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# Prediction of the Rockfill Dam Safety Using Long Short Term Memory

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***Abstract*— Embankment dams are the oldest and the most common type of dam in use today. The rockfill embankment dam is defined as an embankment dam that relies on rockfill as major structural element. Mechanical stability of dam implies stability of slopes and foundation soil. In order to provide dam safety, pore pressures between the particles in the clay core and the phreatic line in the downstream support body should be reduced to a minimum. Measuring and analysing the values of the pore water pressure in the clay core are essential for the dam safety analysis. The idea in this paper was to predict the pore water pressure in the clay core based on the water level in the reservoir and the groundwater level. In this paper we will use a long short-term memory structure. We will try to model a system that predicts value of one pore pressure cell, and if we prove that this system has good characteristics, we can develop an overall system that has 11 pore pressures as its outputs.**

***Keywords*— long short-term memory, rockfill dam, structural safety**

## I. Introduction

Dams are large and important objects not only because of their size, and the huge funds that need to be invested in their construction, but also in terms of participation in the economy of the region in which they are located [1].

According to the materials from which the dams were composed, they can be classified into two main categories - concrete and embankment dams.

Embankment dams are the oldest type of dam, at least 5000 years old, and further, the most common type of dam in use today. Mechanical stability of dam implies stability of slopes and stability of foundation soil.

In order to provide dam safety, pore pressures (PWP) between the particles in the impervious core and the phreatic line in the downstream support body should be reduced to a minimum [2], [3].

Measuring and analysing the values of the pore water pressure in the clay core are the most important for the dam safety analysis [4].

The idea in this paper was to predict the pore water pressure in the clay core based on the water level in the reservoir and the groundwater level.

We will use the long short-term memory structure of artificial neural networks and we will examine what is the optimum number of previous values of pore water pressures used as network inputs that gives the smallest prediction error, i.e. which is the number of previous days that has the most impact on network output.

## II. Theoretical framework

In our previous work we tried to solve this problem in few different ways. First, a common multi-layer perceptron (MLP) was used, then a standard recurrent neural network (RNN), long short-term memory (LSTM), and finally gated recurrent unit (GRU) with a different number of inputs. Within this paper we will show our results regarding long short-term memory structure, shown in Fig. 1.

We chose LSTM structure [5] after considering disadvantages of standard RNNs. In fact, RNNs are very sensitive to input sequence length – the effects of inputs from distant moments in the past vanish as they propagate through the network. This problem with long sequences rises even more when the input sequence is too long. Then there exists a problem that a learning gradient either diverges or converges rapidly in parts of the network which are at a longer time distance from the output, so this causes that network stops learning. This makes RNNs successfully applicable only to sequences of short length.

So, in order to solve the presented problem, the LSTM incorporates a channel called “cell state” along the hidden state channel which is contained in a standard RNN.

The cell state connection spreads across consecutive LSTM cells and it is used to pass and update information that is important to many cells in the chain, no matter of their distance from the current time point.

The cell state is changed when applying activation functions and different matrix operations to its inputs, and also outputs from the previous time step and the previous cell state.

These functions are applied using three activation layers called gates: the forget gate, the input gate, and the output gate.

The function of forget gate is to direct the effect of the previous cell state on the next one - it decides if a piece of information that cell state contains need to be kept or removed.

The function of input gate is to decide if a new cell state should be affected by the input, i.e. if new information based on the input should be added to the cell state or the input should be ignored.

The output gate is of crucial importance since it generates the prediction by appointing the information that will be passed to the next long short-term memory cell depending on the new cell state and the network inputs [5].

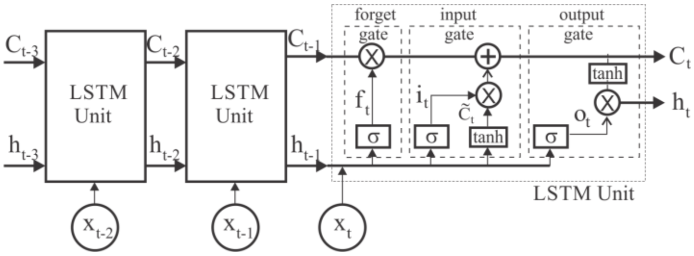


Figure 1 Long short-time memory structure

## III. DEVELOPMENT OF ANN MODEL

As a study embankment dam we used Bovan dam. It is a high rockfill dam with a clay core as impervious sealing element (Figure 2).

This dam is located at the south-east of Serbia, 50 kilometres north from Niš (Figure 3).

Figure 2 The Bovan dam

Based on available measured data for one year period (groundwater level, reservoir water level and air temperature), we tried to model a system that predicts value of one pore pressure cell. If we prove that this system has good characteristics, we can develop an overall system that has 11 pore pressures as its outputs.

By analysing measured data, we concluded that a system is also affected by values of pore pressures in previous time instants.

Based on these presumptions, we created an artificial neural network having all measured data and also previous values of pore pressures as inputs, and actual pore pressure as output.

In the Table 1 hydrometeorological data set for one week is given, in order to get insight into data representation. Measurement unit is meters above the sea level (MASL), for the reservoir water level (RWL), and water level in the piezometers in the dam crest (E1, E3, E4, E6, E7) and dam left and right banks (P2, P3 and P10) (Figure 4).

Figure 3 Location of the Bovan dam in Serbia

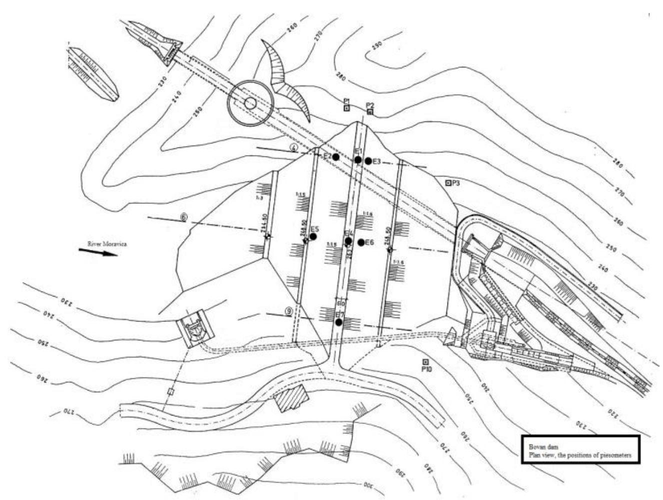

Figure 4 The positions of the piezometers

TABLE 1 WEEKLY HYDROMETEOROLOGICAL DATASET IN YEAR 2020

| Day | RWL masl | P2 masl | P3 masl | P10 masl | E1 masl | E3 masl | E4 masl | E6 masl | E7 masl | T C° |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| August 11th | 253,22 | 245,11 | 221,17 | 218,83 | 261,31 | 244,59 | 235,06 | 219,50 | 249,06 | 26,00 |
| August 12th | 253,22 | 245,11 | 221,16 | 218,84 | 261,3 | 244,59 | 235,06 | 219,50 | 249,06 | 21,00 |
| August 13th | 253,28 | 245,12 | 221,16 | 218,84 | 261,3 | 244,59 | 235,06 | 219,49 | 249,06 | 26,00 |
| August 14th | 253,39 | 245,12 | 221,16 | 218,84 | 261,3 | 244,59 | 235,06 | 219,49 | 249,06 | 28,00 |
| August 15th | 253,32 | 245,12 | 221,16 | 218,84 | 261,29 | 244,59 | 235,06 | 219,49 | 249,06 | 28,00 |
| August 16th | 253,26 | 245,12 | 221,16 | 218,84 | 261,29 | 244,59 | 235,06 | 219,49 | 249,06 | 27,00 |
| August 17th | 253,17 | 245,11 | 221,15 | 218,84 | 261,29 | 244,59 | 235,06 | 219,49 | 249,05 | 23,00 |

As presented in the Table 1, hydrometeorological data are given per day, while pore water pressure data were available per hour, so we used average daily value for pore pressure.

We averaged pore water pressure as presented in the Table 2, but in neural network training process 24 hours available dataset is used, as well as average values for all other days.

Usually a test set takes 30% of overall dataset while the training set makes up 70% of overall dataset [6].

In order to estimate the values that influence the most on measured pore pressure, eight different network structures were analysed concerning numbers of previous days. We created structures with adopted data sets of 1, 3, 5, 10, 15, 20, 25 and 30 previous days.

TABLE 2 ADOPTION OF PWP VALUE FOR 24 HOURS

| Date in 2020 | Time (h) | PWP on PC 6-3 (kPa) |
|---|---|---|
| 1 | 2 | 3 |
| August 17Th | 0.00 | 55,950 |
| August 17Th | 1.00 | 55,941 |
| August 17Th | 2.00 | 55,946 |
| August 17Th | 3.00 | 55,948 |
| August 17Th | 4.00 | 55,948 |
| August 17Th | 5.00 | 55,947 |
| August 17Th | 6.00 | 55,943 |
| August 17Th | 7.00 | 55,946 |
| August 17Th | 8.00 | 55,953 |
| August 17Th | 9.00 | 55,956 |
| August 17Th | 10.00 | 55,955 |
| August 17Th | 11.00 | 55,951 |
| August 17Th | 12.00 | 55,953 |
| August 17Th | 13.00 | 55,945 |
| August 17Th | 14.00 | 55,934 |
| August 17Th | 15.00 | 55,928 |
| August 17Th | 16.00 | 55,924 |
| August 17Th | 17.00 | 55,926 |
| August 17Th | 18.00 | 55,931 |
| August 17Th | 19.00 | 55,928 |
| August 17Th | 20.00 | 55,927 |
| August 17Th | 21.00 | 55,938 |
| August 17Th | 22.00 | 55,934 |
| August 17Th | 23.00 | 55,928 |
| | Adopted PWP value | 55,941 |

The purpose of adopting these various structures was to get results about the best structure, i.e. what is the optimal number of previous days that we use as network input, leading to achieving the best prediction. Results obtained after detailed analysis are given in the following text.

Each of these structures has 10 inputs as given in the Table 1 (RWL, P2, P3, P10, E1, E3, E4, E6, E7, T). Furthermore, each network has additional inputs, depending on its structure (data sets of 1, 3, 5, 10, 15, 20, 25 and 30 previous days).

For example, if we take into account 1 previous day, the network will have 1 additional input, determining pore pressure value for a previous day.

Similarly, if we want to include two previous days, the network will have 2 additional inputs, determining pore pressures for two previous days, and so on.

LSTM structures that we used have 2 hidden layers, where each of them has 128 hidden neurons.

This number of hidden neurons was selected after testing models with different numbers of neurons in the hidden layers. The training process consisted of iterative optimization of network parameters in order to obtain minimal root mean square error between the expected and predicted values. The network models are described in Python 3.7.9, using the Keras deep learning API from the TensorFlow platform for machine learning [7].

TABLE 3 RMSE FOR DIFFERENT NUMBER OF DAYS USED

| Number of previous days used | RMSE for PC 6-3 |
|---|---|
| 1 | 0.058 |
| 3 | 0.064 |
| **5** | **0.054** |
| 10 | 0.073 |
| 15 | 0.055 |
| 20 | 0.055 |
| 25 | 0.092 |
| 30 | 0.122 |

RMSE values for all tested models are given in the Table 3. From this Table we can notice that minimum RMSE is achieved when we consider 5 previous days.

But, if that makes our network robust, we can use also networks with much simpler structure because it is obvious from the Table that error is not significantly different.

## IV. CONCLUSION

The inflection of pore water pressure in the embankment dams is important for estimating dam's safety.

In this paper we considered dependency between pore pressure in the rockfill dam clay core, reservoir water level and groundwater data using LSTM structure. Based on this correlation, the ANN can predict pore water pressure or can assume what their values will be.

The obtained results show that a prediction can be made with negligible errors.

This method can be used for PWP data prediction in flood-rich period, i.e. in the spring when water level in the reservoir is on maximum. Flood periods occur mainly in early spring (March and April), the rainiest season in the Northern Hemisphere, as measured by the number of days with precipitation.

With this method, any anomaly in the PWP dataset can be detected, defining the "weak points" and possible cracks in the dam clay core.

## V. ACKNOWLEDGMENTS

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