Structural Safety 56 (2015) 9–17

Contents lists available at ScienceDirect

Structural Safety

journal homepage: www.elsevier.com/locate/strusafe

An empirical comparison of machine learning techniques for dam behaviour modelling

F. Salazar [a,*], M.A. Toledo [b], E. Oñate [a,c], R. Morán [b]

[a] CIMNE – Centre Internacional de Metodes Numerics en Enginyeria, Campus Norte UPC, Gran Capitán s/n, 08034 Barcelona, Spain
[b] Technical University of Madrid (UPM), Civil Engineering Department: Hydraulics, Energy and Environment, Profesor Aranguren s/n, 28040 Madrid, Spain
[c] Universitat Politècnica de Catalunya (UPC), Barcelona, Spain

ARTICLE INFO

Article history:
Received 10 June 2014
Received in revised form 1 May 2015
Accepted 4 May 2015
Available online 4 June 2015

Keywords:
Dam monitoring
Dam safety
Machine learning
Boosted regression trees
Neural networks
Random forests
MARS
Support vector machines
Leakage flow

ABSTRACT

Predictive models are essential in dam safety assessment. Both deterministic and statistical models applied in the day-to-day practice have demonstrated to be useful, although they show relevant limitations at the same time. On another note, powerful learning algorithms have been developed in the field of machine learning (ML), which have been applied to solve practical problems. The work aims at testing the prediction capability of some state-of-the-art algorithms to model dam behaviour, in terms of displacements and leakage. Models based on random forests (RF), boosted regression trees (BRT), neural networks (NN), support vector machines (SVM) and multivariate adaptive regression splines (MARS) are fitted to predict 14 target variables. Prediction accuracy is compared with the conventional statistical model, which shows poorer performance on average. BRT models stand out as the most accurate overall, followed by NN and RF. It was also verified that the model fit can be improved by removing the records of the first years of dam functioning from the training set.

1. Introduction and background

Dam safety assessment is a complex task due to the uniqueness of each of such structures and their foundations. It is commonly based on three main pillars: visual inspection, engineering knowledge and a behaviour model. The actual response of the dam is compared with the predictions of the model, with the aim of detecting anomalies and preventing failures. Current predictive methods can be classified as follows [1]:

- Deterministic: typically based on the finite element method (FEM), these methods calculate the dam response on the basis of the physical governing laws.
- Statistical: exclusively based on dam monitoring data.
- Hybrid: deterministic models which parameters have been adjusted to fit the observed data.
- Mixed: comprised by a deterministic model to predict the dam response to hydrostatic pressure, and a statistical one to consider deformation due to thermal effects.

It is difficult to predict dam behaviour with high accuracy. Numerical models based on the FEM provide useful estimates of dam movements and stresses, but are subject to a significant degree of uncertainty in the characterisation of the materials, especially with respect to the dam foundation. Other assumptions and simplifications have to be made, regarding geometry and boundary conditions. These tools are essential during the initial stages of the life cycle of the structure, provided that there are not enough data available to build data-based predictive models. However, their results are often not accurate enough for a precise assessment of dam safety.

This is more acute when dealing with leakage in concrete dams and their foundations, due to the intrinsic features of the physical process, which is often non-linear [2], and responds to threshold and delayed effects [3,4]. Numerical analysis cannot deal with such a phenomenon, because comprehensive information about the location, geometry and permeability of each fracture would be needed. As a result, deterministic models are not used in practice for the prediction of leakage flow in concrete dams [1].

* Corresponding author.
E-mail addresses: fsalazar@cimne.upc.edu (F. Salazar), matoledo@caminos.upm.es (M.A. Toledo), onate@cimne.upc.edu (E. Oñate), rmoran@caminos.upm.es (R. Morán).
URL: http://www.cimne.com (F. Salazar).

http://dx.doi.org/10.1016/j.strusafe.2015.05.001
0167-4730/

Many of the dams in operation have a large number of monitoring devices, recording the evolution of various indicators such as movements, leakage flow or the pore water pressure, among others. Although there are still many dams with few observed data, there is a clear trend towards the installation of a larger number of devices with higher data acquisition frequency [5]. As a result, there is an increasing amount of information on the dam performance, which makes it interesting to study the ability of machine learning (ML) tools to process them, build behaviour models and extract useful information [6].

The paper assesses the potential of some state-of-the-art ML techniques to build models for the prediction of dam behaviour. The results are compared with the conventional statistical method.

1.1. Statistical models

The most popular data-driven approach for the prediction of dam behaviour is the hydrostatic-seasonal-time (HST) method, characterised by taking into account three effects:

- A reversible effect of the hydrostatic load.
- A reversible seasonal thermal influence of the temperature.
- An irreversible term due to the evolution of the dam response over time.

This assumption is coherent with the observed behaviour of many concrete dams in terms of displacements. However, it has also been applied to other variables, such as uplifts and leakage [3]. Similar schemes have been used for rock-fill dams, although it is acknowledged that the temperature is not relevant, and that the irreversible effect of settlements prevails on the elastic response to hydrostatic load. Furthermore, rainfall may have a strong influence on leakage [3].

The main drawbacks of HST and other methods based on linear regression are the following:

- The functions have to be defined beforehand, and thus may not represent the true behaviour of the structure [3].
- The governing variables are supposed to be independent, although some of them have been proven to be correlated [7].
- They are not well-suited to model non-linear interactions between input variables [2].

1.2. Advanced data analysis in dam monitoring

The examples of application of innovative techniques to improve the results of HST are becoming more frequent in recent years. As an example, Bonelli and Radzicki [8] used an impulse-response function for predicting the pore pressure in the dam body. The method provided accurate results in the test cases, showing the hysteresis effect by which the pore pressure is lower during filling than it should be in a stationary state, and vice versa. Nonetheless, given that it makes a strong assumption on the characteristics of the phenomenon, it is restricted to specific processes.

Li et *al.* [9] proposed a method to improve HST based on cointegration theory. They tested the stationarity of the monitoring data series before fitting a multi-linear regression (MLR) model.

One obvious weakness of linear regression is that it cannot reproduce nonlinear relations between variables. This problem is typically overcome by introducing higher order terms of the covariates. Neural networks (NN) constitute a powerful alternative to solve this issue. Their flexibility and capability to adapt to highly complex interactions have made them popular in several fields of engineering, including dam monitoring (see for example [3,10–12]).

However, it should be noted that NN have some drawbacks:

- The result depends on the initialisation of the weights.
- The best network architecture (number of hidden layers and neurons in each layer) is not known beforehand.
- The model is prone to over-fitting.
- The training process may reach a local minimum of the error function.

Several techniques have been developed to overcome these shortcomings, which in general lead to an increase in the computational cost [13]. In spite of this, NN stand out as the most popular ML tool in dam engineering, and the results are promising [3]. Further models have been also applied to dam monitoring, such as ANFIS (adaptive network-based fuzzy inference system) models [14], principal component analysis [6], NARX (nonlinear autoregressive with exogenous input) models [15] or K-nearest neighbours [16]. However, these tools are rarely used in practice, where HST still prevails. Moreover, most of the previous studies are limited to one single variable of specific dams [11,12]. Hence, the results are not generally applicable.

1.3. Objectives

The study aims to assess the prediction accuracy of some ML tools, most of which have been seldom used in dam engineering. Specifically, the algorithms selected are: random forests (RF), boosted regression trees (BRT), support vector machines (SVM) and multivariate adaptive regression splines (MARS). Both HST and NN were also used for comparison purposes. Similar analyses have been performed in other fields of engineering, such as the prediction of urban water demand [17].

A further singularity of dams is that the early years of operation often correspond to a transient state, non-representative of the quasi-stationary response afterwards [18]. In such a scenario, using those years for training a predictive model would be inadvisable. This might lead to question the optimal size of the training set in achieving the best accuracy. De Sortis [19] ran a sensitivity analysis and concluded that at least 10 years were needed to obtain acceptable predictions. However, his study was limited to the prediction of the radial displacement in one particular location of a specific dam by using HST. A similar work was performed by Chouinard and Roy [2]. This paper seeks to extend such studies to other learning algorithms and output variables.

2. Case study and variable selection

The data used for the study correspond to La Baells dam. It is a double curvature arch dam, with a height of 102 m, which entered into service in 1976. The monitoring system records the main indicators of the dam performance: displacement, temperature, stress, strain and leakage. The data were provided by the Catalan Water Agency (*Agència Catalana de l'Aigua*, ACA), the dam owner, for research purposes. Among the available records, the study focuses on 14 variables: 10 correspond to displacements measured by pendulums (five radial and five tangential), and four to leakage flow. Several variables of different types were considered in order to obtain more reliable conclusions. Table 1 shows some statistics of the target variables, whereas the location of each monitoring device is depicted in Fig. 1.

The data acquisition frequency is of the order of one record per week. The measurement error of the devices is ± 0.1 mm for displacements, and negligible for leakage flows (measured using the volumetric method). The series span from 1979 to 2008. In all cases, approximately 40% of the records (from 1998 to 2008) were left out as the testing set. This is a large proportion compared with previous studies, which typically leave 10–20 % of the available