Estimation of seepage in earth fill dams using deep learning and wavelet transform

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ABSTRACT

Seepage prediction is one of the important tools in preventing erosion and destruction earth fill dams.In recent years, due to the uncertainty, complexity, and nonlinearity of seepage relationships, the use of artificial intelligence methods for estimation and prediction of this phenomenon has gained attention. The objective of this research is to estimate seepage in the Sattarkhan earth fill dam located in northwest Iran. To achieve this objective, in this research, the long-short-term memory network and the wavelet-deep network hybrid model have been used in two different scenarios, and the results obtained from these models have been compared with the feed forward neural network. The results obtained indicated that deep recurrent networks, in the modeling of the seepage phenomenon, outperformed the forward neural networks in terms of estimation accuracy. This can be attributed to their recursive connection between the output and input at each time step, as well as their ability to learn dependencies from previous time sequences. The modeling accuracy was improved by up to 7% as a result. Furthermore, the combined wavelet-deep network model demonstrated superior performance compared to other models, resulting in a 10% increase in modeling accuracy. In conclusion, the utilization of deep recurrent networks and the combined wavelet-deep network model in seepage modeling holds the potential to enhance estimation accuracy when predicting this phenomenon.

KEYWORDS

Earth fill dam seepage, artificial neural network, long short-term memory (LSTM) network, wavelet transform, Sattarkhan earth fill dam

1. Introduction

Given the limited water resources, dam construction has been one of the oldest civil engineering activities for water control, storage, and transfer. Earth fill dams, made from earthen materials, face challenges such as seepage, slope instability, and surface erosion. Seepage is the most critical issue, as uncontrolled seepage can lead to dam failure [1].Therefore, an optimal model for predicting future seepage is essential. While standard feed-forward neural networks (FNN) have been used in over 90% of artificial neural network applications for modeling water resource variables [2], their forward structure limits their effectiveness in dynamic systems. Recurrent neural networks (RNNs) have emerged as deep learning tools to address this limitation[3]. These intelligent models can process complex and nonlinear data, making them suitable for hydrological time series modeling, such as seepage. RNNs and LSTM networks can accurately predict dynamic behaviors in hydrological systems by learning long-term patterns and identifying complex relationships in the data. Traditional methods often struggle with volatile and non-stationary data, but intelligent models like LSTM can overcome issues like gradient vanishing or exploding, significantly enhancing prediction accuracy. To better understand both short-term and long-term behaviors in hydrological time series, wavelet transforms can decompose the data into several subseries. This study employs deep learning for seepage modeling and uses a hybrid wavelet-deep network model to enhance the results [4, 5].

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2. Methodology

In this study, data from the piezometers of cross-section No. 2 of the Sattarkhan dam were used for modeling. The earth fill Sattarkhan dam, located 110 kilometers northeast of Tabriz on the Ahar Chai River, controls surface flows, providing drinking water for Ahar, irrigation for about 11,000 hectares, and industrial water for local industries. The piezometric data consists of 982 daily readings taken from March 2017 to the end of 2019. In the first scenario, the piezometric head was estimated using data from the piezometer itself and the reservoir water level, along with two other piezometers. In the second scenario, the water level was estimated without using previous readings from the target piezometer, relying instead on data from other correlated piezometers. Modeling began with a feed-forward neural network, which, despite its ability to approximate nonlinear functions, has limitations in dynamic system modeling due to its lack of connections from output to input. To address this, recurrent neural networks (RNNs) were employed, leveraging their recursive connections to utilize previous inputs. However, RNNs face challenges like the vanishing gradient problem, leading to the use of LSTM networks for more effective modeling. The structure of the LSTM cell is illustrated in Figure 1 and described by equations (1) to (6) [6].

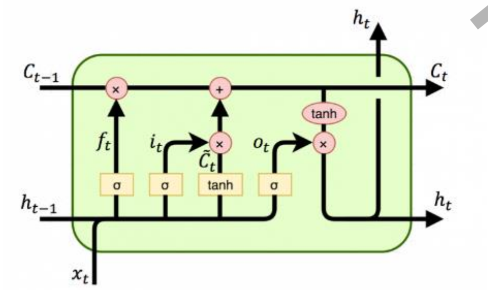

Figure 1 - LSTM Cell

$$f_t = \sigma(W_f\,[h_{t-1}.X_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i\,[h_{t-1}.X_t] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_c\,[h_{t-1}.X_t] + b_c) \quad (3)$$

$$C_t = i_t * \tilde{C}_t + f_t * C_{t-1} \quad (4)$$

$$o_t = \sigma(W_o\,[h_{t-1}.x_t] + b_o) \quad (5)$$

$$h_t = o_t * C_t \quad (6)$$

W_f, W_j, W_C, and W_O are learnable weight matrices, and bz, br, bh, and bo are biases. ft is the output of the forget gate, $\tilde{C}_t$ is the output of the input gate, o_t is the output gate result, C_t is the cell state at time t, and h_t is the final network output. On the other hand, preprocessing input data is a critical and complex step in modeling nonlinear systems, to select an appropriate combination of inputs. In this research, wavelet transform was used for data preprocessing in the design of the recurrent-wavelet hybrid model. A key factor in using this transform is selecting the appropriate mother wavelet. The choice of the mother wavelet is crucial in wavelet-neural network hybrid models and can significantly impact the modeling results. The essence of the mother wavelet lies in identifying the similarity between the analyzed time series and the wavelet sample used [7]. Since the time series studied had gradual changes, the Haar wavelet was used for data decomposition in this study. The Haar wavelet is one of the first and simplest wavelets. For training and evaluating the constructed models, the data was divided into two parts: training data and validation data. The first 70% of the dataset was used for training, while the remaining 30% was used for validation. The network was trained using the training data, and the model's output was compared with observational data to optimize the network's parameters. Finally, the trained network was evaluated using the validation data. In this study, common statistical indices such as Root Mean Square Error (RMSE), Determination Coefficient (DC), and Mean Absolute Error (MAE) were used. RMSE was selected for its precision in measuring prediction errors, DC for its ability to explain data variance, and MAE for its simplicity and robustness against outliers. These indices were used to evaluate the performance of the models employed in this research.

3. Results and Discussion

To perform the modeling, after selecting the input data, the data was first preprocessed; then, by defining the type of recurrent cell and the number of memory units, the architecture of the desired network was specified. With the definition of the loss function and optimizer algorithm, the defined network was fitted to the training data based on the number of iterations and batches determined for each iteration. To optimize the parameters, the model was evaluated using the training data. After the optimal parameters were determined, the validation data was used for prediction, and the defined models were validated using the specified evaluation criteria. For example, the DC value of the modeling performed in Scenario 1 for both piezometers is shown in Table 1.

Table 1. The DC value for Scenario 1 modeling using feedforward and recurrent neural networks.

Network	Train Data	Test Data
FFNN	0.94	0.91

Piezometer 212	Simple RNN	0.92	0.87
	LSTM	0.97	0.93
	WLSTM	0.98	0.96
Piezometer 218	FFNN	1.00	0.82
	Simple RNN	0.99	0.83
	LSTM	1.00	0.86
	WLSTM	0.99	0.88

According to the results in Table 1, after selecting the optimal structure through trial and error for the WLSTM model, the DC values for piezometers 212 and 218 in Scenario 1 were obtained as 0.96 and 0.88, respectively. In Scenario 2, the correlation coefficient was used to identify the two piezometers that were influential in the modeling. The radar chart in Figure 2 illustrates the correlation coefficients of piezometers 212 and 218 with other piezometers present in the Sattarkhan dam body, where piezometer 212 shows the highest correlation with piezometers 211 and 213, while piezometer 218 has the highest correlation with piezometers 215 and 217. After determining the inputs in Scenario 2, the modeling steps were carried out similarly to Scenario 1.

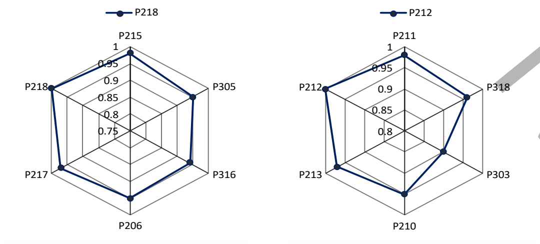

Figure 2 - Correlation coefficient of piezometers 212 and 218 with other piezometers.

In modeling Scenario 2 using the RNN network, the DC values for piezometers 212 and 218 were obtained as 0.96 and 0.71, respectively. For modeling with the LSTM network, the DC values for piezometers 212 and 218 were found to be 0.97 and 0.74, respectively. In the next step, modeling using the wavelet-deep network hybrid model estimated the piezometric heights of piezometers 212 and 218 with accuracies of 0.98 and 0.77, respectively. The modeling results indicate that recurrent networks provide higher estimation accuracy for hydrological time series, like seepage, compared to feedforward networks, making them suitable for dynamic system predictions. LSTM networks, which address the vanishing gradient problem, offer better accuracy than simple recurrent networks. While various artificial neural networks are effective for nonlinear hydraulic and hydrological modeling, their performance declines in time series with significant variations. Employing wavelet transforms as a preprocessing step improves modeling accuracy. In the second scenario of this research, piezometer water levels were estimated using data from other piezometers without relying on previous values, making this model particularly valuable in critical situations or when piezometers are out of service. This approach helps maintain prediction accuracy and reliability, especially when monitoring equipment malfunctions.

4. Conclusions

In this study, the seepage of the Sattarkhan Dam was modeled using feedforward and recurrent neural networks in two scenarios. The results showed that recurrent networks outperform feedforward networks in modeling time-dependent phenomena like seepage, increasing modeling accuracy. Wavelet transformation was applied in the preprocessing stage, leading to improved outcomes, with the combined recurrent-wavelet model achieving up to a 10% increase in accuracy compared to models without wavelet transformation. Additionally, using simultaneous data alongside target data enhanced modeling accuracy, indicating that data from highly correlated piezometers can be effectively utilized in case of piezometer failure. Modeling the piezometer closer to the upstream of the dam yielded more accurate results due to greater correlation with upstream time series data. The study recommends similar modeling for other dam-related quantities, such as seepage. It also highlights the importance of tuning hyperparameters in deep networks and suggests using intelligent methods and algorithms for this purpose. Employing intelligent algorithms in deep learning modeling can reduce the time for hyperparameter tuning, enhance prediction accuracy, and improve overall model performance.

5. References

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