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Editorial

Artificial Intelligence (AI) Applied in Civil Engineering

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1. Introduction

In recent years, artificial intelligence (AI) has drawn significant attention with respect to its applications in several scientific fields, varying from big data handling to medical diagnosis. The use of AI is already present in our daily lives with several uses, such as personalized ads, virtual assistants, autonomous driving, etc. Not surprisingly, AI methodologies have found a wide range of uses and applications in engineering fields, including civil and structural engineering [1,2], with impressive results [3–5]. Figure 1 shows the research articles related to AI published in the field of civil engineering. In particular, these are results from the Scopus database (www.scopus.com, obtained on 2 June 2022), using the query "*TITLE-ABS-KEY* ((*"artificial intelligence" or "AI"*) *and* (*"civil" or "structural" or "transportation" or "geotechnical" or "hydraulic" or "environmental" or "construction" or "shm" or "structural health"*)) *and PUBYEAR* > *1999 and* (*LIMIT-TO* (*SUBJAREA, "ENGI"*))", which returned 14,059 document results in total (for years from 2000 to 2022). The increase in AI studies with great acceleration shows that the use of AI in civil engineering is gaining momentum and will keep increasing in the coming years, bringing new innovations and applications.

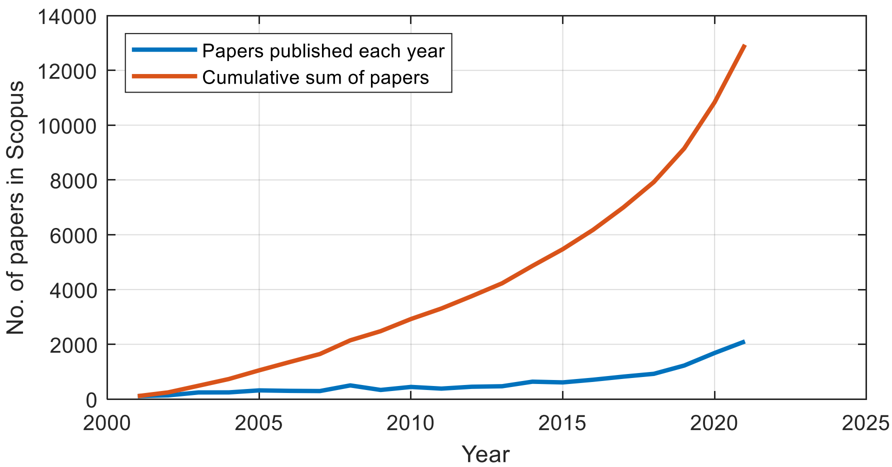

Figure 1. Published articles (in Scopus) using AI in civil engineering-related fields (2000–2021).

This research topic contains applications and recent advances of AI in civil engineering problems, promoting cross-fertilization between these scientific fields. In particular, the focus is on hybrid studies and applications related to structural engineering, transportation engineering, geotechnical engineering, hydraulic engineering, environmental engineering, coastal and ocean engineering, structural health monitoring, as well as construction management.

2. Contributions

The research topic has been quite successful, gathering 35 contributions in total, from 19 different countries around the world, covering a broad range of topics related to the applications of AI in civil engineering. Three MDPI journals participated by cross-listing the research topic. Most of the articles (29) were published in the "Applied Sciences" journal, while 3 of them were published in "Mathematics" and another 3 in "Symmetry".

The articles are divided into 6 groups, as follows: (i) Optimization methods and applications (7 articles), (ii) Combined machine learning and optimization methodologies (2 articles), (iii) Machine learning in identification problems (3 articles), (iv) Applications of convolutional neural networks (8 articles), (v) Combined and multiple AI-based methodologies (6 articles), and (vi) Other AI-based methods, formulations, and applications (9 articles). A brief description of each article, for every category, is presented in the following sections.

2.1. Optimization Methods and Applications

Rosso et al. [6] propose an enhanced multi-strategy Particle Swarm Optimization (PSO) variant to solve constrained problems with a different approach to the classical penalty function technique. The authors propose several improvements to the original algorithm, including a new local search operator based on the Evolutionary Strategy (ES). Li et al. [7], propose an optimization approach with a parallel updated particle swarm optimization (PUPSO) algorithm aiming at minimizing the objective function of the levelized cost of energy of the prestressed concrete–steel hybrid wind turbine towers. This is conducted in a life cycle perspective which represents the direct investments, labor costs, machinery costs, and the maintenance costs.

Cucuzza et al. [8] study the size and shape optimization of a guyed radio mast for radiocommunications, using the genetic algorithm (GA) and carrying out both static and dynamic analyses considering the action of wind, ice, and seismic loads. Guo et al. [9], propose the use of GA, correlation analysis, and two parametric design methods (floor plan generation method and component selection method) for optimizing the building performance of prefabricated buildings.

Uray et al. [10] use the Taguchi method integrated hybrid harmony search algorithm, carry out a statistical investigation of the optimum values for the control parameters of the harmony search algorithm and examine their effects on the best solution. The new hybrid method has been successfully applied to different real-world engineering optimization problems. Sarjamei et al. [11] use the Gold Rush Optimization (GRO) algorithm for the optimal design of real-scale symmetric structures under frequency constraints. The efficacy of the concept of cyclic symmetry to minimize the needed time is assessed with three examples, including Disk, Silo, and Cooling Tower.

Bao et al. [12], investigate the decision-making problem of pavement maintenance prioritization considering both quality and cost. They consider a linear optimization model that maximizes maintenance quality with limited maintenance costs and a multi-objective optimization model that maximizes maintenance quality while minimizing maintenance costs. These models are employed in making decisions for actual pavement maintenance using sequential quadratic programming and GA.

2.2. Combined Machine Learning and Optimization Methodologies

3D printing is already established in the production processes of several industries while more are continuously being added. Lately, parametric design has become popular in the architectural design literature, while topology optimization has become part of the design procedure of various industries. Kallioras and Lagaros [13] propose MLGen, a novel generative design framework which integrates machine learning (ML) into the generative design practice. Several benchmark topology optimization problems are examined to show the ability of MLGen to efficiently handle different engineering problems.

In order to deal with dynamic traffic flow, adaptive traffic signal controls using reinforcement learning are being studied. Gu et al. [14] propose a reinforcement learning-based signal optimization model with constraints. The model maintains the sequence of typical signal phases and considers the minimum green time. It is trained using Simulation of Urban MObility (SUMO), a microscopic traffic simulator and it is evaluated in a virtual environment similar to a real road with multiple intersections.

2.3. Machine Learning in Identification Problems

In recent years, deep learning-based detection methods have been successfully applied to pavement crack detection problems. In this field, Li et al. [15] propose a method to improve the accuracy of crack identification by combining a semantic segmentation and edge detection model. Their work is inspired by the U-Net semantic segmentation network and holistically nested edge detection network. A side-output part is added to the U-Net decoder that performs edge extraction and deep supervision. A network model is proposed, combining two tasks that can output the semantic segmentation results of the crack image and the edge detection results of different scales. The model can also be used for other tasks that need both semantic segmentation and edge detection. On the topic of concrete structures, Liu and Li [16] propose an improved self-organizing mapping (SOM) neural network (NN) model to solve the problem of intelligent detection of damage to modern concrete structures under complex constraints. The method is based on a small number of samples and the use of a self-developed 3D laser scanning system. The improved SOM model method fully combines the network topology and its unique image features and can accurately identify structural damage, contributing to the realization of high-precision intelligent health monitoring of damage to modern concrete structures.

In railway engineering, the performance of the passing train and the structural state of the track bed are common concerns regarding the safe operation of the subway. Monitoring the vibration response of the track bed structure and identifying abnormal signals within it can help address these concerns. In this direction, Li et al. [17] propose an unsupervised learning-based methodology for identifying the abnormal signals of the track beds detected by the ultra-weak fiber optic Bragg grating sensing array. The experimental results demonstrate that the established unsupervised learning network and the selected metric for quantifying error sequences can serve the threshold selection well, based on the receiver operating characteristic curve.

2.4. Applications of Convolutional Neural Networks

In earthquake engineering, the analysis of site seismic amplification characteristics is one of the most important tasks of seismic safety evaluation. Yang et al. [18] propose a new prediction method for the amplification characteristics of local sites, using a CNN combined with real-time seismic signals. The CNN is used to establish the relationship between the amplification factors of local sites and eight parameters, while the training and testing samples are generated through observed and geological data. The results show that the CNN method can provide a powerful tool for predicting the amplification factors of local sites both for recorded and unrecorded positions. Yan et al. [19] propose a measurement method of bridge vibration by unmanned aerial vehicles (UAVs) combined with convolutional neural networks (CNNs) and the Kanade–Lucas–Tomasi (KLT) optical-flow method. The KLT optical-flow method is used to track the target points on the structure and the background reference points in the video to obtain the coordinates of these points on each frame, while the characteristic relationship between the reference points and the target points is learned by a CNN according to the coordinates of the reference points and the target points. The objective is to correct the displacement time–history curves of target points containing the false displacement caused by the UAV's egomotion.

Based on the features of cracks, Wang et al. [20] propose the concept of a crack key point as a method for crack characterization and establish a model of image crack detection based on the reference anchor points method, named KP-CraNet. The accuracy of the model recognition is controllable and can meet both the pixel-level requirements and the efficiency needs of engineering. The results show that the method can improve crack detection quality and has a strong generalization ability. Dos Santos Junior et al. [21] propose an architecture for segmenting cracks in facades with Deep Learning (DL) that includes an image pre-processing step. The authors also propose the Ceramic Crack Database, a set of images to segment defects in ceramic tiles. The proposed model can adequately identify the crack even when it is close to or within the grout.

Blockage of culverts by transported debris materials is the salient contributor to originating urban flash floods, with conventional hydraulic modeling having no success in addressing the problem. Iqbal et al. [22] explore a new dimension to investigate the issue by proposing the use of intelligent video analytics (IVA) algorithms for extracting blockage-related information. Their research aims to automate the process of manual visual blockage classification of culverts from a maintenance perspective by remotely applying DL models. On the other hand, Calton and Wei [23] use transfer learning on three advanced NNs, ResNet, MobileNet, and EfficientNet, and apply techniques for damage classification and damaged object detection to a post-hurricane image dataset comprised of damaged buildings from the coastal region of the southeastern USA. The dataset includes 1000 images for the classification model with a binary classification structure containing classes of floods and non-floods and 800 images for the object detection model with four damaged object classes, i.e., damaged roof, damaged wall, flood damage, and structural damage.

Lin et al. [24] aim at the long-term (24–72 h ahead) prediction of wind power with a mean absolute percentage error of less than 10% by using the Temporal Convolutional Network (TCN) algorithm of DL networks. In their experiment, they perform TCN model pretraining using historical weather data and the power generation outputs of a wind turbine from a Scada wind power plant in Turkey.

Chen et al. [25] propose a text-mining-based accident causal classification method based on a relational graph convolutional network (R-GCN) and pre-trained bidirectional encoder representation from transformers (BERT). The proposed method avoids preprocessing such as stop word removal and word segmentation, but also avoids tedious operations, while the dependence of BERT retraining on computing resources can also be avoided.

2.5. Combined and Multiple AI-Based Methodologies

Some of the research works use multiple AI-based methodologies, either for comparison purposes or in a combined way to achieve better results. In particular, Benbouras et al. [26] elaborate on a new alternative model for predicting the bearing capacity of piles based on eleven new advanced ML methods, in order to overcome the problems of the time-consuming and costly traditional methods. The modeling phase uses a database of 100 samples collected from different countries. Additionally, eight relevant factors are selected in the input layer based on recommendations from the literature. Su et al. [27] propose a data processing framework that uses a long short-term memory (LSTM) model coupled with an attention mechanism to predict the deformation response of a dam structure. The results of the case study show that, of all tested methods, the proposed coupled method performs best. In addition, it was found that temperature and water level both have significant impacts on dam deformation and can serve as reliable metrics for dam management.

Zhao et al. [28] use a sparrow search algorithm to improve a backpropagation NN, and an Elman NN and support vector regression models to predict the thickness of an excavation damaged zone. The proposed model can provide a reliable reference for the thickness prediction of an excavation-damaged zone and is helpful in the risk management of roadway stability. Ma et al. [29] investigate the performance of the extreme gradient boosting (XGboost) method in predicting multiclass of clay sensitivity, and the ability of the synthetic minority over-sampling technique (SMOTE) in addressing imbalanced categories of clay sensitivity. The results reveal that XGBoost shows the best performance in the multiclassification prediction of clay sensitivity.

In transportation engineering, Xiang et al. [30] propose a two-phase approach in an effort to predict highway passenger volume. The datasets subsume highway passenger volume and impact factors of urban attributes. The findings provide useful information for guiding highway planning and optimizing the allocation of transportation resources. Cheng et al. [31] use smartcard data from the bus system to identify important variables that affect passenger flow. These data are combined with other influential variables to establish an integrated-weight time-series forecast model. The results show that the model can improve passenger flow forecasting based on three bus routes with three different series of time data.

2.6. Other AI-Based Methods, Formulations, and Applications

Kruachottikul et al. [32] aim to improve collaboration on bridge inspections that typically require the involvement of many people, personal judgement, and extensive travel to survey bridges across the country of Thailand. One major challenge is to standardize human judgement. To address this, the authors develop a user-centric bridge visual defect quality control mobile application to improve collaboration and assist field technicians to conduct visual defect inspections. Based on nonlinear finite element numerical simulation and synergistic theory, the cooperative control problems of the bridge–subgrade transition section are studied in the work by Zhang et al. [33]. Huang et al. [34] propose a data-driven reinforcement-learning (RL)-based approach to achieve automatic bucket-filling. An automatic bucket-filling algorithm based on Q-learning is developed to enhance the adaptability of the autonomous scooping system. A nonlinear, non-parametric statistical model is also built to approximate the real working environment using the actual data obtained from tests.

Chen et al. [35] summarize the main factors affecting the large deformation of soft rock tunnels, including the lithology combination, weathering effect, and underground water status, by reviewing the typical cases of largely-deformed soft rock tunnels. The method can be used to invert the geological parameters of the surrounding rock mass for a certain point, which can provide important mechanical parameters for the design and construction of tunnels. Lin et al. [36] introduce a modern space remote sensing technology, InSAR, as a direct observable for the slope dynamics. The InSAR-derived displacement fields and other in situ geological and topographical factors are integrated, and their correlations with landslide susceptibility are analyzed. Moreover, multiple ML approaches are applied with the goal to construct an optimal model between these complicated factors and landslide susceptibility. Zenkour et al. [37] introduce the thermoelastic coupled response of an unbounded solid with a cylindrical hole under a traveling heat source and harmonically altering heat. A refined dual-phase-lag thermoelasticity theory is used for this purpose. A generalized thermoelastic coupled solution is developed by using Laplace's transforms technique.

Heo et al. [38] highlight that many human resources are needed on the research and development (R&D) process of AI and discuss factors to consider in the current method of development. Labor division of a few managers and numerous ordinary workers as a form of the light industry appears to be a plausible method of enhancing the efficiency of AI R&D projects. Inspired by the powerful ability of NNs in the field of representation learning, Xie et al. [39] design a hierarchical generative embedding model (HGE) to map nodes into latent space automatically. Then, with the learned latent representation of each node, they propose an HGE-GA algorithm to predict influence strength and compute the top-K influential nodes. Extensive experiments on real-world attributed networks demonstrate the outstanding superiority of the proposed HGE model and HGE-GA algorithm compared with the state-of-the-art methods, verifying the effectiveness of the proposed model and algorithm. Xie et al. [40] incorporate a co-embedding model for KG embedding, which learns low-dimensional representations of both entities and relations in the same semantic space. To address the issue of neglecting uncertainty for KG components, they propose a variational auto-encoder that represents KG components as Gaussian distributions.

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