a computer tool based on the proposed ANN is also developed and further applied to investigate a specific case study on a full-scale hard rock mine site where we have comprehensive monitoring data. A total 20 years (1998-2017) long monitoring data including seepage flow rate and weather conditions (total precipitations and mean temperature) are fed into the computer tool for machine learning. To validate this approach, the seepage flow rate predicted by the trained computer tool is compared with the real measured flow rate in the field, which shows close agreement. In addition, it is found that no peak flow scenario during that 20 years was mistakenly predicted, which demonstrates the high reliability of the proposed ANN algorithm and the developed computer tool.

METHODOLOGY

ANN is a network composed of a series of artificial neurons, which is a mathematical function to simulate biological neurons (Hassoun 1995). The artificial neuron can mimic the basic learning behaviors through receiving inputs, calculating a weighted sum and then passing the sum through a non-linear function known as the activation function to produce the output. The mathematical operation for an artificial neuron in ANN usually can be denoted as below

$$Y_{mn} = \varphi\left(\sum_{i=1}^{k} w_{mn,i} X_{mn,i} + b_{mn}\right) \tag{1}$$

here *m* denotes the number of layer in the network and *n* denotes the number of locations in that layer. For the n^{th} neuron located at the m^{th} layer, there are *k* inputs from $X_{mn,1}$ through $X_{mn,k}$ that comes from the previous $(m\text{-}1)^{th}$ layer, and also weights from $w_{mn,1}$ to $w_{mn,k}$. Here b_{mn} is the bias input for that neuron. φ is called as activation function that enhances the capability to learn more advanced nonlinear behaviors. Y_{mn} is the output of that neuron, which may propagate into the next layer as input or leave the system as the output of the whole network.

In terms of the methodology of this study, a special designed two-layer feed-forward ANN with sigmoid hidden neuron layer and linear neuron output layer is developed to learn the underlying water balance mechanisms for full-scale waste rock dumps in field conditions. The schematic of the proposed ANN structure is illustrated in Figure 1. It is indicated that the weather monitoring data including total precipitation and mean temperature is sequenced in time frames before training the ANN. Then the sequenced monitoring data is set as the inputs of the proposed ANN and the seepage flow rate is then set as the output.

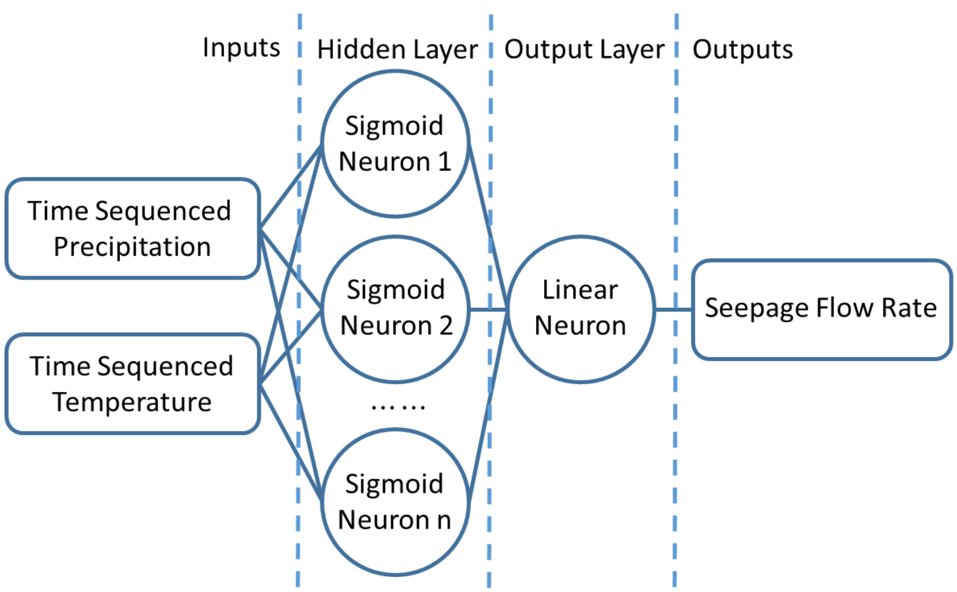


Figure 1. The Schematic of the Proposed Two-Layer Feed-Forward ANN.

Through training the ANN with a large number of samples (pairs of input and output), all unknown coefficients in Equation (1) can be determined through a special data iteration technique called backpropagation algorithm. In the training process, backpropagation automatically updates the weights for all neurons through calculating the gradient of the loss function based on each pair of input and output, until the network gets improved and is able to perform the task for which it is being trained. Theoretically, a well-trained ANN is capable to efficiently predict future seepage flow rate in the field as long as the weather forecast onsite is available.

CASE STUDY

To validate the capabilities of the proposed ANN approach, the correlations between weather conditions and seepage flow rate from the Equity Silver mine located in the central interior of British Columbia, Canada was investigated. The site is located in the central interior of British Columbia, Canada, and contains approximately 80 million tons of waste rock, covering an area of approximately 1.4 km^2. Extensive research has been conducted at the Equity Silver since the 1990s (O'Kane *et al*. 1995; Saretzky 1998; Morin *et al*. 2010; Morin *et al*. 2012; Ma *et al*. 2019, Ma *et al*. submitted). These studies have focused on hydrogeological characterization, cover system modeling, modeling of infiltration, and drainage chemistry.

The Equity Silver mine is situated on a plateau in a humid alpine environment as show in Figure 2. The mine site elevation is about 1300 m. Historical site records indicate that the average annual precipitation is about 600 mm with approximately 60% of the precipitation occurring as snow, which occurs from November to April. Snow starts to melt in April. The rainy season starts late April and typically ends by late June. A soil cover system was installed on the waste rock piles during 1990-1994, with an average thickness of 0.5 m of compacted till and 0.3 m of uncompacted till for reducing the amount of infiltrated water and oxygen into the waste rock dumps.

Figure 2. The Equity Silver mine at Houston, BC, Canada.

The waste rock dumps of Equity Silver mine have been producing acid rock drainage with high concentrations of metal contaminants since the 1980s. The ongoing site maintenance started since then, and extensive monitoring on the Equity Silver mine has been conducted and reported to better understand the acid rock drainage process. In terms of weather conditions and seepage flow rate, we currently have a complete record of 20 years (1998-2017) monitoring data from the waste rock dumps, which is valuable for validating the proposed ANN approach.

In terms of the inputs for ANN to study, the weather monitoring data of the Equity Silver mine can be obtained from the Environment Canada website on a daily basis, which includes minimum temperature, maximum temperature, mean temperature, total rain, total snow, total precipitation and snow thickness on ground.

As the output of ANN, seepage outflow rates from the Equity Silver mine are generally not measured on a fixed time basis. The measurement during March to July is usually more frequent than the remaining time in a year, as increased outflow rate is mainly observed during spring freshet and large precipitation periods. Minimum outflow rate is usually reported in late autumn and winter.

It should be mentioned that most of the outflow rates at Equity Silver mine are not directly measured, however, they are calculated based on manual readings of the water level in v-notch weirs installed at observation stations. In following discussions, the value of seepage flow rate ($m^3 \cdot s^{-1}$) we used for ANN output actually refers to the original measurement of v-notch (cm) from the weirs.

Among all seepage flow data from the Equity Silver mine, C7, C11 and Bessemer Dump (BD) are collected more frequently than other observation stations as they generally have the highest flow rates. The locations for these three observation stations are indicated in Figure 3. Further spectral analysis (Morin 2017) reveals that the flow rate from C7 and C11 has significant hourly fluctuation during spring-summer time. As it is theoretically impossible to use daily based weather condition to predict the behavior of seepage flow with hourly fluctuation, the monitoring data from C7 and C11 is not suitable to be correlated with the current daily based weather monitoring database obtained from Environment Canada website. However, the flow rate from BD is found to be more stable than those from C7 and C11, so the flow rate from BD with less hourly fluctuation is adopted as the output in the case study.

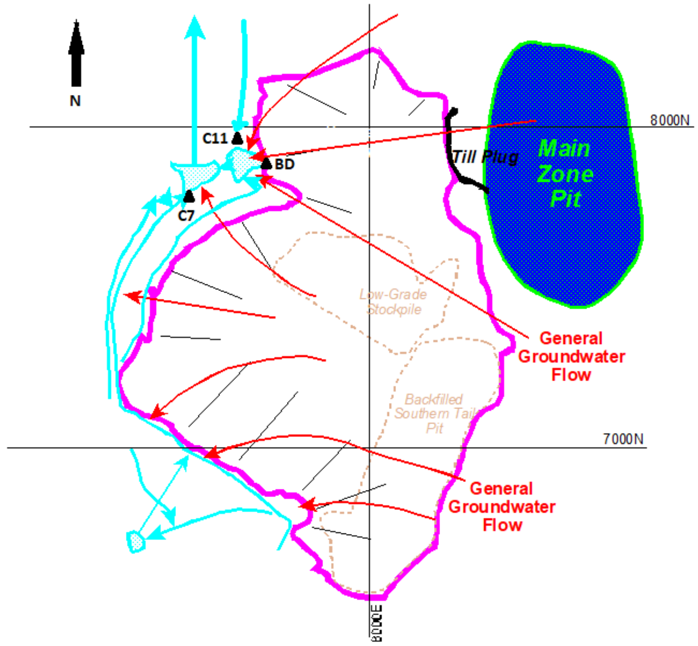


Figure 3. The Locations for C7, C11 and BD observation stations.

Figure 4 illustrates the v-notch value measured for evaluating the seepage flow rate at BD station for the time period of 1998-2017. 1918 measurements are recorded in the database, starting from Oct, 2nd, 1998 when the first ever flow from BD was recorded.

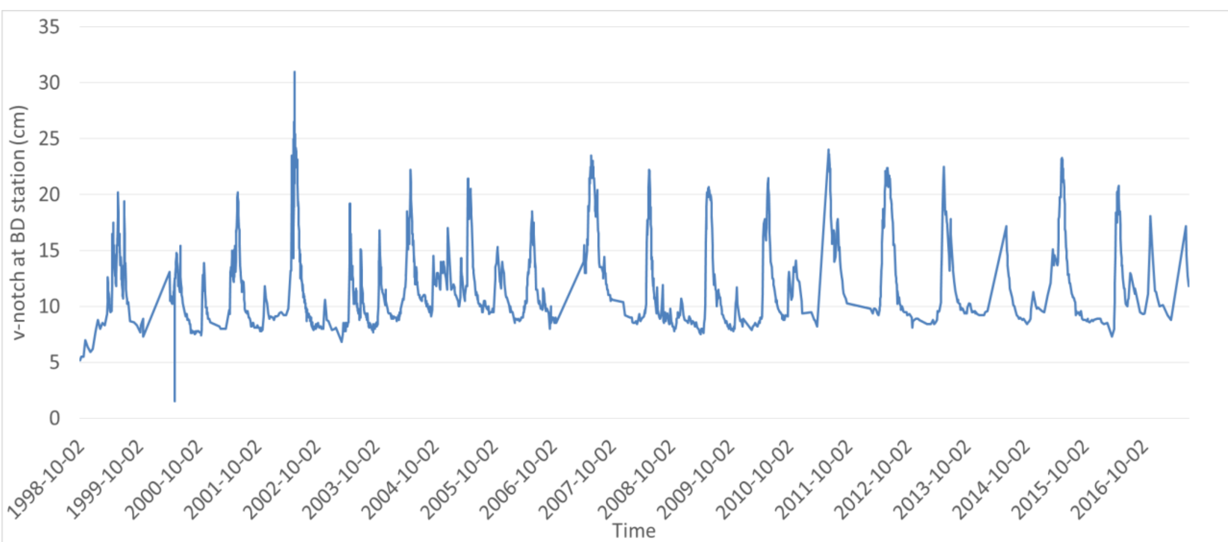


Figure 4. V-notch at BD station from 1998 to 2017.

Instead of defining the parameters and equations to calculate the water transportation and water balance for the whole mine site, the proposed ANN is developed based on the simple logic that the mean temperature and total precipitation shown in Figure 5, as the ANN input, should have certain correlations with the output - seepage flow rate. However, those correlations may be very sophisticated in field conditions. For example, snow and rain on the top of waste rock dump should have different impacts on the seepage flow rate, which may depend on not only current but also previous temperature and precipitation data. The advantage of ANN approach is that none of those underlying hydrogeological mechanisms or processes are required to be investigated or pre-defined. With a well-designed ANN structure and a large number of samples (pairs of input and output), those hydrogeological correlations can be sufficiently captured by the mathematical algorithm through iterating both of the input and output data.

To study some sophisticated and highly nonlinear correlations between input and output, the expansion of the ANN size is generally required. As ANN is expanded, the number of layers and the number of neurons in each layer in the network increase. As a result, the total number of unknown coefficients within the ANN increases accordingly. The quality of machine learning may deteriorate as the amount of sample for study is usually limited. Thus, the key challenge to build a well-designed ANN is to identify which weather condition among all monitoring data is the most correlative to the seepage flow rate, then the identified data is used as the input of the ANN for high efficient training.

In order to determine how long the weather input can effectively impact the seepage flow rate at BD station, two types of input structure are designed in the case study for comparison. When a output - seepage flow rate and its measurement date is selected to train the ANN, Type 1 input structure includes 14 elements including previous 7 days weather conditions (daily total precipitation and mean temperature) to consider short term weather impact on the seepage flow rate, and Type 2 input structures has 16 elements including previous 8 week weather conditions (weekly average total precipitation and mean temperature) to consider long term weather impact.

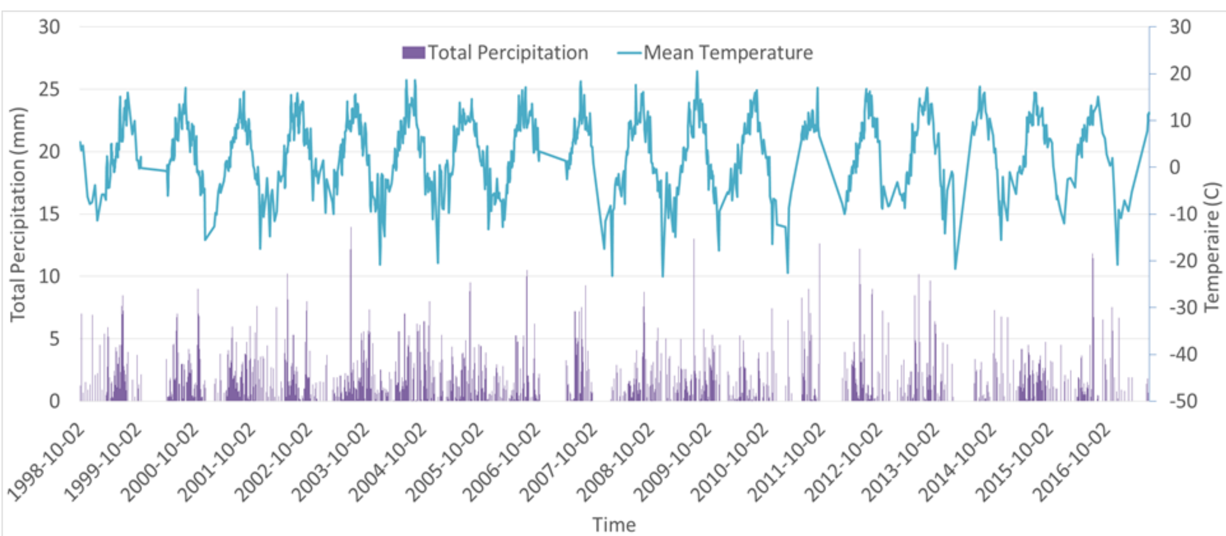


Figure 5. Daily total precipitation and mean temperature from 1998 to 2017.

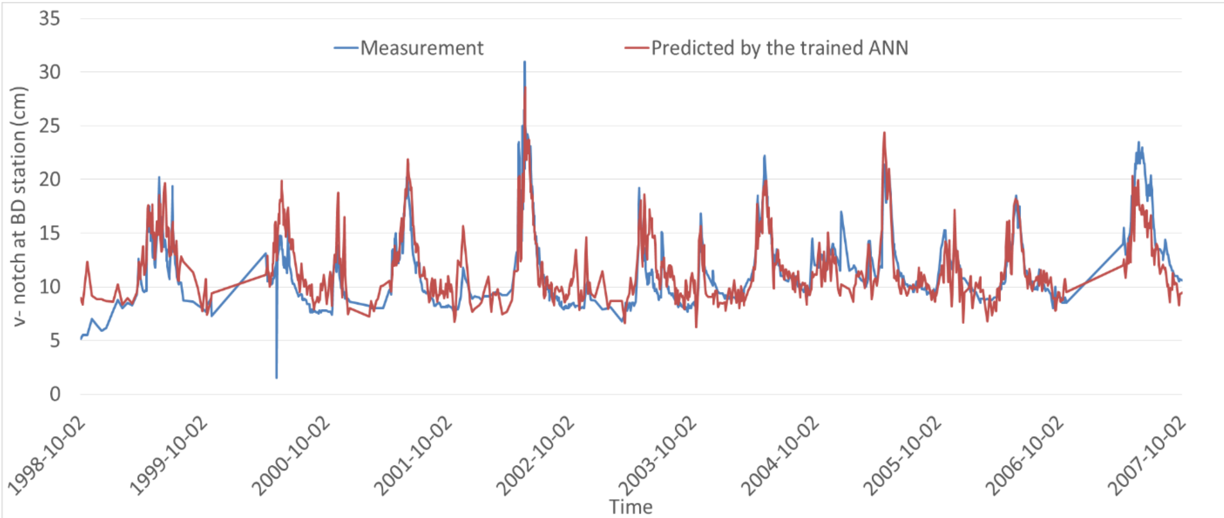
The computer tool based on the proposed ANN algorithm is built on the commercial software Matlab. The weather monitoring data are pre-organized for two different types of input structure through Microsoft Excel, the workstation used for the case study consists of Intel Xeon E5-1650 v4 and RAM 64G.

During the machine learning process, 70% of the total samples (pairs of input and output) are randomly picked up by the computer for training purpose, 15% of samples are randomly selected for measuring network generalization and pausing training when generalization stops improving, the last 15% of the samples has no effect on ANN training and just provide independent evaluation of the ANN performance after the training.

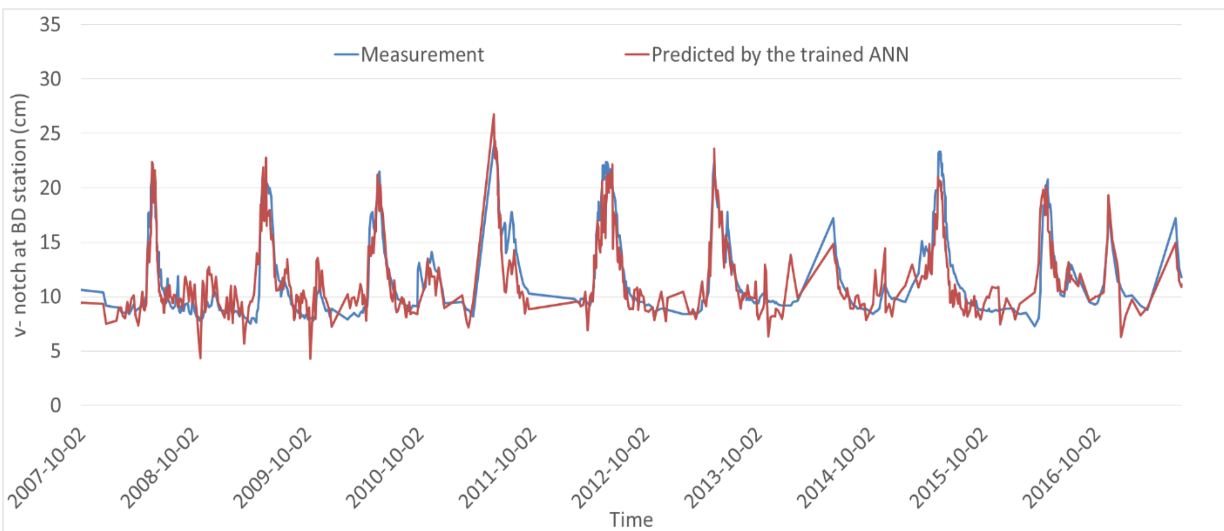
In this case study, the proposed ANN includes 10 neurons with sigmoid activation functions that are set in the hidden layer. The ANN is trained through Levenberg-Marquardt backpropagation algorithm. The training is performed 10 times with random initial conditions for both types of input structure. Mean squared errors (MSE) and regression values (R) are used to evaluate the training performance.

Analyzing the training results, it is found the ANN trained by Type 2 input structure generally has much better performance than that trained by Type 1. It suggests that the seepage flow rate from BD station may be impacted mainly by long term weather conditions in the field. The ANN with the best performance among total 20 times training has MSE = 0.4 and R = 0.92, which is based on Type 2 input structure. This ANN is defined as the best trained ANN used in following prediction and validation.

Figure 6 provides the comparison between the real measured value of v-notch at BD station and the calculated one from the best trained ANN. It is observed that the measurement of seepage flow rates is generally in good agreement with those predicted from the best trained ANN. Considering only 70% of measured data contributes to training and the last 30% does not. Moreover, all peak flow scenarios during the 20 years are fully captured and predicted by the ANN. The comparison results shown in Figure 6 indicate that the proposed ANN approach is able to discover high quality correlations between weather conditions and seepage flow rate data for a full-scale waste rock dump.



(a) Comparison during 1998-2007



(b) Comparison during 2007-2017

Figure 6. V-notch measurements vs calculated one from the trained ANN.

To further validate if the calculated correlations between the weather conditions and seepage flow rate reflect the field conditions at the Equity Silver mine, another ANN training was performed by feeding previous 18 years (1998-2015) data only. The best trained ANN was selected to predict the seepage flow rate for the last 2 years (2016-2017). Figure 7 shows the real measurement from the field, and the ANN prediction based on total 20 years (1998-2017) monitoring data and ANN prediction based on previous 18 years (1998-2015) monitoring data. The results indicate that the peak flow scenarios in the field for April-

May 2016, November 2016 and June 2017 are well captured by both of trained ANNs. Thus, it is concluded that even if the exclusion of samples from 2016-2017 is adopted for training purpose, the proposed ANN is capable to still predict the v-notch efficiently for that time period based on historical data only.

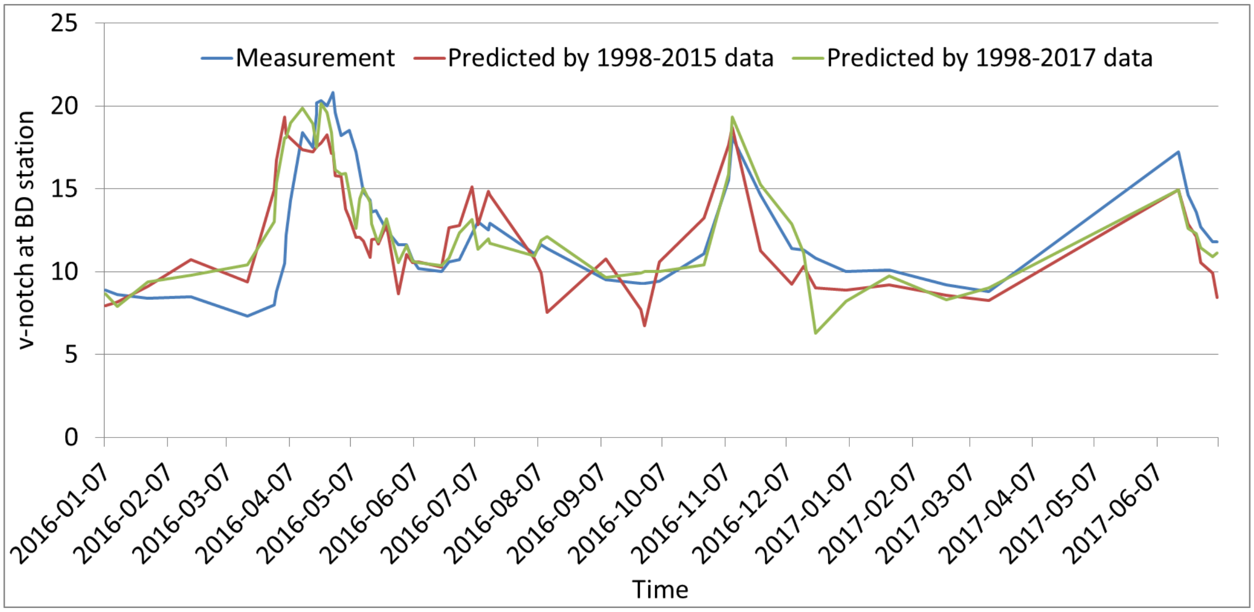


Figure 7. Comparison between real measurement, prediction from 20 years data, and prediction from previous 18 years data.

SUMMARIES

This paper develops an ANN algorithm that can automatically correlate the measurement of seepage flow rate with the weather monitoring data collected from full-scale waste rock mine sites. Compared with traditional water balance approach, the advantages of this approach are that there is no need to pre-define any hydrologic processes and mechanisms in advance, while it can be captured by advanced machine learning through iterating input and output data. A case study on the seepage flow rate at the main waste rock dump of Equity Silver mine is performed based on 20 years of consistent monitoring data. Well predicted results compared with measured ones indicates that the trained ANN can capture the correlation between seepage flow rate and weather monitoring data, which reflects underlying water transport mechanisms in field conditions. Overall, seepage flow rate was impacted mainly by long term weather conditions in the field, best represented in this case study by average weekly total precipitation and mean temperature of the preceding eight weeks. The success of this case study suggests that the ANN is a promising approach to further study the correlation with drainage chemistry and also the impact of climate changes on mine sites.

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