Lecture Notes in Civil Engineering

Limao Zhang
Yue Pan
Xianguo Wu
Mirosław J. Skibniewski

Artificial Intelligence in Construction Engineering and Management

Springer

Lecture Notes in Civil Engineering

Volume 163

Lecture Notes in Civil Engineering (LNCE) publishes the latest developments in Civil Engineering - quickly, informally and in top quality. Though original research reported in proceedings and post-proceedings represents the core of LNCE, edited volumes of exceptionally high quality and interest may also be considered for publication. Volumes published in LNCE embrace all aspects and subfields of, as well as new challenges in, Civil Engineering. Topics in the series include:

- Construction and Structural Mechanics
- Building Materials
- Concrete, Steel and Timber Structures
- Geotechnical Engineering
- Earthquake Engineering
- Coastal Engineering
- Ocean and Offshore Engineering; Ships and Floating Structures
- Hydraulics, Hydrology and Water Resources Engineering
- Environmental Engineering and Sustainability
- Structural Health and Monitoring
- Surveying and Geographical Information Systems
- Indoor Environments
- Transportation and Traffic
- Risk Analysis
- Safety and Security

To submit a proposal or request further information, please contact the appropriate Springer Editor:

- Pierpaolo Riva at pierpaolo.riva@springer.com (Europe and Americas);
- Swati Meherishi at swati.meherishi@springer.com (Asia - except China, and Australia, New Zealand);
- Wayne Hu at wayne.hu@springer.com (China).

All books in the series now indexed by Scopus and EI Compendex database!

More information about this series at http://www.springer.com/series/15087

Limao Zhang · Yue Pan · Xianguo Wu ·
Mirosław J. Skibniewski

Artificial Intelligence in Construction Engineering and Management

Springer

Limao Zhang
School of Civil and Environmental Engineering
Nanyang Technological University
Singapore, Singapore

Yue Pan
School of Civil and Environmental Engineering
Nanyang Technological University
Singapore, Singapore

Xianguo Wu
School of Civil and Hydraulic Engineering
Huazhong University of Science and Technology
Wuhan, Hubei, China

Mirosław J. Skibniewski
Department of Civil and Environmental Engineering
University of Maryland
College Park, MD, USA

ISSN 2366-2557 ISSN 2366-2565 (electronic)
Lecture Notes in Civil Engineering
ISBN 978-981-16-2841-2 ISBN 978-981-16-2842-9 (eBook)
https://doi.org/10.1007/978-981-16-2842-9

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Preface

The construction industry worldwide has been a late bloomer to adopting digital technology, where construction projects are predominantly managed with a heavy reliance on the knowledge and experience of construction professionals. Artificial intelligence (AI) works by combining large amounts of data with fast, iterative processing and intelligent algorithms (e.g., neural networks, process mining, and deep learning), allowing the computer to learn automatically from patterns or features in the data. It provides a wide range of solutions to address many challenging construction problems, such as tunnel-induced damages, risk estimates, and defect detection. A tremendous transformation has taken place in the past years with the emerging applications of AI in the construction industry. This enables industrial participants to operate projects more efficiently and safely, not only increasing the automation and productivity in construction but also enhancing the competitiveness globally.

This book highlights the latest technologies and applications of AI in the domain of construction engineering and management (CEM). Various AI techniques have been developed to make machines mimic human cognitive processes in terms of learning, reasoning, and self-correcting. Relying on the important AI approaches, we put emphasis on nine hot research topics of AI in CEM, including "Knowledge Representation and Discovery" (second chapter), "Fuzzy Modeling and Reasoning" (third chapter), "Time Series Prediction" (fourth chapter), "Information Fusion" (fifth chapter), "Dynamic Bayesian Networks" (sixth chapter), "Process Mining" (seventh chapter), "Agent-Based Simulation" (eighth chapter), "Expert Systems" (ninth chapter), and "Computer Vision" (tenth chapter). Different AI approaches have been proposed to achieve various kinds of functions which are beneficial to CEM in terms of automation, safety, reliability, and digitalization. These applications serve as evidence to verify that AI techniques have created tremendous value in revolutionizing the construction industry, leading to a more reliable, automated, self-modifying, time-saving, and cost-effective process of CEM.

This book expects to (1) reveal complexities in conducting CEM activities and unlock the potential of incorporating AI in supporting and improving CEM; (2) display procedures and algorithms in a detailed manner on how to use AI to discover knowledge and address CEM challenges; (3) present evidence-based practices to highlight the benefits of AI techniques in providing intelligent solutions by learning from multiple data resources in an automatic, efficient, and reliable manner; and (4) improve the understanding of the current development and prominent future works in AI-enabled CEM and promote the more widespread leverage of AI in CEM.

This book is an interesting reference for scientists, engineers, and graduate students in various disciplines, including but not limited to civil engineering, artificial intelligence, system science, mathematics, etc.

Singapore — Limao Zhang
Singapore — Yue Pan
College Park, USA — Mirosław J. Skibniewski
Wuhan, China — Xianguo Wu
February 2021

Acknowledgements It is our sincere desire to thank the anonymous peer reviewers for this work. We further want to thank Dr. Leilei Chang, Mr. Kai Guo, Ms. Ying Wang, and Ms. Weiyi Chen, who are postdoctoral research fellows or Ph.D. candidates at the School of Civil and Environmental Engineering, Nanyang Technological University, Singapore, for their cooperative research and assistances with gathering literature in some of the methods and theories considered.

Contents

Introduction to Artificial Intelligence

1 What Is AI

The term Artificial Intelligence (AI) is a branch of computer science to make computers perform human-like tasks, and thus, computers can appropriately sense and learn inputs for perception, knowledge representation, reasoning, problem-solving, and planning. Various types of innovative AI technologies are designed to imitate the cognitive abilities of human beings, which can, therefore, deal with more complicated and ill-defined problems in an intentional, intelligent, and adaptive manner. Typically, AI can be regarded as a conjunction of machine learning and data analytics. That is to say, machine learning algorithms, a subset of AI, learn sufficiently robust data from multiple sources and then act on the insights of data to make smart decisions adaptively [16]. The investment in AI is experiencing rapid growth, in which machine learning particularly accounts for a major proportion. According to a report from Accenture company, AI is already altering every walk of life, which heralds dramatic potential to boost labor efficiency by 40% and double annual economic growth rates in 2035 [11]. For the purpose of making AI live up to expectations, more and more companies are actively investing in various AI technologies, which put AI into a sharper focus and extend its application scope [2]. As AI talent continues to mature and be applied, it is believed that the topic of AI can become the next digital frontier to drive the increase of automation and intelligence.

1.1 AI Development

AI is not a completely new concept. Its development has gone through three major stages [3]. The early golden age of AI research is during 1956–1974. The name "artificial intelligence" made its advent at the 1956 Dartmouth Conference. Since

L. Zhang et al., *Artificial Intelligence in Construction Engineering and Management*, Lecture Notes in Civil Engineering 163,
https://doi.org/10.1007/978-981-16-2842-9_1

then, researchers have emphasized adopting algorithms to solve mathematical problems and geometrical theorems. However, the very limited data volume and computer memory at that time caused difficulties to create intelligence in machines. The second wave occurred from 1980 to 1990 along with the emergence of expert systems. It is known that expert systems can logically mimic human behavior and knowledge to realize decision making at a high degree of expertise, which is the predecessor of current machine learning and deep learning. However, building an expert system is not a straightforward task, which requires a lot of time and cost to prepare a reliable knowledge base by extracting sufficient rules from human experts. Besides, this system is only suitable for narrow problems and its results are even mistakable. Since the late 1990s, AI is booming again with the help of exponential growth of data, computing power and storage, and more advanced algorithms.

The current AI has moved to a remarkable level, leading to dramatic breakthroughs in categories like machine learning, deep learning, computer vision, natural language processing, virtual assistants, robotic process automation, and others. As a result, AI can power many aspects of society by offering new opportunities for intelligent agents, automated data analytics, and improved decision making in diverse domains, including business, robotics, transportation, healthcare, education, manufacturing, and others. This book mainly presents and discusses how AI is transforming the construction industry for delivering smarter construction management.

1.2 AI Techniques

Many AI techniques have been developed to make machines mimic human cognitive processes in terms of learning, reasoning, and self-correcting. In other words, with the help of AI techniques, machines can perform tasks under a certain degree of intelligence. There are many ways to classify various developed AI techniques. Herein, we category them into five major groups, as illustrated in Fig. 1.

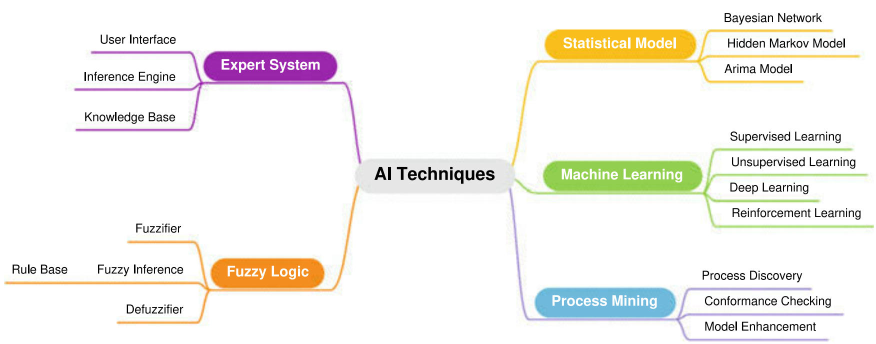

Fig. 1 An overview of common AI techniques

Expert systems: An expert system is a straightforward and understandable method towards intelligent decision making, which contains possible expert knowledge and reasoning to address complicated problems. The earliest expert system was developed in 1965, which achieved the first success of AI. Three essential components are included in an expert system, namely the knowledge base, user interface, and inference engine. More specifically, the knowledge base is a database of information, notions, and rules prepared by different experts in a specific domain. The IF-THEN-ELSE rule is widely used to organize the collected knowledge. More high-quality knowledge will improve the system's performance. The user interface offers the interaction between non-expert users and the expert system to present questions and input data to start the decision-making process in the inference engine. Finally, the inference engine acts as a brain of the system to efficiently deduct reliable solutions based on factual and heuristic knowledge stored in the base.

Fuzzy logic: As a proposal of fuzzy set theory, fuzzy logic was put forward in the early 1960s to handle uncertainty and ambiguity in human language. It offers flexible decision making as similar to human reasoning. In other words, it can deal with input data in vagueness, uncertainty, impreciseness, and incompleteness through converting them into computer understandable forms, and then make responses based on a set of fuzzy rules. The fuzzy logic architecture contains the following parts. The fuzzifier transforms the crisp number into fuzzy sets using membership functions. Then, the fuzzy inference is responsible for the decision process, which conducts the computational procedure to identify the match between the fuzzy inputs and rules. In particular, rules stem from the rule-based expert knowledge, which can be flexibly added and removed from the system. They help to determine the relationship between fuzzy inputs and outputs. Lastly, the defuzzifier converts the fuzzy output back to a crisp number. Since the mathematical concept of fuzzy logic is relatively simple, this method is easy to implement and understand. Moreover, fuzzy logic has been commonly incorporated into the expert system to design the fuzzy expert system [5].

Statistical model: Statistical models employ mathematical equations to inference the relationship between variables, which often implement statistical approaches under certain assumptions to make an inference, like hypothesis testing, confidence intervals, and others. For instance, the Bayesian network, the hidden Markov model, and the autoregressive integrated moving average (ARIMA) model are three typical statistical models. To be specific, the Bayesian network, also known as belief networks, is a kind of probabilistic graphical model to capture casual relations in variables. Its focal points lie in the probability representation to measure the uncertainty. In addition, a method of statistical inference named Bayesian inference can be realized in the forward and backward directions based on the Bayes' theorem, in order to update the network when more evidence is fed in. The hidden Markov model is a statistical Markov model based on the Markov chain, which can consider both the observed and hidden events to calculate the probability distribution over a sequence. The ARIMA model is specialized in time series forecasting. It explains the lagged observation of time series to predict the future value, which is expressed by the form of regression.

Machine learning: Machine learning is a great step of AI to enable machines to have powerful learning abilities from data. Various algorithms are programmed to access data and learn by themselves from these large volumes of available data with no human involvement. That is to say, machine learning aims to teach machines how to discover patterns hidden in large data and realize data-driven predictions on future tasks. Supervise and unsupervised learning are the two main categories belonging to machine learning. The significant difference between these two methods is that supervised learning requires labeled data to create future predictions, while unsupervised learning tries to reveal hidden structures from unlabeled data. As machine learning evolves, deep learning and reinforcement learning have been developed at a higher level to be a new trend. Deep learning is inspired by the neural networks of human brains, which is made up of multiple processing layers to process information, represent features, and gain knowledge. It is skilled in detecting intricate structures in high-dimensional data, which has dramatically improved the state-of-art models in natural language processing, computer vision, and others. As for reinforcement learning, it interacts with the environment to generate trial and error, resulting in suitable actions and decisions sequentially to maximize reward. In other words, it faces a game-like situation, where the next input depends on the output of the previous input.

Process mining: Process mining is still a young discipline to bridge the gap between process management and data science, which incorporates the process aspects into machine learning and data mining. It mainly explores event log data with the intent of monitoring, diagnosing, analyzing, and improving the actual process. In general, three basic tasks are carried out by process mining. It begins with the automated discovery of process models from event logs with the help of proper algorithms. Afterward, conformance checking pairs the process model with the event log to check compliance, detect deviations, and predict bottlenecks, in order to provide guidance to optimize the complicated process. Besides, model enhancement can implement more data analysis methods to provide insights into other aspects of the operation rather than the process perspective. In short, process mining takes full advantage of event logs to create full transparency on processes, which can inform strategic decisions to raise the process efficiency and reliability.

2 What Is CEM

To ensure the resiliency and success of the construction industry, construction engineering and management (CEM) highlights the significant contribution of theoretical and technical knowledge in addressing key aspects of the infrastructure construction project. CEM can be conceived as an executive process of the physical work on the construction site [10]. Architectures, engineers, constructors, contractors, and others work together to provide professional services in constructing buildings for residential, commercial, or industrial applications and solving on-site problems.

2.1 Significance of CEM

Since the assembly process is made up of several order events, there are complicated patterns of individual time requirements along with restrictive sequential and cooperative relationships among the project's many segments embedding in such process [13]. The common interest of CEM chiefly arises from the following two sides.

For one thing, construction, as a large sector of the economy, plays a prominent role in driving economic growth and long-term national development [4]. According to a survey from McKinsey Global Institute in 2017, the global construction industry makes up around 13% of the world's Gross Domestic Product (GDP) and this number is projected to rise to 15% in 2020. Meanwhile, construction projects create a broad range of job opportunities for 7% of the world's working population. Despite its economic importance, an obvious issue is poor labor productivity during the construction procedure, negatively leading to the waste of manpower, material resources, and financial resources. Since construction activities contribute a lot to our society economically, it makes the most sense to take proper construction management to improve product performance. If the construction productivity is enhanced by as much as 50% to 60% or higher, it is estimated to bring an additional $1.6 trillion into the industry's value each year and further boost the global GDP.

For another, construction with inherent complexity is one of the most dangerous industries worldwide, which is greatly susceptible to a variety of unpredictable factors, such as participants in different roles, the changeable environment in large uncertainty, and others [12, 15]. It is likely for workers to be exposed to a great threat to health, and thus, they may suffer from mechanical injuries, degenerative disorders, chemical hazards, psychosocial stress, and others [7]. Therefore, the construction industry tends to cause a small scale of fatal accidents with higher frequency than other domains, which is even responsible for 30–40% of fatalities worldwide [21]. In the Chinese construction market, the number of construction accidents and fatalities remains stubbornly high [17, 18]. Numerous researches have revealed that safety issues are tied up with management, emphasizing the necessity of construction management for safety control and accident prevention [8]. Through identifying, evaluating, and reacting to the potential risk in dynamic construction work at an early stage, it is expected to eliminate safety hazards and then achieve a sustainable reduction in fatalities in the construction industry.

2.2 Activities in CEM

CEM is consisting of a series of physical activities for constructing infrastructures, residential and commercial buildings, which can be defined as a completed process including designing, scheduling, budgeting, building itself. All sorts of construction projects require appropriate management over the lifetime of a project, in order to guide the project towards success under the control of time, cost, scope, quality, and collaboration. Project managers are responsible for project management, who coordinate closely with other participants to draw up plans, schema, timelines, costs, personnel arrangements, and others. They monitor the entire progress of work and concentrate on all aspects of the project (i.e., labor, capital, time, equipment, material, risk), in order to give back corresponding instructions to lower the possibility of delays, budget overruns, high risks, and great conflicts. In short, the main activities in CEM can be categorized into three major phases of construction as follows.

(1) **Planning**

Prior to the start of physical construction, the conception of the project is proposed by clients. Then, its feasibility is analyzed comprehensively to clear the project objectives. For meeting such a specific goal, detailed plans for the project development are created in terms of resources, schedules, budgets, and dependencies, which can potentially help in reducing cost, duration, and irrational process in the practical project. For instance, the schematic design can be drawn to fully describe the building systems. Scheduling can chronologically distribute multiple activities, and then assign dates, workers, and resources to a certain activity. It aims to fit the plan to a reasonable time scale and workflow. Cost estimation is the process of predicting the needed funds and resources for conducting a project within a defined scope. That is to say, the planning phase incorporates activities mainly for forming project plans, drawing design, and allocating labors, sources, and time. These activities assist in rationally streamlining the construction process. They can serve as a reference to monitor the actual process and guide it to be finished punctually within the estimated budget.

(2) **Construction**

This is a phase of executing the physical construction, and thus, the planning made at the previous phase is expected to pay off. For construction workers, they are the manual labor to perform the on-site construction, who conduct a range of basic tasks in a general sequence, including layout marking, excavation, foundation work, column casting, wall construction, lintel, roofing, plastering, fixing of doors, windows, electrical and plumbing works, tiles laying, painting, and others. Some skilled workers are also needed to operate sophisticated machine tools. Regarding project managers, they take charge of the on-site monitoring and assessment. That is to say, managers oversee the actual construction process in terms of scope, budget, and schedule, and then compare the observations to the formed planning. If an inconsistency is detected, the corresponding action can be enacted to bring the process back into conformance or adjust plans to cope with changes. Moreover, managers are also expected to identify the exposure of risk and the associated impact on the performance, schedule, or budget of projects. Furthermore, both the qualitative and quantitative risk analysis can be carried out for quality control, which provides a better understanding of the risk factors and their effects. As a result, timely responses can be created to proactively address the potential issues, which can eventually minimize the risk before it occurs.

(3) **Operation and Maintenance (O&M)**

When construction is completed, the project will enter a new phase named O&M. It is known that O&M takes most of the time within the lifecycle, leading to a large amount of cost accounting for around 60% of the total project budget [6]. The goal of O&M is to operate and maintain a constructed facility to meet the anticipated functions over its lifecycle, which is crucial to ensure the safety and comfort of users. Operation means the provision of day-to-day services to operate and control the facility in an efficient, economical, and reliable manner. Maintenance aims to minimize the possibility of system failure, which can be conducted from two aspects. To be more specific, preventive maintenance creates plans and schedules to adjust and guide the ongoing operation on a regular basis. It is useful in detecting the potential risks, and thus, corresponding actions can be timely taken prior to unexpected events. In contrast, corrective maintenance is implemented after problems have occurred. It strives to repair the problematic parts to get them back on the normal status as quickly as possible. Moreover, recent attention in O&M has focused on sustainability. The execution of O&M must obey some energy regulations and standards to make the facility run long-termly, safely, and energy-savingly. As a result, proper O&M is proven to benefit the facility management a lot, such as to shorten response time to issues, reduce unnecessary repairs, drive down costs, maximize the asset value, and mitigate potential risk, which can eventually prolong the lifespan of the facility and improve the users' satisfaction.

2.3 Characteristics of CEM

Since a construction project is unique, temporary, and progressive in nature for producing the desired objectives, CEM can be considered as a process to handle a series of interrelated tasks over a fixed period within certain limitations. The key characteristics of CEM are outlined from the following five points.

(1) **Uniqueness**

Due to the differences in client requirements, project size, conditions, influences, and constraints, the construction projects differ from one another to enhance the difficulty of project management. That is to say, we cannot simply replicate the scheduling, design scheme, budget, and logistics of an existing project to a new one. Instead, it only allows us to learn from previous projects with similar features to make decisions on the current project. It should be noted that the construction project is very technical and characteristically unique, and thus, a highly customizable solution is deemed as a necessity to ensure the reliability and efficiency of the project. In addition, individuals with differing roles, including designers, engineers, suppliers, contractors, managers, and other service providers are temporarily organized in a project. It means that each project is carried out by a unique team, and each team has its characteristics regarding participants' skills, knowledge, experience, communication, and collaboration.

(2) **Labor-intensive**

Typically, a huge amount of manual labor should be required in a construction project, who can offer great quantities of physical effort in charge of the project implementation, timely completion, and quality assurance. In general, the proportion of labor costs can take up 30–60% of the total project budget, indicating that intensive labor is a critical component in construction. These flexible workforces can be accommodated to the changeable projects dynamically based on their initiative and problem-solving ability. It has been found that 40 million workers were employed in the construction sector in the year 2007, among whom 27% was skilled labor, 55% represented the unskilled labor, and the rest denoted the support staff [7]. Currently, there is fast growth in the demand for skilled and semi-skilled workers with more skills and expertise, since they play an important role in improving the performance and productivity of construction projects. In other words, this kind of labor force can provide useful information and techniques to drive the project forward more easily, efficiently, and safely.

(3) **Dynamics**

Although a project has been clearly defined from the beginning to the end, the actual execution of the project is unable to always stick to the plan. That is to say, inevitable changes or adjustments occur dynamically throughout the whole lifecycle of the project, which are caused by various reasons. For instance, the project alternatives need to be reformulated due to some human factors, including clients' dissatisfaction, designers' and engineers' mistakes, financial problems from contractors, and others. Moreover, unforeseen conditions resulting from the undesired delays, bad weather, complex geologic environment, additional demands of labor, equipment, materials, and others are the major causes of changes. Besides, when additions or reductions are applied to the project scope, the scheduling and budget should be updated accordingly to adapt to the changing circumstances. It is known that managing changes properly is the guarantee of success in a construction project, and thus, project managers need to flexibly identify changes, cope with dynamics, and perform effective controls.

(4) **Complexity**

The complexity of construction projects can arise from two aspects, namely the task and participants. For one thing, construction tasks are heavy and diverse, which can possibly meet conflicting scheduling or performance problems. Therefore, it is not a straightforward job to formulate proper scheduling to align interconnected tasks, resources, and teams. To make the operation process run smoothly, a variety of factors, such as safety, security, environment, weather, workers, and others, should be taken into full consideration. The strict time limit can even negatively boost the pressure in executing the planned tasks. When some unexpected things happen in the construction process, there is no enough time to consider solutions [20]. Additionally, although the advanced technologies and new materials are adopted for more sustainable development, they can possibly contribute to a higher degree of complexity. For another, groups of workers in different roles and varying proficiencies are commonly involved, who can work together, communicate, and share information with each other. This kind of multi-disciplinary collaboration will result in intricate interactions in individuals and tasks. Besides, they tend to have conflicting business interests, and thus, negotiations are needed to pursue the common goal.

(5) **Uncertainty**

Uncertainties are unknown before they actually occur, which can be regarded as threats to unfortunately raise risk in project failure. Notably, a high level of uncertainty is inherent in complicated construction projects, which is closely related to various factors [19]. For instance, before the site construction, scheduling and cost need to be estimated reasonably under great uncertainty. The improper estimation will impede the progress of the project. As for the architecture design, some questions remain to be answered, such as whether the design can pass audits, whether clients are satisfied with the design, and others. Moreover, a great deal of unavoidable uncertainty exists in the construction phase, such as the ground conditions, soil-structure interaction, weather conditions, building material properties, design changes, the reliability of suppliers, and others. If these uncertainties can be detected and measured at an early stage, the project management can be optimized to act as a reliable tool in mitigating potential risk in the construction project.

3 How AI Benefits CEM

Although AI stands out as transformational technology to potentially bring about unprecedented changes in our work and life, its applications in CEM with the nature of complexity, uncertainty, and dynamics are still in its infancy. In the immediate future, the construction industry is projected to increase more focus and investment in AI to catch up with the fast pace of automation and digitalization [9]. With the advent of the building information modeling (BIM) and wireless sensor network (WSN), huge amounts of data can be collected from the worksite every day along with some features of "big data", which yield great values to CEM. AI techniques can, therefore, be deployed in a range of ways to improve the performance of construction projects. In other words, AI has proven to take advantage of such rich data sources to train suitable models and then deliver on its promises, such as prediction, optimization, decision making, and others. The substantial benefits of AI in CEM can be outlined as follows.

- **Automation**. AI drives the process of project management more technically automatable and objective. Conventional construction management is heavily based on experts' knowledge, experience, and subjective judgment, which is more prone to bias and confounding. To overcome these distinct disadvantages, AI-based solutions are taken into account to pursue smart control. For instance, machine learning algorithms can be employed to intelligently handle the mass of accumulated data and discover hidden knowledge. The insights gained from advanced analytics help managers to better understand the construction project and rapidly spot the project concerns in a data-driven manner. These advanced algorithms have also been integrated into project management software, aiming to automate the complete procedure for data analysis and decision making. As for on-site construction monitoring, drones and sensors are utilized to automatically record data and take images/videos for scanning, monitoring, and mapping the construction status, environment, and progress, which offer a more comprehensive picture of the site through various project stages without human interaction. That is to say, evidence obtained by such techniques can replace the traditional manual observation which tends to be time-consuming, tedious, and error-prone.

- **Risk Mitigation**. AI can monitor, recognize, evaluate, and predict potential risks in terms of safety, quality, efficiency, and cost across teams and work areas. In the risk and uncertainty analysis, AI tools based on probabilistic models, fuzzy theory, machine learning, neural networks, and others equip computers with the capability to efficiently learn data collected from the construction site. Thus, computers can explore much more risk-related data than humans could ever review from both the qualitative and quantitative perspectives. In consequence, these identified risks provide assistive and predictive insights on critical issues, and thus, project managers can quickly prioritize possible risks and concentrate on them to take proactive actions instead of reactions for risk mitigation, such as to streamline operations on the job site, adjust staff arrangement, and keep projects on time and budget. In other words, AI presents valuable opportunities to realize early troubleshooting to prevent undesirable failures and accidents in the complex project management [1]. Additionally, robots can take charge of unsafe activities, in order to minimize the number of humans working in dangerous environments.
- **High Efficiency**. AI allows for optimizing the construction process, in order to make the project run smoothly and finish on time and reliability. For instance, process mining is a new AI-enabled approach to generate valuable insights into the complicated construction, such as to track key workflows, predict deviations, detect invisible bottlenecks, extract collaboration patterns, and others. The discovered knowledge is critical to project success, which can guide the optimization of the construction execution process. It is expected to avoid unnecessary steps, reworks and conflicts, potential delays, and poor cooperation. In turn, tactic decisions can be made for trouble-shooting at an early stage, driving the improvement of operational efficiency. It is also effective in preventing costly correction at the remaining stage. Moreover, AI-powered robots and autonomous systems have been directly adopted on construction site. Since they can potentially replace human workers to take over the repetitive and routine construction tasks, such as bricklaying, welding, tiling, and others, they can be an ideal solution to address labor shortages. Besides, they are able to work continuously without taking a break at almost the same rate and quality, indicating that the proper use of smart machinery will ensure efficiency, productivity, and even profitability.
- **Digitalization**. It should be noted that BIM provides a pool of information concerning planning, construction, operation, and management, which has gone far more than the 3D modeling to support various digital solutions. In other words,

BIM has been considered as a digital backbone of future construction, which can be reasonably integrated into AI to facilitate the digitalization of construction projects. For BIM, it can provide a platform for not only collecting large data about all aspects of the project, but also sharing, exchanging, and analyzing data in real-time to realize in-time communication and collaboration among various participants. Thus, all members have immediate access to the latest documents and information, who can cooperatively examine the shared rich data sources. For the AI techniques, they can deeply explore these massive amounts of data from BIM to automate and improve the construction process. Based on the discovered knowledge, strategic decisions can be informed for streamlining the complicated workflow, shortening operation time, cutting costs, reducing risk, optimizing staff arrangement, and others. In addition, the integration of BIM and AI can move the paper-based work towards online management. For one thing, it can deliver the most efficient and effective information to keep continuous updating of the ongoing project. For another, it can take advantage of BIM data to make real-time analysis, and thus, immediate reactions can be performed without delays to prevent unexpected events.

- **Computer Vision**. Computer vision techniques have gradually taken the place of the laborious and unreliable visual inspection in civil infrastructure condition assessment. Current advances in computer vision techniques lie in the deep learning methods based on neural networks to automatically process, analyze, and understand data in images or video through end-to-end learning, which can conduct various tasks, like image classification, object detection, semantic segmentation, and others. Towards the goal of intelligent management in the construction project, computer vision plays an important role in two perspectives, which are inspection and monitoring applications [14]. To be more specific, inspection applications perform automated damage detection, structural component recognition, unsafe behavior, and condition identification. Monitoring applications are non-contact methods to capture a quantitative understanding of the infrastructure status, such as to estimate strain, displacement, and cracks' length and width. To sum up, the vision-based methods in CEM are comparatively cost-effective, simple, efficient, and accurate, which are useful in robustly translating image data into actional information for the purpose of structural health evaluation and construction safety assurance.

4 Organization of the Book

This chapter briefly introduces the concept, development, and techniques of AI and reviews activities, characteristics, and significance of CEM. The substantial benefits of AI in CEM are summarized.

Chapter "Knowledge Representation and Discovery" describes the knowledge representation and discovery and the relevant application in CEM. Many types of knowledge representation and discovery methods are reviewed. One promising method, Structural Equation Model (SEM), is chosen to discover casual relationships underlying safety leadership in construction. A model consisting of 5 latent variables and 26 observed variables is established to learn from data and reveal relationships between different stakeholders' leaderships and construction safety performance. The hypotheses are testified, and the overall model fit is assessed. Impacts of path coefficients, stakeholder participation, and construction dynamics are investigated.

Chapter "Fuzzy Modeling and Reasoning" describes fuzzy modeling and reasoning and its application in CEM. Many types of fuzzy modeling and reasoning methods are reviewed. One outstanding method, Fuzzy Cognitive Maps (FCM), is selected to assess Tunnel Boring Machine (TBM) performance and perform Root Cause Analysis (RCA) in case of unsatisfactory performance. FCM is able to capture and utilize construction experience and knowledge from domain experts, and a cause-effect model consisting of nine concepts is established for simulating the TBM performance. A tunnel case in the Wuhan metro system in China is used to demonstrate the applicability of the developed approach. It is verified to be capable of modeling the dynamics of system behaviors over time and performing many kinds of what-if scenario analysis, including predictive, diagnostic, and hybrid RCA. It turns out to be a more competitive solution that deals with uncertainty, dynamics, and interactions in the approximate reasoning process.

Chapter "Time Series Prediction" describes the time series analysis technique and its application in CEM. Several common time series analysis methods are reviewed. A novel hybrid approach that integrates Wavelet Packet Transformation (WPT) and Least Squares Support Vector Machines (LSSVM) is presented to enhance the accuracy and reliability in time series analysis and prediction. It is used to estimate the magnitude of the tunnel-induced ground settlement over time. The original time-domain signals (i.e., the measured settlements over a time period) are decomposed into a series of sequences using WPT, while LSSVM models are then built to predict the target sequences within high- and low-frequency regions. A realistic tunnel case is utilized to demonstrate the feasibility and applicability of the proposed WPT-LSSVM approach. Results indicate the proposed approach can achieve a higher accuracy and reliability than the traditional time series analysis approaches.

Chapter "Information Fusion" describes the information fusion technique and its application in CEM. Several common information fusion methods are reviewed. A novel multi-classifier information fusion approach that integrates the probabilistic support vector machine (SVM) and the improved Dempster-Shafer (D-S) evidence theory is proposed. It is implemented to fuse classification results provided by the base classifiers at the decision level for an overall risk evaluation. The proposed approach is utilized to perform structural health assessment in operational tunnels. Results indicate that the proposed approach exhibits more outstanding classification performance and can efficiently fuse multi-sensory information with ubiquitous uncertainties, conflicts, and biases.

Chapter "Dynamic Bayesian Networks" describes network modeling and analytics in CEM using AI. An excellent method, dynamic Bayesian network (DBN), is highlighted, as DBN is able to model construction dynamics and update the system status given new observations. Differences between the Bayesian network

(BN) and DBN are reviewed. A DBN model consisting of various geological, design, and mechanical variables is developed to reveal dynamics in tunnel-induced damages over time. Results testify that the developed model is capable of performing feed-forward, concurrent, and back-forward control respectively on a quantitative basis.

Chapter "Process Mining" describes process mining and its application in CEM. Process mining is regarded as an emerging data mining method, which leverages various algorithms and mathematical models for the visualization and investigation of event logs and assists in discovering, evaluating, and improving the existing process. Process mining is applied to deeply mining large volumes of event logs in BIM project execution, aiming to improve the understanding and efficiency of the operation process in the BIM-enabled project. A framework of process mining on BIM event logs with step-by-step procedures is presented, where in-depth knowledge discovery is conducted in terms of the process discovery, conformance checking, social network analysis, and decision tree classification.

Chapter "Agent-Based Simulation" describes the agent-based simulation for improved decision support in CEM. Agent-based simulation provides a near-real solution to perform various what-if experimental scenario analysis, given some experiments are impossible or hard to be conducted in reality, such as pedestrian evacuation under an emergency. Several common methods in the agent-based simulation are reviewed in this chapter. The promising social force model which can reflect the anisotropic characteristics and dynamic features of pedestrian interaction is selected to simulate and optimize pedestrian evacuation behaviors in a subway station. Several route planning strategies are modeled in the simulation environment and validated by actual observations. The developed approach can provide valuable theoretic and practical insights into a deep understanding of route planning strategies during the pedestrian evacuation, and thus, the improvement of safety and economic objectives can further be achieved in the design or re-design of metro evacuation systems.

Chapter "Expert Systems" describes the expert system technique and its application in CEM. The expert system provides a powerful tool for knowledge integration and autonomous inference mechanism, which can solve complex problems to significantly reduce dependence on domain experts. Considered as a digital representation of physical and functional characteristics of a facility, BIM has the capability of generating, storing, exchanging, and sharing the building information in an interoperable and reusable way, providing an ideal solution for risk management. A novel approach integrating BIM and expert systems is proposed to perceive the safety risk at an early stage of the construction. Both case-based reasoning and rule-based reasoning techniques are combined in the inference model to improve the flexibility and comprehensiveness of the system reasoning capacity.

Chapter "Computer Vision" describes computer vision and its application in CEM. Deep learning techniques are driving advances in computer vision, and different types of deep learning techniques are reviewed in this chapter. A novel computer vision approach named a spatial-channel hierarchical network (SCHNet) is proposed to support the automated and reliable concrete crack segmentation at the pixel level.

It not only considers the semantic interdependencies in spatial and channel dimensions, but also adaptively integrates local features into their global dependencies. Experimental results indicate that SCHNet can outperform state-of-the-art models. It is robust to noises with a better generalization ability under various conditions, including shadows, rough surfaces, and holes.

Chapter "Conclusions and Future Directions" summarizes the conclusions and points out future directions. The AI's functions of modeling and pattern detection, prediction, and optimization are highlighted, which create tremendous value in revolutionizing the construction industry, leading to a more reliable, automated, self-modifying, time-saving, and cost-effective process of CEM. Several emerging applications of AI in CEM are put forward, which pave a more affordable and effective way to relieve the burden on manual labor and facilitate smart construction in CEM.

References

1. Chang L, Zhang L, Fu C, Chen YW (2021) Transparent digital twin for output control using belief rule base. IEEE Trans Cybern 1–15
2. Chui M (2017) Artificial intelligence the next digital frontier? McKinsey Comp Glob Inst 47(3):6
3. De Spiegeleire S, Maas M, Sweijs T (2017) Artificial intelligence and the future of defense: strategic implications for small- and medium-sized force providers. The Hague Centre for Strategic Studies
4. Giang DT, Pheng LS (2011) Role of construction in economic development: review of key concepts in the past 40 years. Habitat Int 35:118–125
5. Hassanzad M, Orooji A, Valinejadi A, Velayati A (2017) A fuzzy rule-based expert system for diagnosing cystic fibrosis. Electron Physician 9:5974
6. Hu Z-Z, Tian P-L, Li S-W, Zhang J-P (2018) BIM-based integrated delivery technologies for intelligent MEP management in the operation and maintenance phase. Adv Eng Softw 115:1–16
7. Kulkarni G (2007) Construction industry: more needs to be done. Indian J Occup Environ Med 11:1–2
8. Li X, Yi W, Chi H-L, Wang X, Chan AP (2018) A critical review of virtual and augmented reality (VR/AR) applications in construction safety. Autom Constr 86:150–162
9. Pan Y, Zhang L (2021) Roles of artificial intelligence in construction engineering and management: a critical review and future trends. Autom Constr 122:103517
10. Pheng LS, Hou LS (2019) The economy and the construction industry. In: Construction quality and the economy. Springer, pp 21–54
11. Purdy M, Daugherty P (2016) Why artificial intelligence is the future of growth. In: Remarks at AI now: the social and economic implications of artificial intelligence technologies in the near term, pp 1–72
12. Sacks R, Rozenfeld O, Rosenfeld Y (2009) Spatial and temporal exposure to safety hazards in construction. J Constr Eng Manag 135:726–736
13. Sears SK, Clough RH, Sears GA (2008) Construction project management: a practical guide to field construction management. Wiley
14. Spencer BF Jr, Hoskere V, Narazaki Y (2019) Advances in computer vision-based civil infrastructure inspection and monitoring. Engineering 5:199–222
15. Waehrer GM, Dong XS, Miller T, Haile E, Men Y (2007) Costs of occupational injuries in construction in the United States. Accid Anal Prev 39:1258–1266

16. West DM, Allen JR (2018) How artificial intelligence is transforming the world. Report, 24 Apr 2018
17. Wu C, Song X, Wang T, Fang D (2015) Core dimensions of the construction safety climate for a standardized safety-climate measurement. J Constr Eng Manag 04015018
18. Zhang L, Wu X, Zhu H, AbouRizk SM (2017) Perceiving safety risk of buildings adjacent to tunneling excavation: an information fusion approach. Autom Constr 73:88–101
19. Zhang L, Wu X, Zhu H, AbouRizk SM (2017) Performing global uncertainty and sensitivity analysis from given data in tunnel construction. J Comput in Civ Eng 31(6):04017065
20. Zhang L, Wu X, Chen Q, Skibniewski MJ, Hsu SC (2014) Towards a safety management approach for adjacent buildings in tunneling environments: case study in China. Build Environ 75:222–235
21. Zhou Z, Goh YM, Li Q (2015) Overview and analysis of safety management studies in the construction industry. Saf Sci 72:337–350

Knowledge Representation and Discovery

1 Introduction

Construction is one of the most dangerous industries worldwide, leading to a common interest in improving construction safety performance due to humanitarian reasons and rising costs of worker compensation. Numerous researchers suggested the continuous unsafe conditions were mainly because of a misalignment of management commitment and stakeholders' actions, that is, lack of safety leadership [15]. Effective leadership plays an important role in ensuring the success of temporary construction onsite organizations that are facing a high degree of uncertainty. Strong safety leadership should be the key to enhancing construction safety performance.

Safety leadership has emerged within the Occupational Health and Safety (OHS) literature as a key construct in construction safety management [31]. Many industrial participants/stakeholders are involved in safety issues in construction, and effective collaboration of those stakeholders can contribute to ensuring construction safety performance. Zuofa and Ocheing [32] pointed out that senior managers had played important role in safety leadership by assisting in effective safety management. Other important participators include the owner (O), the contractor (C), the supervisor (S), and the designer (D). Romero et al. [22] summarized that the collective professionalization by multiple stakeholders was the key to strengthening the safety and leadership in the construction industry. The relationship between those safety-related internal and external factors within different stakeholders in construction projects has not been fully investigated.

A long debate on the allocation of duty and responsibility for construction safety management among main stakeholders exists. Wu et al. [27] concluded that the owner's greatest leverage was the leadership to influence safety perception, motivation, and behavior of other stakeholders. Hadidi and Khater [9] emphasized the significance of selecting contractors at the bidding stage to assure loss prevention and better safety orientation during project implementation. Conchie et al. [5] highlighted the importance of supervisors' safety leadership in promoting construction

L. Zhang et al., *Artificial Intelligence in Construction Engineering and Management*, Lecture Notes in Civil Engineering 163,
https://doi.org/10.1007/978-981-16-2842-9_2