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Editorial

Soft Computing and Machine Learning in Dam Engineering

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1. Introduction and Overview

Dams have played a vital role in human civilization for thousands of years, providing vital resources such as water and electricity, and performing important functions such as flood control. The scale and complexity of dam projects have increased in recent years, making their safety evaluation even more challenging. Therefore, it is crucial that dam engineers consider all potential risks and take appropriate measures to ensure the safety and stability of these structures [1]. The nature and existence of dams are highly coupled with concepts such as population growth, climate change, global warming, and water security [2]. According to the International Commission on Large Dams's (ICOLD) [3] most recent update in April 2020, there are about 58,700 registered large dams in the world. Figure 1 illustrates the global distribution of these large dams.

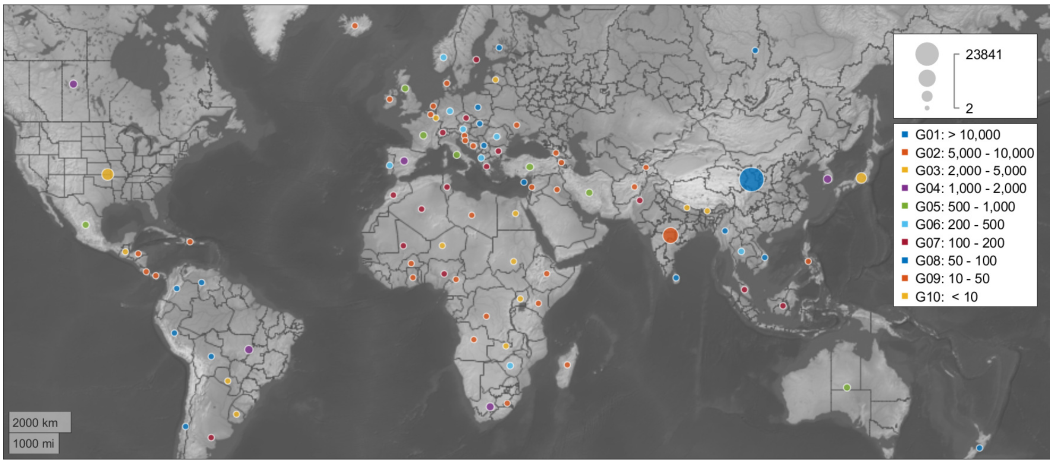

Figure 1. Global distribution of large dams as of 2020.

Traditional dam safety methods, based on visual inspections and manual monitoring, have long been the standard for ensuring the stability and safety of dams. However, as the scale and complexity of dam projects have increased, these methods have become increasingly insufficient. Major limitations of traditional dam safety methods are the existence of deficient observation plans and the potential for human error. Inspectors may miss crucial signs of deterioration or failure, and manual monitoring can be prone to

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inaccuracies. In addition, as the number of (aged and new) dams continues to increase, it becomes increasingly difficult and resource-intensive to manually inspect and monitor each one. Another limitation of traditional dam safety methods is that they are typically reactive rather than proactive. They focus on identifying and addressing problems after they have already occurred, rather than predicting and preventing them.

In contrast, modern techniques such as remote sensing, drones, and sensor networks can provide more accurate, real-time data on dam conditions. They can also be used to continuously monitor dams, providing an early warning of potential problems. Artificial Intelligence (AI) can be applied to the data collected from these modern techniques for identifying patterns and anomalies that may indicate a potential problem. AI algorithms can be used in the decision-making process for dam safety by providing accurate and updated risk analysis.

2. Soft Computing in Dam Engineering

Soft computing is a collection of techniques in computer science that aim to provide solutions to problems that are difficult or impossible to solve using traditional, "hard" methods of computation. Soft computing encompasses various computational techniques that are designed to replicate human-like problem-solving behavior. It includes a variety of techniques such as fuzzy logic, neural networks, genetic algorithms, and probabilistic reasoning, which are used to solve problems that are too complicated for traditional, rule-based approaches [4]. Soft computing has a wide range of applications in engineering, including control systems, signal processing, pattern recognition, and optimization. For example, in signal processing, neural networks and genetic algorithms can be used to improve the accuracy of signal classification and feature extraction. In optimization, genetic algorithms and probabilistic reasoning can be used to solve complex optimization problems.

The use of soft computing techniques, such as fuzzy logic and neural networks, in dam engineering began to gain popularity in the late 1990s and early 2000s. The first application of these techniques for modeling dam behavior is arguably the work by Bossoney [5], closely followed by Hattingh L.C. [6]. The main purpose was to overcome the limitations of the traditional Hydrostatic-Season-Time (HST) model [7] in terms of the identification of nonlinear behavior and consideration of complex phenomena. This has been the main application of soft computing in dam engineering to date, favored by the development of new algorithms and the increase in available monitoring data due to the installation of automatic data acquisition systems (ADAS). In this line, the ICOLD Benchmark Workshop held in 2001 was a milestone, since for the first time solutions were presented with methods such as K-nearest neighbors [8] or nonlinear autoregressive exogenous models (NARX) [9].

Later on, and in parallel with the aforementioned application, soft computing began to be used as a surrogate for finite element models in analyses with high computational costs. The typical example is the study of the probability of failure with Monte Carlo-type methods, which requires executing a extremely high number of numerical simulations [10]. More recently, the use of these techniques in dam engineering has grown significantly, as specific libraries have become available in different programming languages, which are easier to implement and apply [11–14]. Today, soft computing is used in a variety of applications related to dam engineering, such as:

- Early warning systems for dam failure [15];
- Real-time monitoring and control of dam systems [16];
- Predictive maintenance and condition monitoring of dam structures [17,18];
- Hydrological and meteorological forecasting [19];
- Risk assessment and decision making related to dam safety [20];
- Management of dam operation, energy production, and water management [21];
- Dam shape optimization and life cycle cost analysis [22,23];
- Probabilistic safety assessment and uncertainty quantification [24,25];
- Predicting the failure modes under multi-hazard scenarios [26,27].

With all the above-discussed advantages, the soft computing methods have several limitations in dam engineering problems. Machine learning models require a large amount of data to be trained and tested, which can be a limitation in dam engineering, where data collection can be difficult and expensive. Data availability can be the main obstacle to the application of machine learning models in numerical simulation of large-scale dams [28]. The quality of the data used to train and test machine learning models is crucial for the accuracy and reliability of the models. Data in dam engineering can be noisy, incomplete (e.g., missing sensor) or biased, which can negatively impact the performance of the models [29]. Complex machine learning models can be difficult to interpret and understand [30], which can be a limitation when trying to explain the results of the models to non-experts. It is important to validate the models using independent data sets, but this can be difficult and time consuming in dam engineering. Dam systems are dynamic and subject to change. Machine learning models may not be able to adapt to changing conditions, which could lead to poor predictions. Dam engineering is a critical field that affects the safety of human lives, property and the environment. Therefore, the reliability and safety of the machine learning models used in dam engineering need to be carefully evaluated.

The challenges are increasingly complex. The differences among dam owners in terms of financial and human resources is a crucial aspect to consider. The investment is different between the dam owners and between the dams since new surveillance in old dams are many times more difficult to carry out than in new dams. Adopting adequate monitoring plans is mandatory, as is the promotion of surveillance activities by expert engineers. The constitution of multidisciplinary teams and the exploitation of the possibilities of soft computing and machine learning techniques are essential to adequately respond to dam surveillance activities' needs. Sharing knowledge between scientists and practitioners is also a key element for improving surveillance activities.

3. About the Special Issue

In May 2020, a team of guest editors specialized in different aspects of dam engineering and machine learning proposed to launch a Special Issue "Soft Computing and Machine Learning in Dam Engineering " to the journal of "*Water*". This Special Issue aimed to capture the recent increase in research activity at the interface of dam engineering and machine learning methods.

In this Special Issue, we solicited high-quality original research articles focused on state-of-the-art techniques and methods employed in the design and analysis of dams. We welcomed both theoretical and application papers of high technical standards across various disciplines, thus facilitating an awareness of techniques and methods in one area that may apply to other areas.

This book includes ten contributions to this Special Issue published between 2020 and 2023. The acceptance rate was less than 50%, which is an acceptable rate for a technical Special Issue, where nearly all the submissions were by invitation. The overall aim of the collection is to improve our understanding from applications of soft computing in dam engineering including its challenges.

Figure 2 shows a "word cloud" data-mined from all accepted papers, indicating repetition of relevant keywords. The accepted papers cover a wide range of dam engineering-related topics. In a very broad classification, one may identify the following major categories: (1) probabilistic simulations, (2) risk-based methods, (3) stochastic input motion, (4) uncertainty quantification, and (5) applied machine learning including validation.

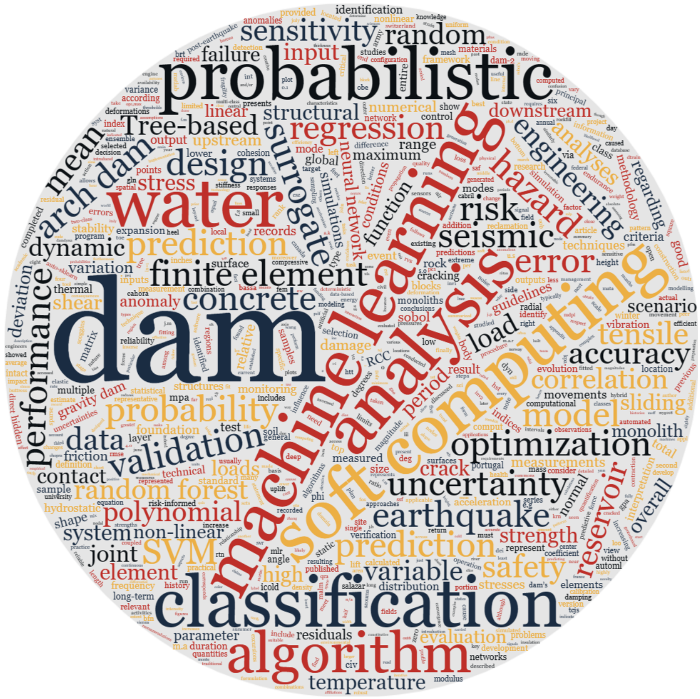

Figure 2. Word cloud from all the accepted papers in this Special Issue journal.

4. Contributions to Current Special Issue

Deterministic analysis never provides a comprehensive performance assessment of structural systems. Therefore, probabilistic methods have emerged as a promising alternative. However, such methods, in addition to being computationally expensive, can produce very different solutions, depending on the input parameters, which can greatly influence the decision making. The importance of probabilistic methods in dam engineering has been discussed previously in [31–33]. In the paper by Segura et al. [34], "Accounting for Uncertainties in the Safety Assessment of Concrete Gravity Dams: A Probabilistic Approach with Sample Optimization", the authors proposed a probabilistic-based methodology for assessing the safety of dams under usual, unusual, and extreme loading conditions. This allows the analysis to be updated while avoiding unnecessary simulation runs by classifying the load cases according to the annual probability of exceedance and by using an efficient progressive sampling strategy. They also conducted a variance-based global sensitivity analysis to identify the most influencing parameters affecting the dam response.

While the probabilistic simulations can be used to extract the structural capacity of dams, it is not always possible to perform hundreds of simulations for highly nonlinear systems. The alternative is to use the approximate methods such as endurance time analysis (ETA) [35]. ETA is a dynamic pushover procedure that evaluates the structural performance of a system from the linear to nonlinear range using single simulations. In a paper by Alegre et al. [36], "Seismic Safety Assessment of Arch Dams Using an ETA-Based Method with Control of Tensile and Compressive Damage", the authors present an ETA-based method for seismic safety assessments of arch dams using tensile and compressive damage models. The seismic performance is evaluated by controlling the evolution of the damage state of the dam, according to predefined performance criteria, to estimate acceleration endurance limits for tensile and compressive damage. They evaluated the dam response at two seismic hazard levels, i.e., Operating Basis Earthquake and Safety Evaluation Earthquake.

The probabilistic seismic performance of dams typically results in fragility curves or capacity functions that are useful for the engineers [33,37,38]. However, they do not provide a direct connection between the failure probability at different seismic hazard levels and the associated risk for downstream population and properties. In a paper by Ferguson [39], "Risk-Informed Design of RCC Dams under Extreme Seismic Loading", the author proposed a practical framework for risk-informed design of concrete dams. The results of 2D and 3D numerical simulations were used to drive the risk metrics and feasibility level design.

The machine learning techniques can be used to process the results of numerical simulations. They can be used for both "analysis" and "design" purposes. In a paper by Shahzadi and Soulaïmani [40], "Deep Neural Network and Polynomial Chaos Expansion-Based Surrogate Models for Sensitivity and Uncertainty Propagation: An Application to a Rockfill Dam", the authors used two machine learning techniques to build a surrogate model of a rockfill dam considering the uncertainties in constitutive soil parameters. Furthermore, they found that shear modulus and the Poisson coefficient are the parameters that play the most significant role in the dam's behavior.

In a separate study by Hariri-Ardebili and Pourkamali-Anaraki [41], "An Automated Machine Learning Engine with Inverse Analysis for Seismic Design of Dams", the authors used automated machine learning (AutoML) for the design of new dams. They first developed a large database of about 24,000 simulations in which the uncertainties associated with shape, material properties, water level, and ground motion records are incorporated. Next, AutoML is used to generate a surrogate model of dam response as a function of input variables. A simple yet robust inverse analysis method is coupled with a multi-output surrogate model to design the new dams in which only part of the data are available. The design shape from the inverse analysis is in good agreement with the design objectives and also the finite element simulations.

Aside from the application of soft computing methods in regression and classification of data, they can be used for the sensitivity analysis of dams too. In a paper by Hariri-Ardebili et al. [42], "An RF-PCE Hybrid Surrogate Model for Sensitivity Analysis of Dams", the authors proposed two techniques for the sensitivity assessment of concrete dams with heterogeneous concrete, i.e., a polynomial chaos expansion and random forest. They used these techniques to identify the areas of dam in which the variation of material properties have the highest impact on the vibration response. Their findings can improve the process of system identification for old dams.

Another complex aspect, which is seldom analyzed, is the effect of ice loads on dam displacements. This, which obviously affects dams in cold regions, was studied with an innovative approach in a paper by Hellgren et al. [43], "Estimating the Ice Loads on Concrete Dams Based on Their Structural Response". The authors estimated the magnitude of ice loads on five dams in Sweden, four concrete buttress dams and one arch dam. The results suggested that the estimates of ice loads from measurement sensors and from design guidelines are over-conservative.

Soft computing techniques are also capable of jointly analyzing a set of monitoring records. In a paper by Salazar et al. [44] "Anomaly Detection in Dam Behaviour with Machine Learning Classification Models", machine learning classifiers based on support vector machines and random forests are tested for detecting anomalies in a double-curvature arch dam. Results show the potential of this approach as a robust procedure for novelty detection. The main limitation, also identified, is the need for high-quality monitoring data.

The dissemination of machine learning techniques has promoted the development of new models for dam behavior prediction. However, validating these models based on the dam engineer's knowledge is fundamental for their adequate use. This issue is tackled in the paper by Mata et al. [45] "Validation of Machine Learning Models for Structural Dam Behaviour Interpretation and Prediction". The authors present a methodology based on several validation techniques, including historical data validation, sensitivity analysis, and predictive validation for the practical application of data-based models for structural dam behavior prediction in daily dam surveillance activities.

Finally, in a paper by Mata et al. [46] "Characterization of Relative Movements between Blocks Observed in a Concrete Dam and Definition of Thresholds for Novelty Identification

Based on Machine Learning Models", the authors present a methodology for the earlier detection of novelties through the analysis of the residuals of prediction models, taking into account the evolution of the records over time and the simultaneity of the structural responses measured in a concrete dam, namely through the threshold definition based on a singular record, a moving time period, and multivariate records.

5. Future Research Directions

The dissemination and implementation of the scientific and technological advances achieved in the dam surveillance area during the last decade are not yet effective for most dam owners, even for large dams. The trend towards the installation and use of ADAS, recommended in monitoring plans of new large dams, is a great opportunity to assess safety conditions in real time, but it requires tools to process big data sets. Machine learning and deep learning provide dam safety engineers with essential functionalities for an efficient and effective enhancement of these tools, in order to adequately satisfy the needs resulting from dam surveillance activities. Some of the future advances in this area to fill existing gaps may include the development of methodologies and tools for:

- The validation of manual measurements in real-time, allowing manual record errors to be immediately identified (resulting from human error or defects in measuring devices). This enables the technicians, in-situ and in real-time, to have the opportunity to repeat the measurement before making the final record.
- The validation of the automated measurements from ADAS taking advantage of the multi-dimensionality of the measurements carried out.
- The definition/confirmation of the best location of the measurement devices that better identify potential failure scenarios, enhancing the definition of subsystems of devices that allow the confirmation of scenarios.
- The construction of advanced predictive models of physical quantities that present a nonlinear behavior, such as seepage and leakage, uplift pressures, and joint movements, among others.
- Multivariate and simultaneous analysis of quasi-static and dynamic quantities for interpreting observed behavior.
- The short-term prediction of the structural behavior under extreme flood scenarios, taking into account the short-term evolution of water level.
- The development of key operational indicators to assess the performance of the observed structural behavior. For example, to assess the efficiency of the waterproofing concrete curtain.
- The development of dashboards that allow, in an easy way for the end user, to assess the quality of the forecast models adopted (including the quantification of the effect of each of the main actions in the final response through sensitivity analyses).
- The identification of potential failure scenarios based on monitoring data.
- Validation, verification, and uncertainty quantification of probabilistic numerical simulations that are used in soft computing models.

We hope that this Special Issue would shed light on the recent advances and developments in the area of soft computing and dam engineering, and attract attention by the scientific community to pursue further research and studies on simulation and modeling of dams and appurtenant structures.

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