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AN OVERVIEW OF APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN CIVIL ENGINEERING

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ABSTRACT

Civil Engineering is a professional engineering discipline that deals with the design, construction of the natural and built environment. Artificial intelligence is to develop the machine elements that analyze the human thinking system and reflect the same to reality. In recent years, artificial intelligence applications have found a

Introduction

Civil Engineering is a professional engineering discipline that deals with the design, construction of the natural and built environment, including public works such as roads, bridges, canals, dams, airports, sewage systems, pipelines, structural components of buildings and railways. Civil engineering traces back to medieval times past the Egyptian pyramids, the Greek Acropolis and the Roman aqueducts. It's also responsible for close to all the useful structures that modern society cannot live without, such as roads, bridges, schools, railways, hospitals and office blocks.

wide range of applications in civil engineering and the other engineering branches. The increase in artificial intelligence studies with great acceleration shows that the use of artificial intelligence in engineering branches will increase in the coming years. This paper discuss the different sub-fields in civil engineering, duties and responsibilities of civil engineers and how artificial intelligence is applied to the various sub-fields as well as the limitations of artificial intelligence in addressing civil engineering problems.

Types of Civil Engineering

Civil engineering is a complex sector composed of many sub-disciplines. The following are its most prominent sub-disciplines:

1. Construction engineering

Construction engineering involves the design, management and erection of residential and public constructions. Engineers in this sub-discipline oversee the projects and ensure that their schedules are maintained and that the work is handled under the relevant specifications and plans.

2. Environmental engineering

Environmental engineering involves the maintenance and improvement of the quality of water, land and air through the promotion of eco-friendly operations. They come up with and implement solutions that reduce waste and pollution or manage projects in public parks. They use a combination of chemistry, biology and engineering to create sound scientific solutions to preserve nature.

3. Earthquake engineering

Earthquake engineering concerns itself with lowering the damage that earthquakes cause. Engineers in this sub-discipline develop strategies and construct structures and strategies that decrease the vulnerability of certain infrastructures.

4. Structural engineering

Structural engineering involves the design and inspection of major construction projects such as bridges, buildings and dams. They focus on the internal aspects of such constructions to ensure that they are durable overall. This ensures that such projects have a lower vulnerability to environmental damage or collapse.

5. Geo-technical Engineering

This sub-discipline of civil engineering focuses on how structures built by other civil engineers, like bridges and dams, interact with the earth, primarily soil and rock. The work of the engineers in this sub-discipline ensures the wholeness of the foundations of built structures. They study a wide range of geological factors and also use their knowledge to design tunnels, retaining walls and slopes.

6. Water Resources Engineering

Engineers in this subset study a wide variety of waterways around the world. They mainly work on projects like sewage system design and wetland restoration.

7. Fire Protection Engineering

Engineers in this subset of civil engineering work to improve and ensure the safety of the public during a fire. They develop strategies and plans that lower the possibility of fires breaking out and mostly work for construction or development companies.

8. Transportation engineering

Transportation engineering involves the planning, designing, operation and maintenance of transportation systems, like highways and streets. Engineers in this subset also plan massive projects like airports, harbors, mass transit systems and harbors. They are concerned with current transportation and trends that will affect the transportation sector in the future. They then use such knowledge in their maintenance and improvement of modern transportation.

9. Mining Engineering

Engineers in this subset focus their efforts exclusively on mining and extraction of coal, minerals and other related materials. Their work might involve the analysis, planning and designing of mineral hubs and overseeing mining teams.

DUTIES AND RESPONSIBILITIES OF CIVIL ENGINEERS

Civil engineers design, develop and link up the world in various ways. They ensure that villages, towns and cities are livable and functional for their residents. They can work for governments or in the private sector designing, erecting and maintaining a wide variety of structures. Their daily duties and responsibilities largely vary with their specialization or the sub-discipline they operate in. However, there are several duties that cut across disciplines, such as:

a. Analyzing long-term plans, survey data, maps and other reports for effective planning and designing of projects

b. Doing risk analysis for a wide variety of projects by considering project costs, potential environmental hazards and government regulations, among other relevant factors

c. Overseeing and analyzing soil test results to determine whether foundations are firm enough to support various structures

d. Compiling and submitting various permit applications to the relevant authorities to verify the compliance of their projects with the relevant regulations

e. Preparing expense reports with cost estimates for equipment, materials and labour to know the economic feasibility of any project

f. Planning and designing a wide variety of structures using design software and in accordance with industry and government regulations

g. Performing or overseeing survey operations for proposed projects

h. Ensuring effective repair, maintenance and restoration of private or public structures

ARTIFICIAL INTELLIGENCE (AI)

Artificial Intelligence (AI) is a science of creating intelligent machines, particularly intelligent computer programmes. It resembles the task of using computers to understand human intelligence. Basically, Artificial Intelligence refers to the intelligence displayed by machines. Artificial Intelligence (AI) has grown extremely prevalent in today's world. It is the simulation of human intelligence in computers that have been programmed to learn and mimic human actions. These machines can learn from their mistakes and do activities that are similar to those performed by humans.

Artificial intelligence is to develop the machine elements that analyze the human thinking system and reflect the same to reality. In recent years, artificial intelligence applications have found a wide range of applications in civil engineering and the other engineering branches. The increase in artificial intelligence studies with great acceleration shows that the use of artificial intelligence in engineering branches will increase in the coming years.

The focus of this work is on applications of artificial intelligence in civil engineering. Especially hybrid artificial intelligence studies in the fields of structural engineering, construction management, hydrology, hydraulic engineering, geotechnical engineering, environmental engineering, transportation engineering, coastal and ocean engineering, and materials of construction form the basis of this work. Besides, review articles including applications of civil engineering using branches of artificial intelligence techniques (ANN, fuzzy system, expert system, and swarm intelligence) is covered by this work.

Liu et al. presenting a risk assessment method for cable system construction of suspension bridges was based on the cloud model. The proposed model can combine randomness and fuzziness of risk information effectively. At the end of their study, the authors concluded that the risk assessment method can provide safety assurance and technical support for cable system construction of the long-span suspension bridge.

S. Petruseva et al. presented a hybrid method for predicting construction time in the early project phase. They used many ANN techniques such as General Regression Neural Network (GRNN), Backpropagation Neural Network (BNN), and Radial Base Function Neural Network (RBFNN). Their study shows that the BNN technique is better than the other techniques when they compared the results obtained. But, their developed model is not suitable for the higher, more intensive risk factors impact during the construction period.

H. Ceylan and T. Ozcan presented a case study on the optimization of headways and departure times in urban bus networks. The authors used the metaheuristic harmony search optimization method to evaluate the user and operator costs. This study gives Pareto solutions in terms of the user and operator benefits. At the end of the study, the authors

concluded that total travel time and total service km could be reduced by 4.8% and 9.8%, respectively, compared with the current bus network.
E.-T. Lee and H.-C. Eun investigated damage detection methods using the stress or stiffness variation rate of the truss element before and after the damage. To predict damaged elements depending on complete and incomplete measurement, the authors of this study consider some methods such as the substructuring method, damage detection methods, and static-based and dynamic-based substructuring method. The detailed knowledge about these methods can be found from the paper submitted to this special issue.
G. B. Jumaa and A. R. Yousif proposed three prediction models by using ANN. They are ANN, gene expression programming (GEP), and nonlinear regression analysis (NLR). The authors used a large database including 269 shear test results and the genetic programming to predict the shear capacity of FRP-reinforced concrete beams without stirrups. Their parametric study indicated that the ANN model defines accurately the interaction of all parameters on shear capacity prediction.
C.-Y. Kao et al. develops a two-step computer-aided approach for pozzolanic concrete mix design. The first step is establishing a dataset of pozzolanic concrete mixture proportioning which conforms to American Concrete Institute Code. In the first step, ANNs are employed to establish the prediction models of compressive strength and the slump of the concrete. Sensitivity analysis of the ANN is used to evaluate the effect of inputs on the output of the ANN. The two ANN models are tested using data of experimental specimens made in a laboratory for twelve different mixtures. The second step is classifying the dataset of pozzolanic concrete mixture proportioning. A classification method is utilized to categorize the dataset into 360 classes based on compressive strength, pozzolanic admixture replacement rate, and material cost. Thus, one can easily obtain mix solutions based on these factors. The results show that the proposed computer-aided approach is convenient for pozzolanic concrete mix design and practical for engineering applications.
N.-D. Hoang's research establishes an automatic approach for asphalt pavement pothole detection. Image processing techniques including

Gaussian filter (GF), steerable filter (SF), and integral projection (IP) are used synergistically to extract features from pavement digital images. Two levels of GF are utilized as an image denoising technique. SF assisted by GF is used to generate a pothole resilient map. IP analysis based on such map is performed to numerically present the feature of an image with the particular interest in pothole recognition. A simple moving average technique is put forward to reduce the number of the extracted features from 300 to 60. Based on the image features, two artificial intelligence (AI) approaches of ANN and the least squares support vector machine (LS-SVM) have been employed to construct classification models to predict the existence of pothole on the pavement surface. Experimental results with a repeated subsampling procedure with 20 runs confirm that ANN and LS-SVM are capable AI methods for pothole detection. It is because the classification accuracy rates (CARs) of both methods are higher than 85% and the area under the curve (AUC) values surpass 0.9. Moreover, LS-SVM has been identified as the better approach for the task of pothole detection with a desired accuracy of approximately 89%.

S. Golnaraghi et al. used four different ANN methods: Backpropagation Neural Network (BNN), Radial Basis Network (RBF), Generalized Regression Neural Network (GRNN), and Adaptive Neuro-Fuzzy Inference System (ANFIS) to model labour productivity. Weather (temperature, humidity, wind speed, and precipitation), crew (gang size and labour percentage) and project (work type, floor level, and work method) data were selected as inputs in the models. According to R^2 values, the best result in the models was obtained from BNN with 0.98 for the training set and from RBF with 0.85 for the test set. In the three methods other than RBF, it was determined that temperature was the most important parameter affecting labour productivity. It was determined that the best model BNN obtained as a result of this study can help save time and cost associated with quantifying loss of productivity.

J. A. Álvarez et al. predicted energy performance of a house using ANN models to evaluate building energy efficiency. The dataset obtained from 453 buildings located in the northern area of Spain with a total usable area of 570,438.30 m^2 was used in the models. The data were divided into two: 90% of them were training set, and 10% of them were validation set. Together with this study, it is possible to estimate the energy efficiency of a building in a certain region by using some characteristics belonging to that building with high accuracy without interfering with the building or using any measuring device.

A. M. al-Swaidani and W. T. Khwies applied the ANN and multilinear regression (MLR) models to estimate 2, 7, 28, 90, and 180 days compressive strength, water permeability, and porosity of concretes containing volcanic scoria as cement replacement. Cement content, volcanic scoria content, water content, superplasticizer content, and curing time were used as model inputs. The data used in the ANN models were divided into 70% training, 15% testing, and 15% validation pattern, respectively. Sensitivity analysis showed that all parameters used as an input in this study have significant effects on the properties of concrete containing volcanic scoria as cement replacement. The results showed that ANN models were much more accurate than MLR models and that ANN can be used successfully to predict the investigated concrete properties.

X. Cao et al. developed a new dynamic multicriteria decision-making approach for low-carbon supplier selection in low-carbon building construction projects. This approach includes interval-valued triangular fuzzy numbers intuitionistic fuzzy. According to the demand from the constructors during the considered projects, 5 main criteria and 17 subcriteria were established for the selection of low-carbon suppliers in the construction sector. In conclusion, the authors revealed that the proposed model can be easily extended to analyze other management decision problems as a structural model.

N.-D. Hoang and Q.-L. Nguyen suggest a hybrid model that includes image processing and machine learning approaches for automatic pavement crack recognition. They used advanced image processing techniques (fast local Laplacian filter, Sobel filter, SF, and IP) to extract digital properties from digital images. They benefited from the adaptive boosting classification tree to perform pavement crack recognition tasks. To generate and validate the performance of the adaptive boosting classification tree, a set of image samples consisting of five classes, crocodile cracks, diagonal cracks, longitudinal cracks, no cracks, and cross cracks, were collected. The results of the study revealed that the crack classification accuracy of the proposed approach was approximately 90%. It is considered that the model can be used in the assessment of the pavement condition of the transportation agencies.

ARTIFICIAL INTELLIGENCE IN CIVIL ENGINEERING

Deep learning technologies have been effectively employed in a variety of industries for many years, including civil engineering. Indeed, with the emergence of complex constructions such as skyscrapers, machine learning techniques grabbed centre stage in the sector a long time ago. We are seeing the application and growth of AI in the construction industry more than ever before, with intelligent algorithms, big data, and deep learning machines transforming productivity performance.

AI has been used by practising civil engineers, contractors, and service providers to tackle a wide range of challenges. Artificial Intelligence in civil engineering, for example, has advanced to the point where efficiencies are fed directly into construction processes. AI is also used in the early stages of many projects to improve design, risk management, and productivity. It is critical to understand that construction organizations who have already begun to apply AI processes are 50% more profitable. More importantly, Artificial Intelligence (AI) as a whole offers a wide range of applications in civil engineering. Engineers can make better decisions and deliver their services more effectively in an age where robots can think rather than just do.

RELEVANCE OF ARTIFICIAL INTELLIGENCE IN CIVIL ENGINEERING

For many years, deep learning technologies have been successfully applied in many different sectors, civil engineering included. In fact, machine learning technique took the center stage in the industry long ago with the emergence of complex buildings such as skyscrapers. Now more than ever, we see the application and development of AI in the construction industry, which includes the use of intelligent algorithms, big data, and deep learning machines that have transformed productivity performance.

Practicing civil engineers, contractors, and service providers have all been using AI to solve a whole range of problems. For instance, artificial Intelligence in civil engineering has become more sophisticated, with efficiencies feeding directly into construction processes. AI is also applied in the initial stages of many projects in design optimization, risk control, and improving productivity.

It is imperative to realize construction companies that have already started implementing AI practices are 50% more profitable. More importantly, Artificial Intelligence as a whole has a range of functions in civil engineering. In an age where machines can think rather than just do, engineers can make better judgments while discharging their services more effectively, here are some uses of AI in civil engineering that have revolutionized the industry.

1. AI for Better Designs of Buildings

With skylines of major cities around the world peppered with iconic buildings of all shapes and sizes, we can all agree that the boundaries and standards of design and engineering have been pushed beyond their limits. This is all thanks to the biggest game-changer in the industry—Artificial Intelligence in 3D Building Information Modelling (BIM). BIM tools help civil engineers to facilitate the creation and design of more accurate 3D models prior to the construction work. Now, the addition of AI-based design exploration allows engineers to improve design using collected data from simulations, models, and past projects.

In terms of incorporating machine learning into the BIM process, civil engineers can create buildings blueprints, floor plan designs, and more. Also, they can make the necessary changes across all areas of design with peak accuracy.

2. Overcoming Cost/Schedule Overruns

Most mega construction projects go over budget and are susceptible to inaccuracies since they are often prepared within a limited timeframe and with limited information regarding the scope of the entire project.

Although cost overruns can't be prevented, using AI in construction allows an engineer to have a clear picture of cost estimates and outcome from previous projects to come up with better plans and more accurate budgeting. Learning algorithms that employ characteristics of completed projects allow civil engineers to predict cost overruns and envision realistic timelines for existing projects.

Furthermore, AI offers remote site access and helps engineers to implement real-time training resources in order to enhance skills and improve team leadership. A good example is Doxel, an AI company that uses deep learning algorithms, LIDAR, and Camera equipped drones on job sites to recognize objects, access quality of construction, and quantify materials used. This information is then used to provide real-time feedback to all stakeholders on the actual costs and time spent in comparison to the original budget and schedule. Gathering such information helps to mitigate cost/schedule overruns and improve overall productivity on the job site.

3. Identifying and Mitigating Risks

The construction process involves safety risks that can lead to actual accidents. AI provides the opportunity for more accurate data gathering from real-world context models to help civil engineers identify potential hazards in the construction process. Enabling the creation and use of relevant technology in construction helps an engineer to implement useful measures for risk control as AI can interpret a collection of construction site information to draw meaningful conclusions.

Also, AI-enabled cameras and networks can continuously monitor all areas of construction and allow engineers to assess equipment use, track progress, and analyze activities in real-time, which helps in the early detection of potential risk hazards.

A good example of the application of such technology lies in the popularity of Indus.ai. This San Francisco tech company set AI-supported cameras around construction sites to provide real-time footage while collecting and evaluating data to give construction managers insights on things like the movement of materials and labor deployment at various areas of the site. This interactive dashboard also allows civil engineers to anticipate anything that may prove dangerous and make better decisions with regard to worker's safety.

4. Smart Construction On-site to Speed Project Delivery

Civil engineers can use AI models for accurate, cheaper, and less disruptive construction projects. This includes relying on off-site facilities operated by independent robots that assemble essential components of a construction project, which are then pieced together by human workers on the construction site.

Such off-site builders, according to one June report by McKinsey, gives the construction industry a huge productivity boost with a quicker turnaround as compared to on-site construction.

AI-supported machines can complete prefabricated structures such as walls, and building panels more efficiently than human workers, allowing them to focus on achieving more complex tasks such as plumbing, and installing electrical, and HVAC systems.

5. AI for more Efficient Facility Management

AI-powered database systems can inform engineers on the best methods of on-site construction, based on preexisting information of blueprints and design from previous projects. Also, AI can be used in an administrative capacity, such as allowing employees to schedule leave days and input sick days, monitor deliveries of construction materials, and indicating delays.

This collection of huge amounts of data makes it perfect to use AI to adjust the construction project in question accordingly and automatically detect understaffed construction areas that might need more employees.

6. **Adopting Artificial Intelligence for Construction Solutions**

Artificial Intelligence's applications in building may become nearly endless as time goes on. With one of the largest consumer bases and a market worth billions of dollars, the addition of artificial intelligence to the civil engineering field helps solve many problems in design optimization, parameter estimation and identification, and damage detection in a sector that is still severely under-digitized. We are convinced that the continued use of artificial intelligence in civil engineering will result in a significant transformation in the construction industry.

7. **Artificial intelligence helps to alleviate labour shortages**
Construction companies are investing in AI and data science due to labour constraints and a drive to improve the industry's low productivity. Construction firms are beginning to employ artificial intelligence (AI) and machine learning to better arrange the distribution of manpower and equipment across jobs.

Project managers can instantly know which job sites have enough people and equipment to complete the project on time, and which are falling behind and might use additional personnel, thanks to a robot that is continually analyzing job progress and the placement of workers and equipment.

8. **Artificial Intelligence in Off-site construction**
Off-site workshops staffed by autonomous robots are increasingly being used by construction businesses to piece together building components, which are subsequently patched together on-site by human workers. Walls, for example, can be built more effectively on an assembly line by autonomous machinery than by humans, leaving human workers to handle the specific work such as plumbing, HVAC, and electrical systems once the building is put together.

Artificial Intelligence for post construction
Building managers can employ AI even after the project is finished. Advanced analytic and AI-powered algorithms offer useful insights into the operation and performance of a building, bridge, roads, and nearly anything in the built environment by gathering information about a structure using sensors, drones, and other wireless technologies. As a result, AI can be used to track developing issues, identify when preventative maintenance is required, and even direct human behaviour for maximum security and safety.

9. **Structural health monitoring in construction**

Structural Health Monitoring (SHM) is the process in which data is collected and evaluated to analyse and assess the vulnerabilities in the structural system or frame work. Bridges, pipelines, dams and various other large-scale infrastructure projects can be analyzed using the Structural health monitoring process. Genetic Algorithm (GA), a method of incorporating artificial intelligence can be used in synonymous with structural health monitoring to detect damages in the buildings. A successful application of the same is done in the Tamar Bridge project in the United Kingdom.

Figure 1.0: Tamar suspension bridge

In this case, rather than manual collection of data for detailed analysis, artificial intelligence techniques are used. From raw data acquired by artificial intelligence, important features can be learn by using a two-stage learning method.

i. Automatic feature extraction from structural vibration signals of the bridge is done using Nyström method in the first stage.

ii. Based on features that are extracted, health conditions of the bridge are classified using Moving Kernel Principal Component Analysis (MKPCA) in the second stage.

A study on three-storey framed aluminium structure of the bridge, the proposed health monitoring system proved good enough to analyse damages and overall bridge health.

APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN CIVIL ENGINEERING

On a general note, artificial intelligence has the following applications in civil engineering:

1. For estimating the percentage of soil moisture content and further classifications.
2. In the structural engineering field machine learning can be applied to detect damages using sensory or image data, identifying it's location and extent.
3. Improving productivity by reducing idle time.
4. For predicting maximum dry density and optimum moisture content in concrete.
5. Using image recognition for proper site monitoring, including aspects of safety and dangerous working conditions.
6. Identifying gaps and requirement of materials to cover the tasks without delay.
7. For travel time prediction and sign AI optimization in transportation engineering.
8. Efficient planning, designing and managing of infrastructure using Building Information Modelling (BIM).
9. Utilizing Artificial Neural Network for predicting properties of concrete mix designs.
10. To monitor activity in the construction site and predicting changes in the costing based on raw material market rates.
11. To analyse settlement of foundation and slope stability.
12. For monitor real time structural health of the building, giving warnings on when and where repair is required.
13. Helping in tidal forecasting to aid construction in marine environment.
14. Reducing errors in the project by automatic analysis of data.
15. To develop site layouts and predict risks as part of project management.
16. Finding a solution for damage related to pre-stressed concrete pile driving in foundation engineering.
17. To solve complicated problems in different stages of the project.
18. To make decisions in the design field.
19. In the construction waste management domain and handling of smart materials.

20. For expert monitoring and optimization if costs in the work system.

SHORTCOMINGS OF ARTIFICIAL INTELLIGENCE

Technology advancements have unquestionably made living easier. The construction industry, which had hitherto been immune to software intrusion, is suddenly changing. More advancement in artificial intelligence and machine learning concepts are expected in the following years! Technological breakthroughs are accompanied by an increase in cost. In the realm of building, artificial intelligence application necessitates periodic software upgrades.

A lack of job prospects for people is also a consequence of technology invasion. Artificial intelligence allows for the better replacement of manpower with robotic functions. Construction jobs are on the decline, and the present workforce will continue to be impacted.

Even though artificial intelligence has proven to be effective in reducing potential risks on the job, it has one major drawback: it can only execute the activities that it has been trained to accomplish. Trained manual employees, on the other hand, can use their brains to complete jobs by thinking outside the box. Complex algorithms relevant to the construction industry demand highly skilled employees and a significant amount of time to implement.

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