Chapter 1
Applying advanced data analytics and machine learning to enhance the safety control of dams

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Abstract The protection of critical engineering infrastructures is vital to today's society, not only to ensure the maintenance of their services (e.g., water supply, energy production, transport), but also to avoid large-scale disasters. Therefore, technical and financial efforts are being continuously made to improve the safety control of large civil engineering structures like dams, bridges and nuclear facilities. This control is based on the measurement of physical quantities that characterize the structural behavior, such as displacements, strains and stresses. The analysis of monitoring data and its evaluation against physical and mathematical models is the strongest tool to assess the safety of the structural behavior. Commonly, dam specialists use multiple linear regression models to analyze the dam response, which is a well-known approach among dam engineers since the 1950s decade. Nowadays, the data acquisition paradigm is changing from a manual process, where measurements were taken with low frequency (e.g., on a weekly basis), to a fully automated process that allows much higher frequencies. This new paradigm escalates the potential of data analytics on top of monitoring data, but, on the other hand, increases data quality issues related to anomalies in the acquisition process. This chapter presents the full data lifecycle in the safety control of large-scale civil engineering infrastructures (focused on dams), from the data acquisition process, data processing and storage, data quality and outlier detection, and data analysis. A strong focus is made on the use of machine learning techniques for data analysis, where the common multiple linear regression analysis is compared with deep learning strategies, namely recurrent neural networks. Demonstration scenarios are presented based on data obtained from monitoring systems of concrete dams under operation in Portugal.

1.1 Introduction

Dam safety is a continuous requirement due to the potential risk in terms of environmental, social and economical disasters. In the International Commission on Large Dams' bulletin number 138 [31], it is referred that the assurance of the safety of a dam or any other retaining structure requires "a series of concomitant, well directed, and reasonably organized activities. The activities must: (i) be complementary in a chain of successive actions leading to an assurance of safety, (ii) contain redundancies to a certain extent so as to provide guarantees that go beyond operational risks".

Continuous dam safety control must be done at various levels, and must include an individual assessment (dam body, its foundation, appurtenant works, adjacent slopes, and downstream zones) and as a whole, in the various areas of dam safety: environmental, structural and hydraulic/operational. Environmental safety, as the name suggests, is related to the environmental impacts originated by the dam, both in terms of maintenance of ecological flows, with direct influence on the fauna and flora existing upstream and downstream, and in terms of the control of the characteristics and quality of the reservoir water and soil. Hydraulic/operational safety is related to the exploitation and operation of hydraulic devices, as well as the implementation of early warning and alert systems for emergency situations. Structural safety can be understood as the dam's capacity to satisfy the structural design requirements, avoiding accidents and incidents during the dam's life. Structural safety includes all activities, decisions and interventions necessary to ensure the adequate structural performance of the dam.

Structural safety control is based on making decisions during the different phases of a dam's life through safety control activities. Thus, the main aim of structural safety control is the multiple assessment of the expected dam behavior based on models and on the measurements of parameters that characterize the dam's behavior and its condition. The main concern is the assessment of the real and actual dam behavior, under exploitation conditions, in order to early detect possible malfunctions.

To be effective, dam safety control must be considered as an ongoing process. The assessment of the dam's structural behavior and condition through the use of monitoring systems is a continuous improvement process based on three activities: monitoring, data analysis and interpretation of the dam's behavior, and dam safety assessment and decision-making, as represented in Fig. 1.1.

Monitoring considers the observation of a phenomenon or event, involving visual inspections and taking measurements to quantify in order to better describe it. The purpose of the analysis and interpretation activities is to provide the necessary background about dam behavior for a better definition of the requirements (data selection, type of models, etc.), to enhance the conceptual understanding and to represent the dam's behavior through models. Once a model is constructed, the assessment of the dam's condition is based on test hypotheses and scenarios using monitoring data, and the prediction of the structural behaviour in space and time.

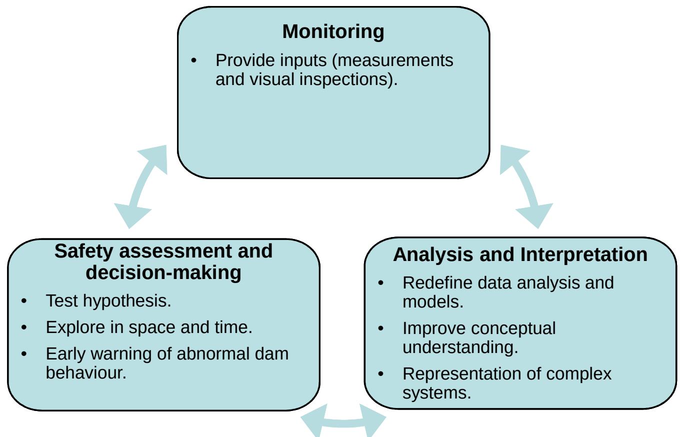

Fig. 1.1: Main activities of structural dam safety control.

The procedure of providing information for the assessment of the dam's structural condition and behavior is itself a form of critical thinking and analysis in order to reduce the degree of uncertainty about the structural behavior. Our ideas about the actual dam behavior, or even the validity of the hypothesis and models, are put into question when new evidence that do not match the existing hypothesis are found.

In the design phase of a dam, the intention is to create a structural form which, together with the foundation and the environment, will most economically [27]: (i) perform its function satisfactorily without appreciable deterioration during normal scenarios expected to occur in the dam's life (ensuring performance and dam safety conditions) and, (ii) will not fail catastrophically during the most unlikely (but possible) extreme hazard scenarios which may occur (ensuring dam safety condition).

During the dam's life, the performance and dam safety conditions are reassessed for the same scenarios, and for other scenarios ”suggested” by the observed behavior through the analysis of relevant parameters (such as self weight, water level and temperature variations, among others), as represented in Fig. 1.2. Typically, these parameters will describe: the loads or operating conditions to which the system may be subjected, the materials from which the structure is constructed, the materials upon which the structure is to be founded, and the structural response of the dam.

The assessment of the structural dam behavior and dam condition must be performed for each dam independently, even for dams of the same type, because of several aspects, such as heterogeneities in the dam's foundation and in the surrounding areas of the dam, or different loads (as a consequence of environmental or operational conditions).

Models used for dam safety control should incorporate all information available. Note, however, that in the point of view of the design, the values for the structural properties and the loads are assigned and the dam safety condition is assessed based on the responses obtained through numerical models, whereas, in the point of view

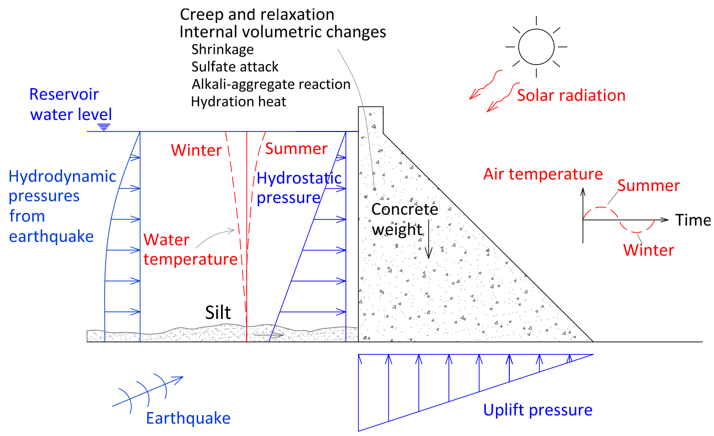

Fig. 1.2: Some parameters analyzed for the assessment of dam safety and performance.

of the safety control, and when there is a large amount of observations of loads and responses, the structural properties that characterize the model can be determined and compared with the values of these structural properties effectively observed.

During the dam's life phases, the models used are updated to take into account the observed dam behavior through the monitoring systems. This is the case of quantitative interpretation models, whose parameters can be updated based on the measured dam response over time.

Present and past observations of loads and responses provide a continuous representation of the dam state, creating an updated model that accurately represents the real behavior of each dam. Such data is the most powerful tool to support decision making by dam specialists, since:

- it supports informed decision making as a data-driven decision support system, where dam specialists can analyze the actual behavior of each dam;
- it provides historical data about relations between actions/responses, making it possible to create predictions about the future dam responses, allowing a model-driven decision support system.

As a consequence, dam safety specialists create behavior prediction models to represent the expected behavior of each dam. The predicted values are then compared with the real response (values observed by the monitoring system), aiming to identify deviations from the real behavior to the expected one (considered as the normal behavior). Identified deviations between the predicted behavior and the observed behavior can mean: (i) structural anomaly; (ii) structural adaptation to new conditions, which means that the prediction model is outdated; (iii) inadequate prediction. Indeed, it is of most importance to adequately identify deviations that represent any kind of structural anomaly, reducing as much as possible any deviations related to outdated or inadequate prediction models.

Traditionally, dam specialists use Multiple Linear Regression models [10] to predict the expected behavior of each dam. Current advances in the machine learning field, specially on the class of deep learning models, can be seen as a breakthrough for dam safety if they manage to better predict the dam behavior in time. Based on this challenge, this chapter proposes the use of Recurrent Neural Networks to model the behavior of dams, represented by the sensor data generated by the monitoring system installed at each dam.

The remainder of this chapter is organized as follows:

- Section 1.2 presents the data lifecycle in the safety control of concrete dams, explaining how the data is captured; what are the main processing and data storage capabilities that are required for dam safety data; how data quality and outlier detection can be achieved is this field; how quantitative models can be used in dam safety and, finally, what is the current state of the art in the usage of machine learning techniques in the safety control of concrete dams;
- Section 1.3 surveys the use of deep learning for sensor data prediction with a specific focus on deep learning in time series;
- Section 1.4 presents the research method followed in this chapter to design the proposal of the usage of deep learning strategies to predict the structural dam behaviour;
- Section 1.5 details the deep learning methods used to predict the structural dam behaviour;
- Section 1.6 presents the evaluation of the methods proposed on section 1.5, using a real case study of the Alto Lindoso dam;
- Section 1.7 details the main conclusions of this chapter.

1.2 The data lifecycle in the safety control of concrete dams

To understand the implications of dam safety data we need to consider its lifecycle. Figure 1.3 shows the dam safety engineering oversight proposed by M. Ljunggren and Campbell [48], where the data management lifecycle includes: (i) raw data collection; (ii) processing and data storage; (iii) data analysis.

Based on this structure, this section analyses raw data collection in subsection 1.2.1, processing and data storage capabilities in subsection 1.2.2, data quality and outlier detection in subsection 1.2.3, analysis of the structural response with quantitative interpretation models in subsection 1.2.4 and, finally, subsection 1.2.5 surveys how machine learning techniques are currently being used in dam safety to support the analysis process.

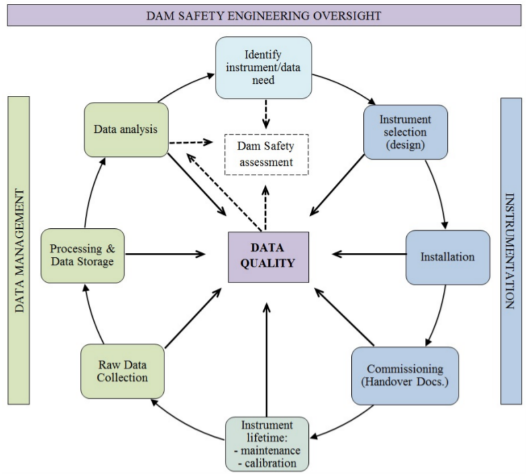

Fig. 1.3: Dam Safety Engineering oversight. Retrieved from [48].

1.2.1 Raw data collection

Visual inspections[1], tests[2] and measurements provided by monitoring systems are the methods used to maintain an updated knowledge required to exercise safety control.

Dam safety control begins with the preparation of a monitoring plan, in principle before the start of construction. The monitoring plan must pay attention to the hypotheses and critical aspects considered in the project, taking into account the assessment of potential risks, and the definition of the necessary resources to guarantee the safety control and the dam functionality over time, and the timely detection of any abnormal phenomena. The monitoring plan is established for the entire life of the dam, however, it must be understood as being dynamic and must be revised and updated, if necessary.

During construction, the good quality of materials and construction processes should be ensured. During the first filling of the reservoir, the dam behavior must be followed with particular attention, not only because it is in this period that a potential risk is created with the formation of the reservoir (it is the first load test), but also because experience has shown it to be a critical period of the dam safety (the dam is subjected to loads that was never subjected). During operation, monitoring focuses on supporting the analysis and interpretation of the dam behavior. At this point in the life of the dam, a significant body of information has most likely been

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[1] Inspections are either of a routine nature, or may follow unusual occurrences, such as earthquakes or large floods.

[2] Laboratory and in situ tests, and long term monitoring are used to measure changes in structural properties, actions, and their effects and consequences.

developed about the dam and dam site. The information and data collected during previous phases of the dam can be used to identify the dam safety issues of current concern [57].

The assessment of dam condition, through the use of the information provided by the monitoring system, is achieved by having an up-to-date knowledge of the dam so that anomalous behavior is detected in sufficient time to allow appropriate intervention to correct the situation or to avoid serious consequences.

A monitoring system, defined in the monitoring plan, is designed according to the possible accident and incident scenarios, taking into account aspects related to: (i) the dam safety and functionality, (ii) characterization of the dam behavior (actions, structural properties and effects), (iii) accuracy of the instrument concomitant with the expected range of the physical quantities that will be measured, (iv) reliability and redundancy, (v) access to the dam (some dams have no access during the winter, for example).

Monitoring systems must be adequate and reliable. The insurance of good performance and the functionality of the monitoring system throughout all of the dam's life phases are main requirements. For these reasons, the use of instruments that can easily be replaced or repaired without compromising the continuity of the monitoring process (both time continuity and in compatibility of the measurements) is recommended. The redundancy of measurements must be considered to avoid possible wrong conclusions based on a possible malfunction of a single instrument. Besides the economic aspects, the instrumentation must take into account practical aspects. For example, the installation of high precision instruments with short range, may not be acceptable.

The variables to be measured, the general information about the devices to be installed, and the procedures to be followed in the installation and maintenance are also presented in the monitoring plan. The methods used for dam monitoring can be classified by their purpose [29]:

- Characterization of the structural properties: in situ and laboratory tests of samples of the materials used in the dam construction, forced vibration tests, and tests under fast loads or permanent loads over time in cells installed in the dam.
- Monitoring of the actions: the observation of the sequence and techniques used in the dam construction, water levels, air and water temperatures, earthquakes (including induced earthquakes by the filling of the reservoir), through the use of limnimetric scales, thermohygrographs, maximum and minimum thermometers and seismographs, among others.
- Monitoring of the direct effects of the actions: the pressures in the pores and cracks, seepage and leakage, and concrete temperatures, through the use of piezometers, drains, weirs and thermometers.
- Monitoring of the indirect mechanical effects: absolute and relative displacements, joint movements, stresses and strains, through survey methods, and through the use of direct and inverted pendulums, rod extensometers, jointmeters, stress meters and strain gauges.

Instrument measurements are manually collected by human operators, using specific measuring instruments, or automatically collected by data acquisition units connected to a network of sensors.

1.2.2 Processing and data storage

After the acquisition process, the data is transformed into engineering quantities (e.g. relative displacements, seepage) by specific algorithms that use a set of calibration constants. In fact, the term reading does not correspond to raw data, since a reading is also a transformation from the raw data.

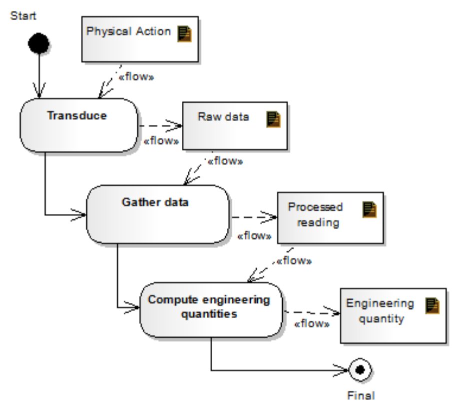

Fig. 1.4: Data transformation workflow for an electrical instrument.

Figure 1.4 illustrates a typical data transformation workflow for an electrical instrument (e.g., a Carlson Extensometer). Instruments (transducers[3]) convert a physical action (e.g., displacement) into an electrical signal (raw data produced as a voltage in mV), which is then converted by a gathering instrument (or by the sensor) into processed readings (e.g., resistance, relation of resistances). Finally, the readings are converted into engineering quantities (e.g., extension), which is the information used to assess the structural behavior of the dam. The dam safety monitoring information includes, essentially, instrument properties, calibration constants, readings and engineering quantities to quantify the physical actions and the response of the dam.

Since dams can be in-service for several decades or even a century, past data collected during the construction and exploitation phases is critical to support the assessment of current structural safety. As a consequence, the data lifecycle in the safety control of concrete dams must be seen as a long-term cycle where data must

[3] A transducer is a device that converts any type of energy into another.

be preserved. Data management of such long cycles is usually known as digital preservation, where current efforts are often built upon the Open Archival Information System (OAIS) reference model [32], which addresses fundamental issues surrounding trust and provides the basis of a certification standard for digital repositories [67, 33].

The OAIS model provides a high level model designed to support static processes and static information types for longterm preservation. Figure 1.5 shows the high-level functional entities of OAIS in relation to its contextual environment, which is comprised of producers, consumers, and management. Content enters the archive through the Ingest function in the form of a Submission Information Package (SIP). It is processed and passed onto Archival Storage as an Archival Information Package (AIP). For access, a Dissemination Information Package (DIP) is created upon the request of a Consumer. These primary functions are managed, supported and controlled by Preservation Planning, Data Management, and Administration. The OAIS also defines a conceptual information model describing the structure of the information packages handled within the archive during ingest, archival storage, and access.

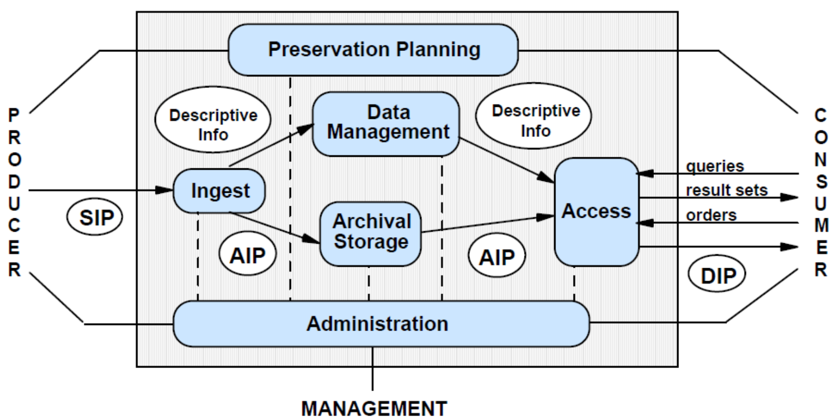

Fig. 1.5: OAIS functional model. Retrieved from [32].

The OAIS focus on the ”inner walls” of an archive, ensuring that data captured during the dam entire lifecycle is accessible for analysis and reuse, dealing with the data storage requirement for dam safety data.

Due to the properties and value of dam safety data, specially the one generated by sensors that can not be recovered or repeated in case of loss, dam owners and national authorities must use long-term repositories that ensure adequate management of dam safety data and long term preservation to support access to data during the entire data lifecycle in the safety control of dams, which can encompass several decades or even a century of observations.

1.2.3 Data quality assessment and outlier detection

Data quality is focal when talking about dam safety engineering. As seen in Fig. 1.3, dam's data quality is impacted by every single process in the cycle, however, in the reverse direction, data quality directly impacts data analysis and dam safety assessment. The effects of bad data quality will only be observed in the final stages of the cycle, with the greater risk of not being detected at all and misinforming dam safety experts.

To correctly analyze the behavior of a dam, measurements of physical quantities, collected by the dam monitoring system, should be representative of the dam real behavior, i.e., the measurement result (collected value) and the correspondent measurand (real physical value) should have the same value. The real value is always unknown, however there are ways to determine if the measured value is wrong (e.g., domain limits). If a measurements does not correspond to the real physical value of the quantity measured, the dataset contains errors (dam behavior interpretation is distorted) and therefore is not of quality [51].

With the advances of technology, automated systems are utilized to monitor dams, providing an increase of information that beforehand had to be collected manually and with less frequency. However, with this increased amount of information, the potential for measurement errors also increases. Automated measurements can be compared with the manual ones (manual measurements) and use them as reference elements to assess the quality of stored data [52], as seen in Fig 1.6. Estimating the Probability Density Functions (PDF) can be useful to characterize both the manual and the automated measurements (similar PDF are expected if the sensors are paired).

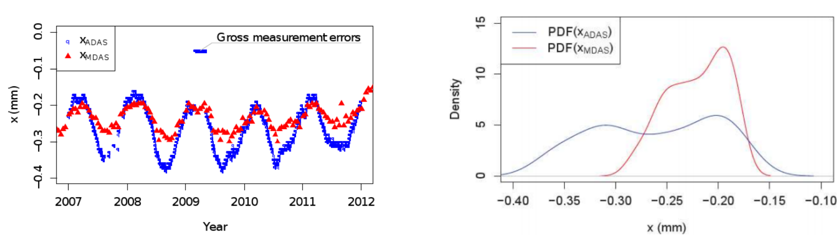

Fig. 1.6: Left: Manual Data Aquisition System (MDAS, in red) vs Automatic Data Acquisition Systems (ADAS, in blue) measurements; Right: MDAS (in red) vs ADAS (in blue) PDF comparison. Retrieved from [52].

Regarding gross errors, such as outliers, they can be caused by various factors. Mechanical and instrumental errors (like sensor failure), IT errors (overrides in databases or data corruption), human errors (manual entries) or even deviations in the system behavior (if the outlier is caused by this, the information gathered by detection is very important to the creation of knowledge) [24]. In order to detect outliers, several techniques can be applied from simple 2D scatter-plots or Whiskers-Box-plot to Machine Learning (ML) algorithms. However, some techniques are faster and more accurate than others, and a manual outlier detection process does not suffice in an Automatic Data Acquisition Systems (ADAS) scenario, where acquisition frequency is higher and therefore a larger amount of data is collected and needs to be pre-processed before it is available to dam safety experts.

Multiple Linear Regressions (MLR) and other predictive algorithms can be used in outlier detection. After predicting a set of values, incoming measurements can be labeled as outliers if they are found outside of a certain distance from the expected value limits (defined by a boundary based on standard deviations) [53, 80]. Other ML algorithms, like Density-Based Spatial Clustering of Applications with Noise (DBSCAN), an unsupervised clustering algorithm, can also be useful in this task [2].

1.2.4 Data analysis and dam safety assessment based on quantitative interpretation models

Quantitative interpretation models for the prediction of the structural response of concrete dams, typically used by dam engineers, are based on the estimation of parameters, and on several simplifying assumptions concerning the behavior of materials, such as:

i The analyzed effects refer to a period in the life of a concrete dam for which there are no relevant structural changes.
ii The effects of the normal structural behavior for normal operating conditions can be represented by two parts: a part of elastic nature (reversible and instantaneous, resulting from the variations of the hydrostatic pressure and the temperature) and another part of the inelastic nature (irreversible) such as a time function.
iii The effects of the hydrostatic pressure, temperature, and time changes can be evaluated separately.

Quantitative interpretation models are typically obtained through multiple linear regression (MLR). If the hypotheses that support the MLR models are true, the separation of effects is valid, which is advantageous to quantify the contribution that a particular action has on the structural response. The main actions are the hydrostatic pressure variation caused by the variation of the water in the reservoir, the temperature changes in the dam body that results from the air and water temperature variations, and other phenomena not reversible in time (mainly due to changes in the properties of the materials). HST (Hydrostatic, Seasonal, Time) models are statistical models widely used because they consider that the thermal effect considered as the sum of sinusoidal functions with an annual period, similar to variations of air and water temperatures [50]. However, the effect of the real annual wave of the air temperature variation does not follow a shape similar to a sinusoidal function (the winter and summer periods are not well represented by sinusoidal waves, and, as a consequence, extreme values on the structural response due to the temperature effect are not accurate). To overcome this drawback, some models use recorded temperatures, also known as HTT (Hydrostatic, Thermal, Time) models that better represent the thermal effect on dam behavior (instead of the seasonal function like HST models). However, the choice of the thermometers (usually devices embedded in the dam body) to be considered or even the use of air temperature measurements also have its difficulties.

Table 1.1 shows the main advantages and disadvantages of multiple linear regression models (HST and HTT models) regarding the quantification of the temperature effect. In both types of models the air temperature is not considered because the structural response presents, in average, a phase offset and a amplitude change when compared with the annual air temperatures variation.

Table 1.1: HST and HTT models - Quantification of the thermal effect through multiple linear regression

Model	Advantages	Disadvantages
HST	• Simple • Thermal effect obtained through sinusoidal functions	• Thermal effect estimated without knowledge of the air, water or dam body temperatures evolution • The prediction approximates the maximum measured values by default and the minimum measured values by excess
HTT	• More accurate quantification of the thermal effect through the knowledge of the embedded thermometers in the dam body	• Thermometers in the body that present a phase offset similar to the structural response under analysis is required • Difficulty in the selection of the thermometers and its adequate functioning along time

Structural safety control activities are based on the interpretation of the observed behaviour. Models are used to support the interpretation of the observed structural behaviour along time. The portion not explained by the model, called residues ($\varepsilon = \delta_{measured} - \delta_{model prediction}$), is obtained through the difference between the observed behaviour and the model prediction. The interpretation of the residues (and of their evolution) is equally important since they are related to the measurement uncertainty and the portion of the structural response that could not be explained by the used model.

Formulation by separation of the reversible and irreversible effects in HST models

HST models consist in approximating the shape of the deterministic indicators through simple functions which are easier to manipulate [80]. It is considered that the effects (such as horizontal displacements at the crest of the dam) associated with a limited time period at a specific point can be approximated by

$$\delta_{HST} = \delta_H + \delta_S + \delta_T + k \tag{1.1}$$

where δ_{HST} is the observed structural response; δ_H is the portion of the structural response due to the elastic effect of hydrostatic pressure; δ_S is the elastic portion of the structural response due to the effect of temperature depending on the thermal conditions represented by seasonal terms; and δ_T is the portion of the structural response due to the effect function of time considered irreversible.

The separation of effects requires the consideration of a constant k due to the fact that the structural response, measured on the reference date, has a value different from zero.

The portion of the structural response due to the effect of hydrostatic load, δ_H, is usually represented by polynomials depending on the height of the water in the reservoir h:

$$\delta_H(h) = \beta_1 h + \beta_2 h^2 + \beta_3 h^3 + \beta_4 h^4. \tag{1.2}$$

The portion of the structural response due to the effect of the temperature changes can be considered as a proportional function of the environmental temperature changes, with a phase shift, depending on the depth into the section. The portion of the structural response due to temperature changes is considered instantaneous with respect to the temperature field in the dam body, but it is deferred with respect to the measured air and water temperatures [62].

Very simple models, like these HST models, usually do not use temperature measurements because it is assumed that the annual thermal effect $\delta_S(d)$ can be represented by the sum of sinusoidal functions with a one-year period. Thus, the effect of temperature variations is defined by a linear combination of sinusoidal functions, which only depend on the day of the year:

$$\delta_S(d) = \beta_5 \sin(d) + \beta_6 \cos(d) + \beta_7 \sin^2(d) + \beta_8 \cos^2(d) \tag{1.3}$$

where $d = \frac{2\pi \cdot j}{365}$ and j represents the number of days between the beginning of the year (January 1) until the date of observation ($0 \le j \le 365$).

To represent the time effects, δ_t, it is usual to consider the functions presented in Eq. 1.4, where t is the number of days since the beginning of the analysis.

$$\delta_T(t) = \beta_9 t + \beta_{10} e^{-t} \tag{1.4}$$

1.2.5 Data analysis and dam safety assessment based on machine learning models

Machine learning techniques are used to aid in the interpretation of the observed behavior and the structural safety control of dams. Predicted values, obtained through the use of machine learning models, are compared to the real value of sensor readings, in order to detect any major deviation of response (which can point to possible structural damage). Studies in the field of research mainly focus on obtaining a meaningful set of predictors (e.g., water level, air and water temperature, etc), and a good machine learning method capable of correctly predict the response variable (e.g., radial displacements, crack openings, etc).

Tatin et al [81] presented the HST-Grad model, a hybrid of the HST model with the inclusion of air and water thermal variation. The model can be seen as a Multiple Linear Regression (MLR) where the effects of lag predictors (temperature gradients) were enough to slightly increase the performance of the previous models for radial displacement prediction in French dams. HST models can also be used to individually quantify a specific effect in the dam response due to one of the main actions (e.g., effect of hydrostatic pressure in crest displacement shown by De Sortis and Paoliani [10]). In Tatin et al [82], the structure is seen as a group of horizontal layers that allow the observation of the effect of thermal effect of both water and air temperature throughout the dam.

Several adaptations from the HST model can be found. The utilization of measured concrete temperatures instead of the seasonal temperature variation (the HTT model, as seen in Perner and Obernhuber [62]); the inclusion of an Error Correction Model (ECM) for increased precision in time-series, proposed by Li et al [41]; the use of a hybrid with a genetic algorithm, increasing robustness and predictive power of MLR shown in Stojanovic et al [76]; the Hydrostatic Seasonal State (HSS) model, proposed by Li et al [42], that represents time-effect deformation as a state equation proved able to provide a better fitting to radial deformations than the HST model; and the EFR (EFfet Retard - Delayed effect) model, utilized by Guo et al [18] to predict pore water pressure by taking in account the delayed hydrostatic effect, are some examples.

Feed-forward Neural Networks (FNN) proved to be an powerful tool in assessing concrete dam behavior, as shown by Mata [50]. The FNN model's prediction for horizontal displacements, using water level and seasonal temperatures variations, obtained better results when compared to MLR models. FNNs models can also be used to predict piezometric water levels in piezometers. Ranković et al [66] compare FFN with MLR (both trained with three values of water level from previous days of each measurement) and concludes that FNN provide better prediction of the target variable. Tayfur et al [83] obtained improved performance, on average, using FNN when compared with a Finite Element Model (FEM), however this was not the case in every analyzed dataset. Kang et al [36] utilizes Extreme Learning Machine, a type of FNN with a single hidden nodes layer, obtaining better results of displacements prediction when compared to MLR, backpropagation-trained NNs, and Stepwise Regression.

Modification to Support Vector Machines (SVM) were used by Cheng and Zheng [6] in order to create a model able to simulate the non linear mapping between environmental and latent variables. The LS-SVM (Least squares SVM) model presented good performance when predicting uplift pressure and horizontal displacements. Ranković et al [65] use Support Vector Regression (SVR), an application of SVM for function estimation, to predict tangential displacements. To predict displacements, Su et al [77] combines SVM with other methods, such as wavelet analysis to resolve some problems identified with SVM (e.g, kernel function and parameter optimization). SVM can also be useful to detect failure, categorized damage states and predict local responses, as can be seen in the FEM-SVM based hybrid methodology presented by Hariri-Ardebili and Pourkamali-Anaraki [19].

Principal Component Analysis (PCA) is used by Yu et al [88] to provide data reduction, noise filtering and multivariate analysis and monitoring. PCA is followed by a HST model to predict crack size opening. Mata et al [54] makes use of PCA to obtain a HTT model, where the goal of PCA was to select which thermometers had more impacting/correlation to the response variable, and therefore should be used as predictors. This was also done by Prakash et al [63] when obtaining a hydrostatic, seasonal, temperature, and time (HSTT) model. PCA was utilized as a data reduction tool before using HSTT to predict the dam responses (displacement and strain).

Bui et al [5] presents SONFIS (Swarm Optimized Neural Fuzzy Inference System) as a promising tool for modeling horizontal displacements. When compared to other algorithms, like SVM and Random Forest (RF), SONFIS outperformed the presented benchmarks by using the PSO (Particle Swarm Optimization) algorithm to optimize parameters for the neural fuzzy inference system (water level, air temperature and time are used as predictors).

Other regressions besides the HST model can be found in Jung et al [34], where a Robust Regression Analysis is used with PCA to predict piezometric readings in time-series data with periodic or dominant variations, and in Xu et al [85], which combined a genetic algorithm (for predictor variables selection) and a Partial Least Squares (PLS) regression to predict crack opening in a Chinese dam. Random Forest Regression (RFR) is used by Dai et al [9] to predict horizontal displacements and in Li et al [43] to create a uplift pressure model, obtaining better results than SVM. Li et al [43] also studies 18 different predictors, stating that the model can be used to extract correlations and rules between the variables (the influence of rainfall was considered the smallest when compared to the other factors). Boosted Regression Trees (BRT) are used in Salazar et al [69] to predict radial displacements and leakage flows. Different predictors were explored, and relative influence of each predictor was obtained for each target variable. BRT can also be used in a anomaly detection scenario as seen in Salazar et al [71].

Most of the authors use HST models or adapt it to obtain good predictive models. However, the diversity of ML algorithms available is increasing daily, and researchers are using them to create better models. PCA, SVM, and NN are some algorithms already used by the community (Salehi and Burgueño [72] presents a survey of ML techniques used in structural engineering) that help increasing prediction performance, and therefore, increasing safety control mechanisms accuracy in concrete dams. In Salazar et al [68], RF, BRT, NN, SVM and Multivariate Adaptive Regression Splines (MARS) are utilized to predict radial and tangential displacements and leakage (in a total of 14 different datasets). An extensive comparison between several machine learning techniques applied to dam behavior prediction is presented in Salazar et al [70].

1.3 Data analysis and data prediction using deep learning models - an overview

Deep learning methods [73, 39, 15] are a class of machine learning methods that learn multiple layers, or levels, of representations by composing simple non-linear modules at one layer into more abstract representations one layer above. What is more, this representation learning is done mostly automatically, without a strong dependence of a human doing manual feature engineering requiring time and expert domain knowledge - the features are learned from the input data by a general-purpose learning mechanism. Of course the domain specialist is still fundamental to interpret and validate the quality of the model within their knowledge expertise. In recent years, deep learning has achieved state of the art or highly competitive results in fields such as image recognition [37], natural language understanding [8], drug discovery [49], recommendation systems [84], and board and video games playing [56, 74, 75].

Recurrent Neural Networks (RNN) are a class of deep learning models which have proved effective at solving tasks involving input and/or output sequences [16, 44, 38]. They process an input sequence one element at a time (possibly a vector) and maintain an internal ”state vector” that contains information about the sequence of previous inputs. In principle, a RNN can map from the entire history of the previous inputs to each output, effectively allowing it to simultaneously capture dependencies on multiple timescales. RNNs have recently seen a surge in application including in such diverse fields as machine translation [79] and natural language processing [55], urban mobility and traffic prediction [89, 47], speech recognition [17], clinical diagnosis [45] and DNA sequencing [64].

Given an input sequence $(x_1, x_2, \ldots, x_t)$ where each $x_t \in \mathbb{R}^p$, p is the number of input features and t is the number of timesteps, a RNN is defined by the following recurrent relation:

$$h_t = \sigma(Wx_t + Uh_{t-1} + b), \tag{1.5}$$

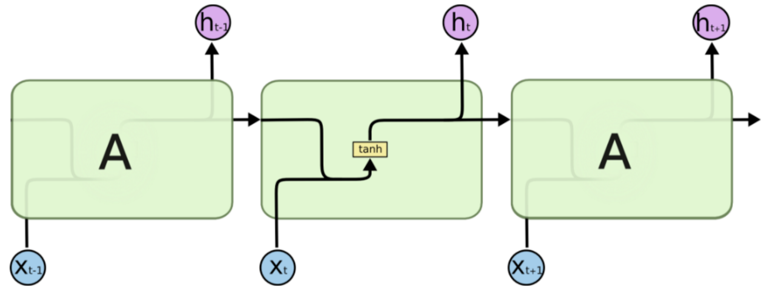

Fig. 1.7: Graphical representation of the recurrence relations defining a RNN. In this diagram, the non-linear activation function σ is represented as the hyperbolic tangent, a common choice. Retrieved from [59].

where $W \in \mathbb{R}^{n\times p}$, $U \in \mathbb{R}^{n\times n}$, $b \in \mathbb{R}^{n}$ are matrices representing the hidden state whose values will be learned during training, and n is the dimension or size of the RNN cell. The n-dimensional hidden state vectors at time t and $t-1$ are denoted by h_t and h_{t-1} respectively, and σ is a non-linear activation function such as the hyperbolic tangent, the logistic sigmoid or the rectified linear unit [14]. Figure 1.7 shows a graphical representation of the recurrent relation above, and figure 1.8 depicts two representations of an RNN, namely (a) a compact (or folded) cell in which outputs are connected back as inputs, and (b) an unrolled series of cells explicitly showing each time step. This re-feeding of outputs as inputs and the sharing of the cell's parameters across layers (or timesteps) are the main differences from the classical feedforward neural network.

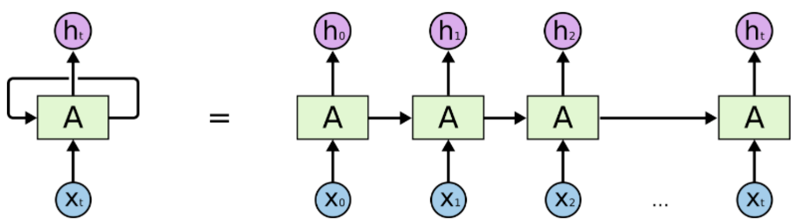

Fig. 1.8: Two representations of the same RNN model. Left: A compact (or folded) representation, in which the parameter sharing between different timesteps is accentuated. Right: An unrolled representation of an RNN putting in evidence the relationship between different elements of the input sequence, the internal state of the network and the output. Retrieved from [59].

The most common architectures of RNNs are sketched in Figure 1.9 in an unrolled representation. For a timeseries prediction problem one will typically use the sequence vector to single vector architecture for the one-step prediction (b) or, in the case of multi-step prediction, one of the two sequence-to-sequence architectures (d) and (e).

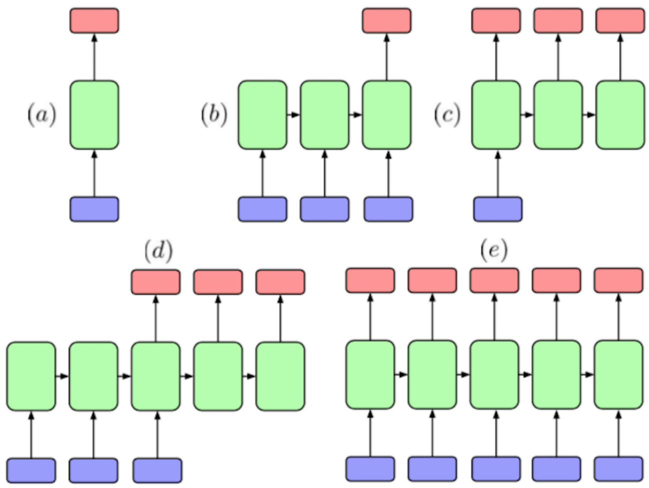

Fig. 1.9: Different kinds of RNN architectures. (a) One-to-one: the traditional feed-forward neural network; (b) Many-to-one: sequence prediction or classification, includes one-step time series prediction tasks, such as, for example, financial or weather forecasting, product recommendations, anomaly detection, sentiment analysis or DNA sequence classification; (c) One-to-many: sequence generation, including for example image labeling; (d) and (e) Many-to-many: sequence to sequence learning of which some example applications would be sentence translations, multi-step time series prediction, program execution, text summarization, and text and music generation. Retrieved from [44].

Despite its representational power, training RNNs has been considered difficult [4, 78]. When unrolled in time, RNNs resemble a very deep FFN with as many layers as timesteps. The naive application of backpropagation leads to the problem of exploding and vanishing gradients. In 1997, Hochreiter and Schidhuber introduced the Long Short-Term Memory (LSTM) network as a solution to this problem by adding to the vanilla RNNs a memory cell and a gating mechanism that regulates the information flow [23, 13]. This gating mechanism (which includes an input, forget and output gate) is responsible for managing which information persists, for how long, and when to be read from the memory cell. Because the cell state is updated with an addition operation (and not a sigmoidal transformation as in vanilla RNNs) it does not suffer from the vanishing gradient problem. Figure 1.10 shows a depiction of this mechanism, which can be formalized in the following equations:

$$
\begin{aligned}
f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f) && (1.6)\\
i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) && (1.7)\\
\tilde{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) && (1.8)\\
c_t &= i_t \odot \tilde{c}_t + f_t \odot c_{t-1} && (1.9)\\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) && (1.10)\\
h_t &= o_t \odot \tanh(c_t) && (1.11)
\end{aligned}
$$

where, $f_t, i_t, \tilde{c}_t, c_t, o_t$ and h_t, represent the outputs of forget gate, input gate, candidate state, cell state, output gate and the final cell output, respectively, $\odot$ represents the element-wise Hadamard product, and h_t can be used as the final output.

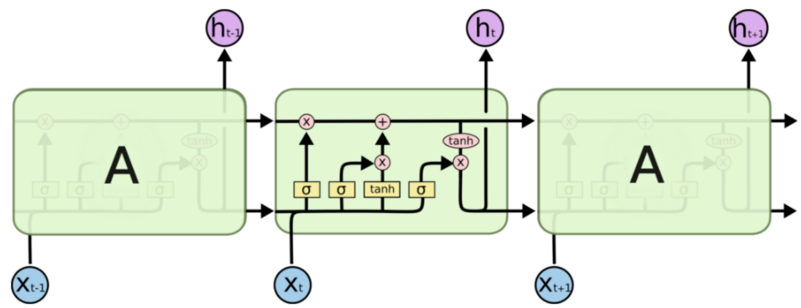

Fig. 1.10: Graphical representation of the recurrence relations defining a LSTM cell. Retrieved from [59].

There are several extensions, or deep learning alternatives, to the vanilla RNN and LSTM architectures and numerous related techniques which we do not pursue in this work, but which have already shown to be promising approaches to effectively model timeseries prediction tasks. These include attention mechanisms [86], convolutional neural networks [39, 87], stochastic regularization techniques (such as dropout [22]), grid LSTMs [35], multimodal learning [58, 60] and probabilistic methods [12, 90].

1.4 Adopted problem solving process - the Design Science Research Methodology

The Design Science Research Methodology (DSR) is a problem solving process that focuses on the relevance of creating and evaluating different artifacts to meet and solve relevant objectives and problems [20]. As proposed by Peffers et al [61], the design science research methodology encompasses six steps triggered by possible research entry points, as represented in Fig. 1.11.

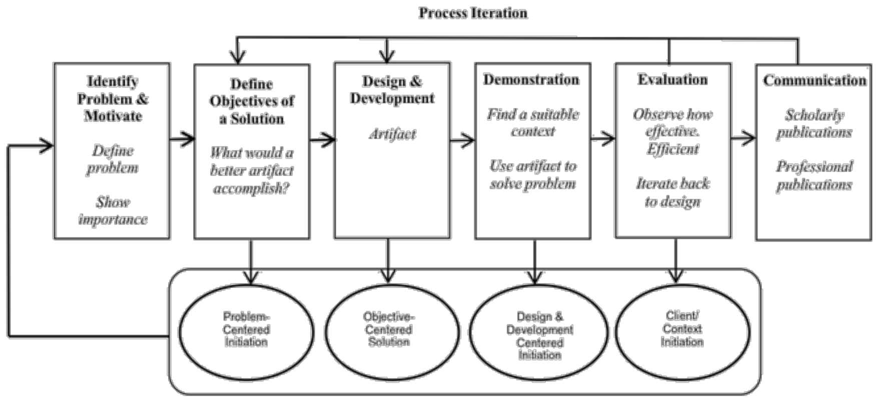

Fig. 1.11: Design Science Research Methodology . Retrieved from [61].

This chapter follows a DSR methodology and is driven by the relevance of dam structural safety, being a recognized problem, not only due to the value produced by these critical infrastructures, but also to the potential catastrophic consequences in the case of structural failures. As such, the objective of this research is to improve the support to the decision making process performed by dam safety specialists, through better prediction models for data captured by sensors installed on dams. To accomplish this objective, methods based on prediction models that use recurrent neural networks (namely Long Short Term-Memory networks) are presented on section 1.5, demonstrated and evaluated on a real case study provided by the Alto Lindoso dam on section 1.6. Note that the evaluation of the proposed method is performed based on the results of the multiple linear regression, which is the traditional method used by dam specialists and, as a consequence, is used as the baseline for this study.

1.5 Proposed methodology - adding value to the interpretation of the monitored dam behaviour through the use of deep learning models

HST models based on MLR methods are widely used and allow a big picture of the structural dam behaviour, but a portion of the measured behaviour is not explained. To overcome this drawback, the model proposed aims to take advantage of the knowledge of :

- the multiple linear regression models (HST models in this case study), commonly used, through the use of the predicted values obtained by the model.
- the evolution of the air temperature, represented by mean ($T_{air,mean}$), the 10-quantile ($T_{air,10Q}$) and the 90-quantile ($T_{air,90Q}$) of the air temperature. It is ex-

pected that the LSTM neural network model will be able to identify the structural response pattern (phase offset and amplitude change) due to the air temperature effect, which the MLR model is not able to.

- the reservoir water level evolution along time. For example, an increase of the reservoir water level tend to increase the uplift pressures in the dam foundation, and indirectly, the evolution, along time, of the observed displacement measured in the dam body.

Based on the referred before, two strategies to take advantage of property of LSTM models in processing sequential data could be adopted: i) the use of a LSTM to model the structural behaviour or ii) the use of a LSTM model to model the part of the structural response that is not explained by the MLR model.

1. The use of LSTM to model the structural behaviour. In this case, the main inputs of the LSTM model are the predicted values obtained from the MLR model δ_{MLR}, to represent the overall pattern regarding to the hydrostatic, thermal and irreversible effects; $T_{air,mean}$, $T_{air,10Q}$, $T_{air,90Q}$ and h^4 to represent the "missing component" related reversible effect; and t or e^{-t} to represent the "missing component" related to the irreversible effects along time. The output is the observed structural behaviour, δ.
2. The use of a LSTM model to model the part of the structural response that is not explained by the MLR. In this case, the main inputs of the LSTM model are $T_{air,mean}$, $T_{air,10Q}$ and $T_{air,90Q}$ and h^4. The output is the observed structural behaviour not explained by the MLR model, $\delta - \delta_{MLR}$, eq. 1.12. Besides the information related to a possible anomalous phenomena, the residuals $\varepsilon_{MLR} = \delta - \delta_{MLR}$ contain information related to errors (measurements and model) and other unknown effects.

The last strategy was adopted because the innovation based on the proposal is clear for both academy and future stakeholders and final users. Knowledge developed along years is used (taking into account that worldwide countries have different levels of knowledge and practices regarding the dam safety activities) and improved based on the use of LSTM models[4].

In this way, we model the part of the structural response not explained by the MLR,

$$\delta = \delta_{MLR} + \varepsilon_{MLR} \tag{1.12}$$

The unexplained pattern ($\varepsilon_{MLR} = \delta - \delta_{MLR}$) of the structural behaviour (obtained from the MLR model, eq. 1.12) will be explained by the LSTM model taking advantage of the knowledge of the MLR models (designed as $\delta_{LSTM|MLR}$), as follows

$$\delta - \delta_{MLR} = \delta_{LSTM|MLR} + \varepsilon_{LSTM|MLR} \tag{1.13}$$

[4] New developments must take into account that dam safety is a continuous requirement due to the potential risk in terms of environmental, social and economical disasters.

Finally, the predicted value for the structural behaviour is obtained by summing both δ_{MLR} and $\delta_{LSTM|MLR}$, being the $\varepsilon_{LSTM|MLR}$ the new residuals, as in

$$\delta = \delta_{MLR} + \delta_{LSTM|MLR} + \varepsilon_{LSTM|MLR}. \tag{1.14}$$

The model we propose is a single layer LSTM that takes as input a sequence of N x_t input vectors from x_{T-N} to x_T to predict the value of $\delta - \delta_{MLR}$ at time T. Each input vector x_t has as components the values of $T_{air,mean}$, $T_{air,10Q}$, $T_{air,90Q}$ and h^4 at time t. In general, this model can be easily expanded by adding other input features as new components of x_t.

The hyperparameters of the LSTM are chosen through a validation set approach. These hyperparameters include the size of LSTM cell, the number of timesteps of each input sequence, the loss function, the optimization method and the batch size. To carry out this approach one splits the available dataset into three disjoint sets: the training, the validation and the test set. Holding out the test set, one trains the LSTM model on the training set optimizing the loss function for different combinations of the hyperparameters. The error of each of the resulting models is evaluated on the validation set, and one which achieves the best compromise between a low value of the validation error and computational cost (for example, more timesteps and a larger value of the size of the LSTM cell correspond to longer training and inference times).

1.6 Demonstration and evaluation - assessment and interpretation of the monitored structural behaviour of a concrete dam during its operation phase

1.6.1 The case study - the Alto Lindoso dam

The Alto Lindoso dam, depicted in Fig. 1.12, is a double curvature concrete dam whose construction finished in 1992 in a symmetrical valley of the Lima river, in the north of Portugal. The dam is 110 m high, the crest elevation is 339.0 m, and the total crest length is 297 m. The thickness of the central block is 4 meters at the crest and 21 meters at the base. There are three internal horizontal inspection galleries (GV1, GV2 and GV3) across the dam and a drainage gallery (GGD) close to the foundation [11]. The dam is founded in a good quality granitic rock mass, but with some heterogeneity. The rock mass deformability was characterised through mechanical "in situ" and laboratory tests, and geophysical tests for the determination of propagation velocities of longitudinal waves were performed, before and after the foundation treatment [11].

The dam body was built between April 1987 and July 1990. The injection of contraction joints was carried out between March and May 1991. The reservoir first filling was initiated in January 1992, with the reservoir water elevation at 234 m, and

Fig. 1.12: Alto Lindoso dam.

the retention water level with the reservoir water elevation at 338.0 m was achieved in April 1994.

In 2008, an analysis of the structural dam behaviour, carried out by the Portuguese National Laboratory for Civil Engineering, concluded that the Alto Lindoso dam presented, globally, satisfactory structural dam behaviour [40].

In accordance with best technical practices, the monitoring system of the Alto Lindoso dam aims at the evaluation of the loads; the characterisation of the geological, thermal and hydraulic properties of the materials; and the evaluation of the structural response [46].

The monitoring system of the Alto Lindoso dam consists of several devices which make it possible to measure quantities such as: concrete and air temperatures, reservoir water level, seepage and leakage, displacements in the dam and in its foundation, joint movements, strains and stresses in the concrete, and pressures, among others.

The system used for the measurement of the reservoir water level comprises a high precision pressure meter with a quartz pressure cell, which provides a record of the water height over time, and a level scale. The air temperature and humidity are measured in an automated weather station placed on the right bank, approximately 50 m apart from the dam crest.

The concrete temperature is measured in 70 electrical resistance thermometers distributed across the dam thickness in 16 sections of several blocks. The location of the thermometers was defined taking into account the remaining electrical resistance devices (strain gauges, embedded jointmeters and stress gauges) that also allow for the measurement of the concrete temperature.

Displacements are measured using an integrated system that includes five pendulums, 18 rod extensometers (Fig. 1.13) and geodetic observations. The relative movements between blocks are measured by superficial and embedded jointmeters.

The deformation of the concrete is measured with electrical strain gauges arranged in groups, distributed in radial sections, allowing the determination of the

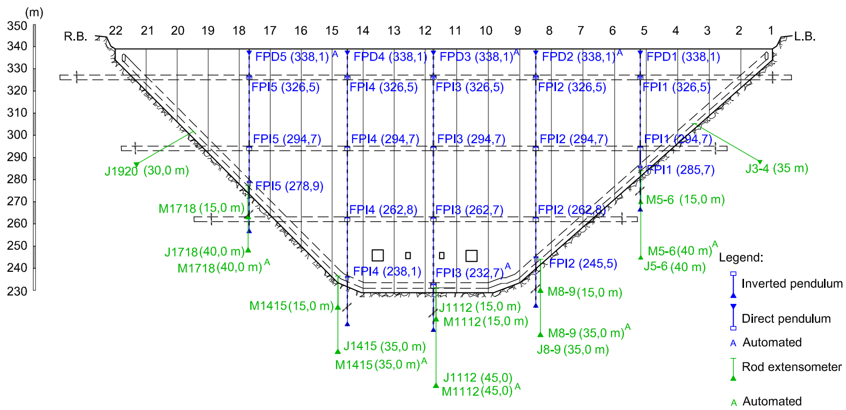

Fig. 1.13: Pendulum and rod extensometer distribution in the Alto Lindoso dam.

stress state through the knowledge of the deformation state and of the deformability law of the concrete. Stress gauges, which allow for the direct measurement of normal stress components, were also placed.

The quantities of drained and infiltrated water are measured individually, in drains of the drainage system installed in the dam foundation and in weirs that differentiate the total quantity of water that flows in the drainage gallery in several zones of the dam. The drainage system comprises a set of 52 drains, distributed over the drainage gallery with two drains per block, except for the central blocks 11/12 to 13/14 and block 18/19 where four drains were executed. All the water extracted from drains and leakages is collected in three weirs. Weir named Bica 1 collects the water from blocks 1/2 to 9/10 on the left bank, while weir named Bica 2 collects water from blocks 14/15 to 21/22, on the right bank. Finally, weir named Bica 3 receives all the water that flows in the drainage gallery.

The measurement of the uplift pressure in the foundation is performed by a piezometric network that comprises 23 piezometers. The pressures within the concrete are observed by two groups of three pressure gauges embedded in the concrete in two sections (at levels 310 m and 236 m) in the central block (block 11-12).

In the recent past, an automated data acquisition system was installed but it is still in a testing phase. ADAS includes the measurement of horizontal displacement along pendulums (telecoordinometers), relative displacements in the foundation (rod extensometers), relative movements between blocks (superficial jointmeters), discharges (in weirs) and the uplift pressure (piezometers). Figure 1.14 illustrates the location of the ADAS devices of the Alto Lindoso dam. Manual measurement is also possible in these places.

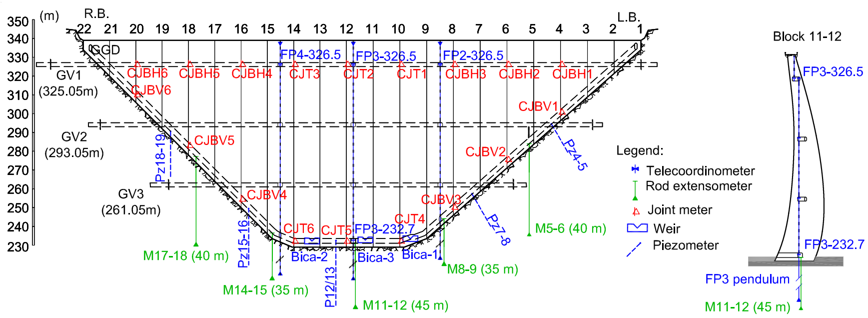

Fig. 1.14: Location of ADAS devices in the Alto Lindoso dam.

1.6.2 *The dataset - horizontal displacements measured by the pendulum method*

As referred before, horizontal displacements in the Alto Lindoso dam, with reference to a vertical, are measured by the pendulum method. Pendulums are installed in shafts either built during construction or drilled after. The pendulum method is based on the position of a steel wire through a vertical line that crosses the dam body. One extremity of the wire is fixed and defines one of two possible variants for this method, direct pendulum or inverted pendulum [28, 30, 3].

In the direct pendulum, one end of the wire is fixed on a high point of the dam, whereas on the opposite end, a weight of approximately 600 N strains the wire. In this case, displacements obtained in the various access points to the wire are relative to the fixed high point.

In the inverted pendulum, one end of the wire is fixed in a deep zone of the dam foundation, out of the zone affected by the main actions. The other end of the wire its connected to a float. In this case, absolute displacements are obtained.

As a consequence of the geometry of the dam, the horizontal displacements are obtained by a combination of direct and indirect pendulums.

In specific points near the pendulum, measuring tables are installed, fixed to the dam, to support the sensitive reading devices which allow for the measurement of the data raw (distance of the wire to the dam) according to the radial and tangential components, Fig. 1.15 and 1.16. The most sensitive reading devices are optical instruments (e.g. coordinometers or electro-optical coordinometers). Reading instruments accuracy may be greater than 0.1 mm [25] (for example, the coordinometers used in Portugal presents resolution equal to 0.01 mm), Fig. 1.17. In recent years, automated systems (such as telecoordinometers with an accuracy equal to 0.01 mm) have been adopted to measure displacements by the pendulum method [26, 30], Fig. 1.15.

Figure 1.18 provides an overview of the dataset used to evaluate the LSTM models for dam safety monitoring and prediction. This dataset provides data back to the year 1992 to the present. The first grid represents the daily evolution of wa-

Fig. 1.15: Pendulum, measuring table and automated system for horizontal displacement measurements.

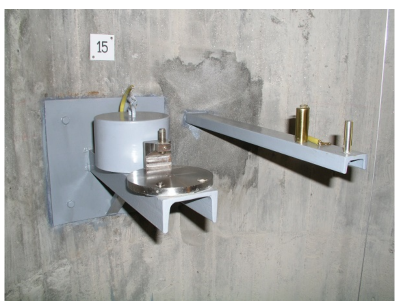

Fig. 1.16: Measuring table.

Fig. 1.17: Coordinometer.

ter height (in meters), while the second grid represent the average of the daily air temperature evolution in (°C) and the third grid represents the horizontal radial displacement measured, $\delta_{measured}$, at the FP3-326.5m, near the crest arch at the block 11-12, through the pendulum method (in millimeters) .

Note that reservoir water height and air temperature represent the main actions to the dam and can be directly or indirectly used as input features to the model, while the horizontal radial displacement is the final target for prediction by the proposed model.

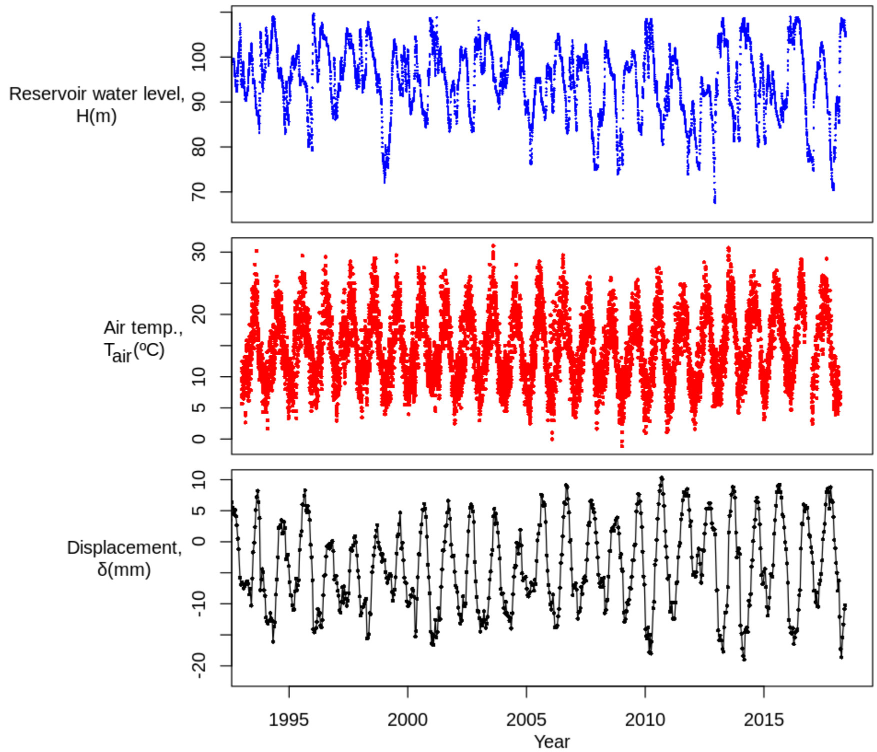

Fig. 1.18: Evolution of the reservoir water height, air temperature (daily average) and horizontal radial displacement at the FP3-326.5m for the training, validation and test periods.

1.6.3 Main results and discussion

In this section we present, evaluate and comment on the LSTM|MLR model put forward in Section 1.5 and designed to predict $\delta - \delta_{MLR}$, that is, the difference between the values of δ, the horizontal radial displacement in the crest of the Alto Lindoso dam and the predicted values of the MLR model, at timestep t. We will refer to this model interchangeably as LSTM|MLR or LSTM.

The LSTM model evaluated in this section is built on top of MLR model, as described above in section 1.5. The inputs of the MLR model are: the reservoir water height standardized, h, to the fourth power (h^4) to represent the effect of the hydrostatic pressure; and the effect of the temperature was considered through the implementation of both the sine ($sin(d)$) and the cosine ($cos(d)$) of annual period, where $d = \frac{2\pi \cdot j}{365}$ and j represent the day of the year, between 01 January and 31 December ($0 \leq j \leq 365$. the time effect did not seem to have a significant importance in the period examined by this study. The MLR model can be represented in equation form in the following way:

$$\delta_{MLR} = -3.73 \times h^4 - 4.22 \times sin(d) - 2.75 \times cos(d) - 4.30, \quad (1.15)$$

where the notation of Eq. 1.1, 1.2 and 1.3 was followed. Fig. 1.19 shows the measured displacements δ and the predictions of the MLR model.

Fig. 1.19: Measured displacements ($\delta_{measured}$) and MLR model (δ_{MLR}) fit on the training set (1994 to 2015) and evaluated of the prediction set (2015-2018).

For both the MLR and the LSTM model, the dataset was split into three disjoint sets: training, validation and test set. In the case of the MLR model, there are no hyperparameters to choose with a validation approach, and we have denoted the union of the validation and test sets as prediction set, as depicted in Fig. 1.19. The test set corresponds to the period of the last year of data, and the validation set to period of two years before the test set. Accordingly, the prediction set corresponds to the last three years of data. Fig. 1.20 shows the residues of the MLR model (the differences between the measured value of the displacement and the prediction of the MLR model) which are the quantity to be learned by the LSTM model.

The inputs to the LSTM model are: i) the time series related to hydrostatic effect, based on h^4, and ii) the temperature effect through the use of the average, the 10th and the 90th percentile of the air temperature recorded during the time period of 15 days immediately before each time-step.

As mentioned in section 1.5, the hyperparameters for the LSTM model were chosen via a validation set approach. Each model consisted of an LSTM cell of dimension 32. The training was carried using the Python deep learning library Keras [7] with Tensorflow [1] as a backend, a batch size of 4, 'Rmsprop' [21] as an optimizer and Mean Squared Error (MSE) as a loss function. The models receive a sequence of 30 time-steps of the inputs (corresponding to 15 months of data). The MLR model was trained on the dataset with the last 3 years of data held out, and used as a prediction set. For the LSTM model, the last year of data was used test set.

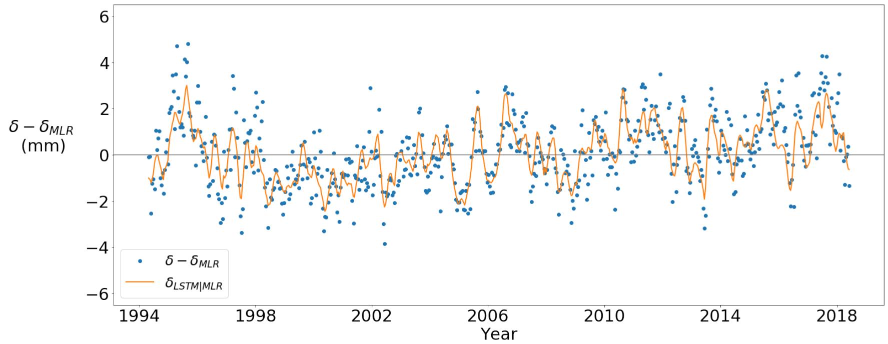

Fig. 1.20: Differences between the measured displacements and the MLR predictions ($\delta_{measured} - \delta_{MLR}$) and LSTM|MLR model fit to these differences (in orange).

The data corresponding to the period of two years before the last year was used as validation set to choose the hyperparameters.

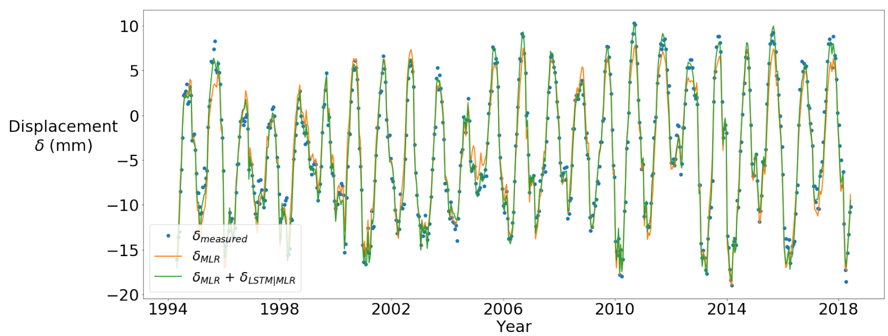

Fig. 1.21: Measured displacements, MLR model predictions and MLR + LSTM|MLR model predictions.

Fig. 1.20 shows the fit of the LSTM model to the residues of the MLR, and in Fig. 1.21 the predicted values, $\delta_{MLR} + \delta_{LSTM|MLR}$, are depicted. These predictions are shown in greater detail for last three years of data, corresponding to the validation and the test set, in Fig. 1.22. Collectively these figures illustrate the adequateness of the strategy proposed since the LSTM|MLR can in fact learn the pattern of the structural behaviour prevailing in the residues of the MLR model (Fig. 1.20) and provide through the MLR+LSTM|MLR model better predictions of the relevant quantity, namely the displacements, than the baseline MLR model (Fig. 1.21 and 1.21).

We have plotted the predicted values of the MLR model and of the MLR + LSMT|MLR model against the measured values in Fig. 1.23. Again, comparing the

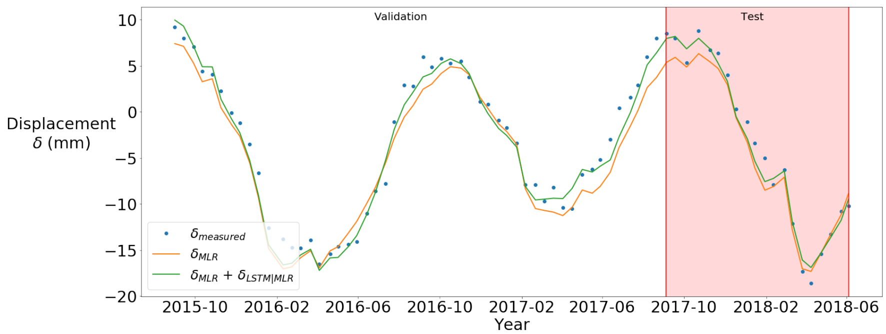

Fig. 1.22: Measured displacements, MLR model predictions and MLR + LSTM|MLR model predictions in the Validation and Test sets.

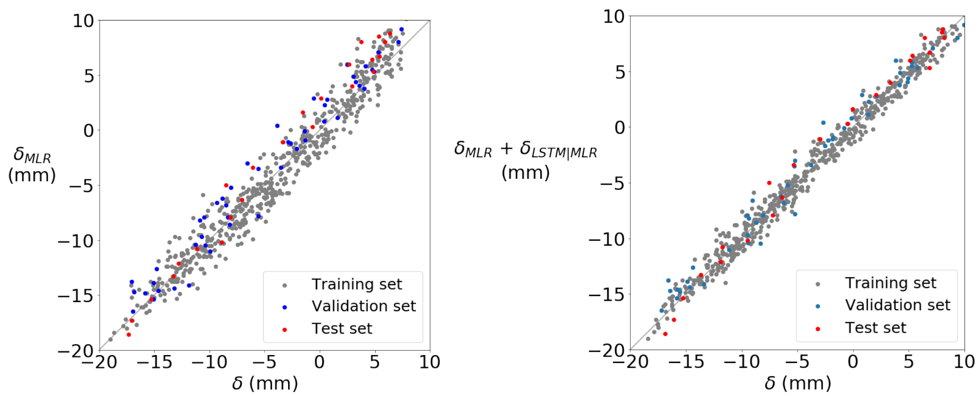

Fig. 1.23: Left: Predicted values δ_{MLR} versus measured displacements δ, Right: Predicted values $\delta_{MLR} + \delta_{LSTM|MLR}$ versus measured displacements δ.

two plots it is clear that the MLR+LSTM|MLR model is a model which provides a better prediction, since the cloud of points depicted is denser and closer to the identity line.

Table 1.2 presents the main performance parameters such as the mean squared error (MSE), the mean absolute error (MAE), the standard deviation of the errors (SD), and the maximum absolute error for each of the models for the training dataset (period between April 1994 and August 2015), the validation set (period between August 2015 and June 2017) the test dataset (period between July 2017 and June 2018). The last row of Table 1.2 shows the gain between the two models in the different error metrics. The MLR+LSTM|MLR model has a gain in every metric ranging from 27% (for the MaxAE of the validation set) to 68% (for the MSE of the test set).

Table 1.2: Performance parameters obtained from the MLR model and from the new MLR+LSTM|MLR model

Model	Training set				Validation set				Test set			
	MSE (mm^2)	MAE (mm)	SD (mm)	MaxAE (mm)	MSE (mm^2)	MAE (mm)	SD (mm)	MaxAE (mm)	MSE (mm^2)	MAE (mm)	SD (mm)	MaxAE (mm)
δ_{MLR}	2.08	1.15	0.87	4.81	3.48	1.53	1.07	4.27	4.29	1.67	1.23	4.26
δ_{MLR} + $\delta_{LSTM\|MLR}$	0.72	0.66	0.54	3.10	1.66	1.03	0.77	3.12	1.36	0.97	0.66	2.57
Gain (%)	65	43	39	35	52	33	28	27	68	42	46	40

The results presented in this section, demonstrate the added value of the LSTM|MLR model for the monitoring of dam safety. This model is capable of learning the pattern of residues obtained from the MLR model by capturing the non-linearities and the sequential, long-term effects. The remaining error of the MLR+LSTM|MLR model corresponds to measurement errors and other smaller errors not explained by this model. It is also expected that with more data, such as higher frequency of data collection or longer observation time, these results would improve since the LSTM model would be better able to capture the non-linearities and long-term dependencies. The gain of the MLR+LSTM|MLR model is particularly significant since monitoring of dam safety is focused on the analysis of the residues.

1.7 Final remarks

Current societies strongly depend on civil engineering infrastructures that support basic services, such as water supply, energy production and transport. As a consequence, structural safety problems can produce catastrophic consequences, especially if we consider critical infrastructures such as large dams, bridges or nuclear facilities. In order to manage structural safety risks, large civil engineering structures are continuously monitored by several sensors to provide accurate models of the current state of each structure.

This chapter analyzed the main activities of the safety control of concrete dams, explaining the common data lifecycle since the dam construction until its decommissioning, and surveying the current state of the art with regard to the use of machine learning techniques to aid the decision making process during the structural safety control of concrete dams.

Taking advantage of advances in deep learning, namely in the field of time-series prediction, this chapter proposed prediction methods based on recurrent neural networks with gains approximately near to 30% regarding to maximum absolute error. The design of these methods followed the design science research methodology and were evaluated in the real case study of Alto Lindoso dam located in the North of

Portugal. The evaluation results showed an improvement when compared to traditional baseline method based on multiple linear regressions.

The contribution of the deep learning based approach to the analysis and interpretation of the monitoring data for dam safety control is not limited to the proposed methodologies. It is considered that the benefits of deep learning over traditional machine learning approaches illustrate the potential improvement that these models can provide to the analysis of the monitoring data and to the interpretation of structural dam behavior. They clearly illustrate the benefits in the knowledge extraction from the information embedded in the monitoring data.

This chapter demonstrated how recurrent neural networks can be used to support decision making of dam specialists for concrete dam safety control. The improved results are promising and motivate detailed exploitation (e.g., additional input features, distinct target predictions) to create improved models for significant monitoring systems, improving the capability to anticipate structural safety problems in large civil engineering structures.

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