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OPEN ISSUES IN STRUCTURAL HEALTH MONITORING AND LOCAL FAILURE DETECTION IN CONCRETE DAMS

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Abstract. Assessing the structural health of strategic infrastructures such as concrete dams is of paramount importance for clean energy production and flood control in the current context of climate change. Monitoring aimed at early detection of possible local failures is particularly important for long-standing, aging facilities located in the Alpine region. For this purpose, a sensor system is usually installed in the dam body and collects information on the structural response to external actions, mainly consisting of seasonal variations in temperature and water level. Additional measurements could be acquired using drone-mounted equipment. This large amount of data can be processed by various approaches, such as statistical models or machine learning tools trained to predict the dam behaviour and highlight anomalous trends. However, despite the enormous progress made in recent years by the available analysis tools, some limitations are difficult to overcome. In particular, information concerning damaged dams is scarce and hard to transfer from one situation to another. In fact, these structures are quite resilient, and almost all represent unique prototypes due to their particular geometry and environmental conditions. The scarcity of data can be partly overcome by developing a digital twin of the structure under study, with the aim of reproducing its behaviour under the conditions expected to be most critical. To return reliable predictions, the model should be calibrated and continuously updated based on monitoring data. However, measurable quantities may show limited sensitivity to key parameters that enable the identification of local faults. This document illustrates and discusses these aspects with reference to some specific examples.

1 INTRODUCTION

A network of sensors such as clinometers, collimators, pendula, calipers, and thermometers is usually installed in concrete dams to collect information on environmental conditions (e.g., air and water temperature) and the structure response to external actions.

In newly built facilities, the monitoring system may consist of a large number of devices that facilitate the development of data-driven models, capable of reproducing the behavior of the dam and tracking its evolution over time [1]. Measurement anomalies can thus be detected, although the accuracy of predictions and, consequently, the effectiveness of potential warning systems may be affected by incomplete or imperfect data [2]. Moreover, since training datasets do not normally include information on damage, purely data-driven approaches are generally unable to identify the underlying causes of degradation [3].

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The problem can be partly overcome by the consideration of physics-based digital twins of the structures under study, mainly implemented in the Finite Element (FE) framework [4]. In this case, monitoring data are exploited to determine model parameters such as the material properties. The information provided by sensors installed in the facility can be supplemented by non-contact full-field measurements performed by instruments that can be mounted on drones [5]. In addition, uncertainties related to the foundation rock and other out-of-sight details can be eliminated by taking into account reduction and sub-structuring techniques [6].

A reliable numerical model of the dam system can interpret its response even in situations that have never occurred before, such as unusual combinations of water level and temperature due to climate change. The model can also simulate the most critical situations that could occur and provide synthetic data for the training of self-learning algorithms. However, a further limitation that is difficult to overcome is the possible low sensitivity of the measurements that can actually be performed to the effects of common degradation processes, as illustrated below.

2 PREDICTION MODELS

The mechanical behavior of dams is traditionally predicted by statistical models that reproduce the structural response using predefined functions for each individual action [7]. Displacements associated with changes in water level are usually described by polynomials, temperature effects are represented by periodic functions, and aging is often described by linear or exponential expressions over time. The combination coefficients are calibrated and, possibly, updated periodically to adapt the model to the available monitoring data.

A series of approaches based on machine learning and deep learning are also under development. Models built up in this context do not rely on explicitly defined functions but improve their performance by learning from data [8]. Among the most popular alternatives, techniques based on decision trees divide the dataset into smaller and more uniform groups by applying a set of rules to the input variables. At each step, the condition that best separates the data based on the target variable is selected [9]. The Boosted Regression Trees (BRT) methodology defines a sequence of regression trees, training each new tree to correct the errors made by the previous set [10]. This sequential process allows the model to implicitly capture complex non-linear relationships.

The reliability of the predictions provided by statistical and machine learning regression models can be seriously compromised by incomplete and imperfect data. In the dam context, an additional limitation is the scarcity of information on actual damage cases, partly due to the resilience of these structures. Furthermore, the available information cannot be transferred from one situation to another, as each dam is a kind of prototype due to the different geometries and ambient conditions that characterize them.

The problem can be partly overcome by integrating actual measurements with synthetic results produced by physics-based simulation models of the facility, often developed within the FE framework (Figure 1). These models must in turn be calibrated against experimental observations, using the information available to identify the current material properties. In this approach, the characteristics of the foundation rock are among the main uncertainties that must be addressed. The same applies to the temperature distribution across the dam body as only average water and air temperatures are usually recorded.

Uncertainties can be mitigated by integrating the usual measurements with full-field data acquired by infrared and optical cameras [4]. The measured displacements can be used to define the characteristics of the connection between the dam body and its foundation in a reduced model, shown for example in Figure 1b.

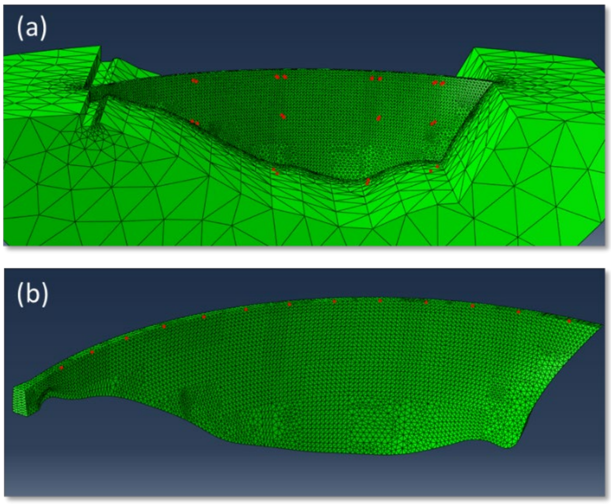

Figure 1: Finite element models of the dam proposed as ICOLD benchmark problem in 2022 [11]: (a) structure and foundation rock; (b) dam body.

The regions to be discretized can also be defined in more detail, for example by focusing on dam sections around construction and natural joints, as shown schematically in Figure 2. The measured displacements provide the boundary conditions of the region of interest and can be used to deduce the characteristics (friction, cohesion) of the sliding and opening interfaces by means of inverse analysis procedures [12].

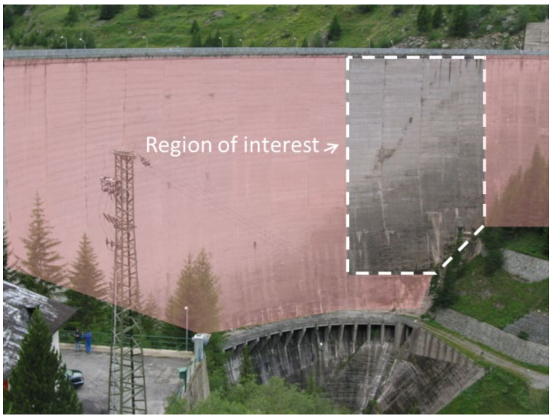

Figure 2: Schematic of a dam section to be monitored and modelled based on full-field measurements

Infrared or drone-based optical measurements could also feed data-driven models. However, since these data are generally short-term and cannot replace the continuity of traditional monitoring, their main value lies in supporting the calibration of finite element models, which can then provide synthetic data for machine learning.

3 ANOMALY DETECTION

Figure 3 visualizes the displacement at one point of a real dam, measured and predicted by data-driven (BRT) and physics-based (FE) models. The initial monitoring period (up to 2018) provides the information used for BRT training and FE calibration [13]. The graphs highlight the merits of these alternative approaches. The BRT model closely reproduces the displacements during the training phase and maintains good accuracy in subsequent predictions. However, the FE model shows stronger extrapolation capabilities and yields more reliable results in summer 2022, when an unusual combination of temperature and water level occurred.

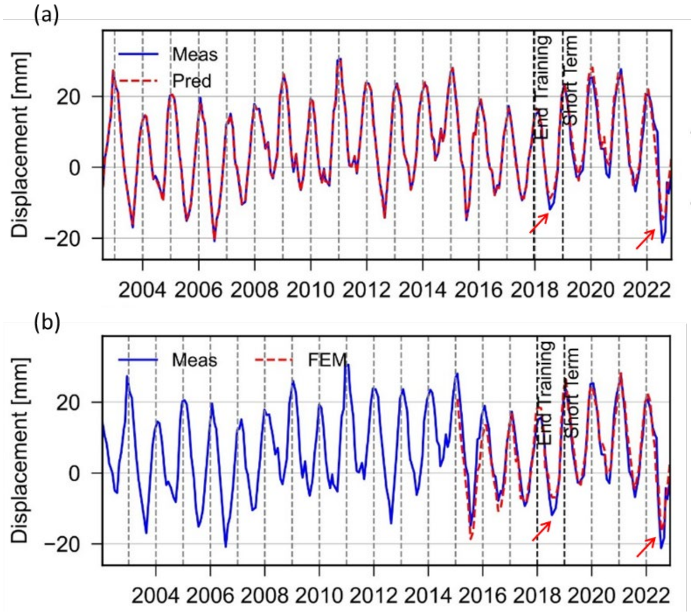

Figure 3: Dam displacement measured and predicted by: (a) BRT and (b) FE approaches [13].

Differences between measured and predicted values highlight degradation processes or malfunctioning of the installed devices. Clearly, the recognition of normal and potentially harmful conditions depends on the criteria used to evaluate deviations from the expected behavior. Thresholds can be based on the standard deviation of training residuals, or on empirical quantiles that are more robust to outliers and skewed distributions [14]. More interpretable assumptions rely on envelopes of historical datasets or specialized loss functions applied to the output of the predictive models. Alert limits can also evolve over time and adapt to new input conditions not yet considered in previous training phases [15].

One issue that remains unresolved concerns the automatic distinction between instrumental errors and potential physical damage. The problem can be partly overcome by enriching the monitoring data with the results of simulations that take into account critical scenarios that could occur. Joint degradation is one of these. However, it should also be considered that the influence of these processes on measurable quantities could be almost negligible as shown, for example, in Figure 4, which refers to a benchmark problem formulated by the International Committee on Large Dams (ICOLD) [16]. The graph shows the simulated response to the recorded values of temperature and water level of Tsankos Kamak dam. FE analyses are performed assuming linear-elastic behavior of the dam blocks, connected by frictional interfaces. Damage is simulated by a significant reduction in the friction coefficient. The figure displays the displacement in the upstream-downstream direction at the crest point indicated in the schematic insert, located near a joint subject to sudden degradation at the beginning of 2022.

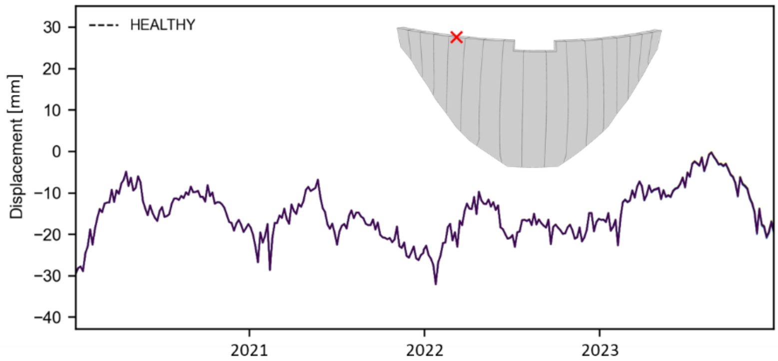

Figure 4: Simulated response of Tsankos Kamak dam [16], schematized in the insert: the (practically overlapped) lines represent crest displacement in healthy (dashed) and damaged (continuous) conditions.

Other numerical results show that the sensitivity to friction of relative displacements depends on the position of both the deteriorated joint and the measurement point, and that joint degradation is mainly reflected in relative sliding, while openings are practically unaffected by the interface characteristics in the structure examined. In any case, typical values for relative movement between dam blocks are in the order of a few millimeters, or less [4]. Therefore, variations due to initial damaging processes are likely to be masked by inherent instrumental inaccuracies.

4 CONCLUSION

The safety assessment of existing structures can benefit from current technological and computational developments. In particular:

- installed sensors can be supplemented by monitoring equipment that can be mounted on drones and perform contactless measurement;
- the information collected can be transferred in near real time via digital networks, and processed automatically to evaluate the structural status;
- digital twins of the facilities under study can be appropriately calibrated based on the results of surveillance activities;
- digital twins can produce synthetic data for training self-learning algorithms capable of recognizing potentially critical situations that have never occurred before.

However, the sensitivity of measurable quantities to some damage phenomena may be weak, and the accuracy of currently available instrumentation may be inadequate for defining reliable early warning systems. Nevertheless, technological and computational advances expected in the near future could reduce measurement uncertainties and improve the reliability of health assessment procedures.

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