

Systematic review of application of artificial intelligence tools in architectural, engineering and construction

Artificial
intelligence
tools

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Abstract

Purpose – This study reviews the extent of application of artificial intelligence (AI) tools in the construction industry.

Design/methodology/approach – A thorough literature review (based on 165 articles) was conducted using Elsevier's Scopus due to its simplicity and as it encapsulates an extensive variety of databases to identify the literature related to the scope of the present study.

Findings – The following items were extracted: type of AI tools used, the major purpose of application, the geographical location where the study was conducted and the distribution of studies in terms of the journals they are published by. Based on the review results, the disciplines the AI tools have been used for were classified into eight major areas, such as geotechnical engineering, project management, energy, hydrology, environment and transportation, while construction materials and structural engineering. ANN has been a widely used tool, while the researchers have also used other AI tools, which shows efforts of exploring other tools for better modelling abilities. There is also clear evidence of that studies are now growing from applying a single AI tool to applying hybrid ones to create a comparison and showcase which tool provides a better result in an apple-to-apple scenario.

Practical implications – The findings can be used, not only by the researchers interested in the application of AI tools in construction, but also by the industry practitioners, who are keen to further understand and explore the applications of AI tools in the field.

Originality/value – There are no studies to date which serves as the center point to learn about the different AI tools available and their level of application in different fields of AEC. The study sheds light on various studies, which have used AI in hybrid/evolutionary systems to develop effective and accurate predictive models, to offer researchers and model developers more tools to choose from.

Keywords AI tools, Architectural, Engineering and construction industry, Forecasting, Prediction

Paper type Literature review



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1. Introduction

Artificial intelligence (AI), which combines algorithm, math and creativity and incorporates various techniques, has played a significant role in several application areas (Zadeh, 1994; Jalal *et al.*, 2013). It aims to exploit the tolerance for uncertainty and imprecision in achieving robustness, traceability as well as low solution cost (Momeni *et al.*, 2018). Its principal components are probabilistic reasoning, neuro computing and fuzzy logic, which have been used in the field of prediction and forecasting (Maier and Dandy, 2000).

Due to poor performance of the conventional models in complex non-linear systems, researchers and practitioners have been seeking to improve prediction tools (Chou and Pham, 2013). Secondly, due to a complex and uncertain process, soft computing methods are preferred over conventional models for prediction and forecasting (Garg and Tai, 2014). Machine learning (ML) has also been widely used in the last decade throughout computer science (CS) and beyond (Fateh and Hejazi, 2020), which is a clear evidence of the advantage of the learning from data over learning “manually”.

The new techniques that apply AI tools have been widely used in various engineering fields for forecasting and prediction (Veeramachaneni *et al.*, 2003; Sadowski *et al.*, 2018; Manzoor *et al.*, 2021). For example, data mining is acquired through a combination of technological methods in many areas, such as expert systems, CS, ML, information retrieval and statistics (Liao *et al.*, 2012). Furthermore, ML models, which have also been used in a wide range of engineering practices, offer predictive and descriptive capability (Jing and Hudson, 2002). Thus, these features are utilized to generate new knowledge and explore through learning (Aladag *et al.*, 2013).

Reportedly, AI tools and predictive models also offer practicality, feasibility and quickness in solving engineering problems (Roosta *et al.*, 2014; Avunduk and Copur, 2018; Zhang *et al.*, 2019). Artificial Neural Network (ANN), Support Vector Machine (SVM) and Multivariate Adaptive Regression Spline (Mars) are examples of tools and models that have been used in various engineering disciplines, such as analyzing the effect of curing time, dosage of bentonite, addition of silty clay and amount of water on the outputs (Amlashi *et al.*, 2019), prediction of the fracture energy of asphalt specimens (Majidifard *et al.*, 2019) and a 28-day compressive strength of a high and normal strength self-compacting concrete (Prasad *et al.*, 2009) among others.

AI tools, which can contribute in solving complex problems (Tinoco *et al.*, 2018), have also emerged as a powerful device to be used in the construction (hereafter, AEC) practices (Lagaros and Papadrakakis, 2012; Jodaei *et al.*, 2012; Momade *et al.*, 2020). The ongoing developments in the CS areas of AI and CI have led the researchers to apply them successfully in various fields of AEC industry (Mohammadhassani *et al.*, 2013; Hamza *et al.*, 2019). By applying AI in design, modelling and prediction, it can be helpful to efficiently use main construction resources, which will ultimately result in a lower cost for the work done (Tayfur *et al.*, 2013). A comprehensive review of the context is a clear indication of a global interest in using different AI tools in various fields of AEC. Taking this as a point of departure, this study aims at longitudinally reviewing the context to understand the trends and investigate the developments in the scoping area. By doing so, the study fills the gap (lack of a robust review that focuses on, particularly, the application of AI in AEC) by providing insight into the body of knowledge on the subject.

The findings can be used, not only by the researchers interested in the application of AI tools in construction, but also by the industry practitioners, who are keen to further understand and explore the applications of AI tools in the field. There has been a significant rise in application of AI tools in the AEC industry and there are no studies to date that serve as the center point to learn about the different AI tools available and their level of application in different fields of AEC. The study can help researchers and practitioners develop AI tools that can improve the performance and accuracy in prediction and modelling in different

aspects. It will also shed light on various studies that have used AI in hybrid/evolutionary systems to develop effective and accurate predictive models, to offer researchers and model developers more tools to choose from.

The article is structured in the following manner. First, a timeline is provided on the AI tools currently in use in the AEC body of knowledge. After that, the methodological approach, which is adopted by this study, has been described. This is followed by the results of a robust review of the context on the subject as well as the discussion of the findings that were pulled out of the reviewed publications. Lastly, the study presents concluding remarks and recommendations for future research.

2. Timeline and application of AI tools

The authors have created a timeline, seen in Figure 1, with respect to the year where AI tools were developed. It can be noted that AI tools are not a recently created tool as assumed but rather have been utilized heavily with advancements in computer and technology in recent



Figure 1. Review search code

years. As illustrated by [Supplementary Figure 1](#), one AI tool found in 1894 by Galton was called LR. Most of them were created from 1991 to 2010 whereby a total of 24 new tools were generated by respective researchers for purposes of forecasting and modelling. From 2011 to 2020, a total of eight new tools have also been developed so far which further solidifies the statement, that a lot more research is now dependent on the abilities of these AI tools. Also, the authors are of the opinion that the advancement in computers and technology has facilitated and provided the researchers with more advanced tools in modelling and forecasting abilities.

3. Research method

This study provides a review (as described by [Durdyev and Hosseini, 2019](#)) of the research conducted on the application of AI tools in various areas of the AEC industry. To this end, a thorough literature review was conducted using Elsevier's Scopus (due to its simplicity and as it encapsulates extensive variety of databases ([Falagas *et al.*, 2008](#); [Durdyev, 2020](#))) to identify the studies related to the scope of the present study.

3.1 Sampling

A systematic search (including all the search categories) was performed (refer to [Figure 1](#)). A preliminary survey carried out using keywords, "Artificial Intelligence", "modelling", "modeling" AND "construction", which retrieved 2,585 publications. Limiting those publications to the source title and only journal articles (regardless of their status or type) resulted in 818 publications. It is worth mentioning that, due to a significant increase in the number of studies on the area during this period, the search was limited to the 2014–2020 period. Lastly, a quick review of the abstract was performed to eliminate the studies that are irrelevant to the aim of the present study, which resulted in 165 journal articles of interest published by the prominent outlets on the subject.

4. Results

A total of 165 articles were extracted from the scientific journals. As can be noted from [Table 1](#), several journals have published studies that focused on the application of AI tools in AEC fields. It is worth to point out that the top three journals are focusing primarily on automation, modelling and use of computers in engineering, while [Table 1](#) also provides evidence (journals' scopes) of how widely (wide range of topics) the AI tools have been used.

From the studies reported from different geographical regions/countries, application of AI tools is one of the important issues that need to be assessed and discussed. Thus, [Table 2](#) presents the geographical distribution of the retrieved studies that are conducted in the field of AI tools in AEC. Most of the reviewed studies on the application of AI tools are reported from the following countries: China, Turkey, Iran and USA. The geographical distribution shows that most of the studies reported are from developing countries, which is clear evidence of an increasing R&D trend in the implementation of AI tools in the AEC field. It is also worth pointing out that very few studies have been conducted in Oceania, South America and Africa.

5. Discussion

5.1 Types of AI tools and disciplines where they were used

A detailed review of the retrieved articles was conducted to identify all AI tools that have been used in various disciplines of the AEC industry. Thus, [Supplementary Figure 2](#) illustrates a comprehensive list of all AI tools and the disciplines they were applied for.

Table 1. Number of studies per journal published on the subject

Journal	# of articles
"Automation in construction, Engineering with computers, Mathematical methods in the applied sciences"	9
"Neural computing and applications"	8
"Science of the total environment, Construction and building materials"	7
"Energy and buildings, Advances in engineering software"	6
"Energies, computers and concrete"	5
"Journal of computing in civil engineering, Journal of cleaner production, Journal of materials in civil engineering, Construction management and economics, Computers and structures"	4
"Engineering structures, building and environment, Computers and geotechnics, Radiation measurements"	3
"Canadian journal of civil engineering, Journal of civil engineering and management, Advances in structural engineering, International journal of civil engineering, Hydrological processes, Frontiers of structural and civil engineering, Archives of civil and mechanical engineering, Cement and concrete research, Canadian geotechnical journal, Engineering applications of artificial intelligence, Composites part B: Engineering, Journal of Zhejiang University: Science A, KSCE journal of civil engineering, Sustainability, Scientia iranica"	2
"Computers and operations research, Applied soft computing journal, Computer-aided civil and infrastructure engineering, Safety science, Neurocomputing, Advanced engineering informatics, Energy, Journal of construction engineering and management, Journal of water resources planning and management, Structure and infrastructure engineering, Hydrological sciences journal, Journal of hydrology, Environmental modelling and software, Road materials and pavement design, Computational materials science, Energy conversion and management, Accident analysis and prevention, Expert systems with applications, Tunnelling and underground space technology, Structural engineering and mechanics, Applied soft computing journal, Structural concrete, Soft computing, European journal of environmental and civil engineering, computational intelligence and neuroscience, Civil engineering and environmental systems, Ecological modelling, Mathematical problems in engineering"	1
<i>Total</i>	165

Country	# of studies	% of studies
USA	15	North America
Canada	8	(14%)
China	23	Asia (60%)
Turkey	17	
Iran	15	
India	11	
Taiwan	7	
Vietnam	6	
Korea	5	
Malaysia, Hong Kong	4	
Japan, Singapore, Indonesia	2	
Iraq, Syria, Nepal, South Korea, Abu Dhabi, Saudi Arabia, Kuwait	1	
Poland	6	Europe (20%)
Spain	4	
Portugal, France	3	
UK, Italy	2	
Greece, Germany, Netherlands, Czech Republic, Austria, Norway, Sweden,	1	
Cyprus		
Australia	5	Oceania (3%)
Brazil	2	South America (1%)
Nigeria, Egypt	1	Africa (2%)

Table 2. Geographical distribution of the reviewed studies

The five most popular AI tools used in the retrieved studies are ANN (91), SVM and ANFIS (twelve), MARS and RF (nine), SVM and Fuzzy Logic (seven) and LR and PSO (six), which were used in a variety of disciplines. It is worth to point out that there are three main reasons for ANN being a widely used tool, which are: (1) ANN as a parallel processor of problems (violation of the constraints by any of the neurons would not affect the output of the problem); (2) its ability to extrapolate from historic data to generate forecast and (3) it provides solution for nonlinear problem (Murat and Ceylan, 2006). Thus, eight disciplines have been established to group each study, where AI tool(s) were applied into a category. The eight categories are materials, geotechnical, hydrology, project management, transportation, energy, structural and environmental.

5.1.1 Construction and building materials. Notably, most of the studies, for which AI tools were used, have been carried out for materials related topics. ANN has been the most popular (thirty-five studies) in the construction/building materials field, while ANFIS and SVM were used by five, and FL and MGGP by four studies. In terms of the sub-disciplines where the AI tools were used, the list comprises a wide range of topics, such as predicting compressive strength of concrete (Pham *et al.*, 2019; Dutta *et al.*, 2018; Tanyildizi, 2018; Liu and Zheng, 2019; Ghanizadeh and Rahrovan, 2019; Al-Gburi *et al.*, 2018; Sadowski *et al.*, 2018; Gazder *et al.*, 2017; Reddy, 2018; Behnood and Golafshani, 2018; Nguyen *et al.*, 2019), measuring the adhesion/cohesion force between asphalt molecules at nanoscale level (Hassan *et al.*, 2018), estimating the shear strength from the relative density, particle size, distribution (gradation), material hardness, gradation and fineness modulus (Yang *et al.*, 2019; Li *et al.*, 2019), confining (normal) stress, forecasting atmospheric corrosion of metallic materials (Zhu *et al.*, 2019) and modelling the surface roughness in the turning of hardened AISI H11 steel (Saini *et al.*, 2012).

5.1.2 Structural engineering. In the structural engineering field, ANN, ANFIS and SVR have 17, six and three applications, respectively. Examples of subtopics where AI tools were used in the structural field are automatic identification of defect in the bearing (Sun *et al.*, 2018), predicting the stable cross-sectional geometry of alluvial channel profiles (Armaghani *et al.*, 2018; Jung *et al.*, 2019; Gholami *et al.*, 2019), developing new afflux methods for arched bridge constructions (Hajihassani *et al.*, 2019), prediction of vertical settlement in the ERP system (Bui *et al.*, 2019), detecting beam failure and joint failure (Yavuz, 2019; Yaseen *et al.*, 2018; Alwanas *et al.*, 2019; Nikoo *et al.*, 2018), predicting settlement of shallow foundations and calculating the complexity of the grouting efficiency level (Zhu *et al.*, 2019).

5.1.3 Energy. For energy-related studies, ANN and Mars have a total of 12 and three studies, respectively, while SVM and SVR have been used by two studies each. Some examples of the energy-related sub-disciplines are an accurate estimation of direct horizontal irradiance (Notton *et al.*, 2019; Ozoegwu, 2019) and estimating the cooling load of a building (Deng *et al.*, 2018; Do and Cetin, 2018; Goudarzi *et al.*, 2019).

5.1.4 Environment. As can be noted from Supplementary Figure 2, very few studies (two), which focused on developing models for forecasting carbon emission intensity (Acheampong and Boateng, 2019; Pour *et al.*, 2018), were reported on environmental related topics that were used in AI tools. Thus, future researchers can consider this to be an area to explore further.

5.1.5 Geotechnical engineering. For geotechnical-related topics, ANN and RF were used by eight and five studies, respectively, while two studies used RBF, LR, DT, SVM and BRT. The sub-disciplines focused on the literature are landslide susceptibility modelling (Chen *et al.*, 2019b; Rahmati *et al.*, 2019), determine movement in landslide (Zhu *et al.*, 2019; Park and Kim, 2019) and prediction of the open stope hanging wall (HW) stability (He *et al.*, 2019; Chen *et al.*, 2018; Lian *et al.*, 2018).

5.1.6 Hydrology. In the hydrology field, ANN has again been the widely (four studies) used tool, SVM by two studies and GP, FNN, ELM, LSM by one study each. The AI tools were

primarily used to model groundwater quality parameters (Kisi *et al.*, 2019), measure water level and support real-time environmental monitoring of water quality parameters (Azad *et al.*, 2019; Ao *et al.*, 2019; Fijani *et al.*, 2019; Delafrouz *et al.*, 2018).

5.1.7 Project management. In the project management related studies, ANN was used by nine, and FL and SVM by two studies each. The researchers used the AI tools in the following sub-disciplines: labour productivity (Golnaraghi *et al.*, 2019; Zhang and Fang, 2019; Momade *et al.*, 2020), construction cost prediction (Golnaraghi *et al.*, 2019), quality control (Fijani *et al.*, 2019), construction litigation (Arditi and Pulket, 2010), cost optimization and prediction of incidents at construction sites (Ayhan and Tokdemir, 2019; Sarkar *et al.*, 2019).

5.1.8 Transportation. For transportation, ANN and GEP have four applications each, SA has two and Mars and GP have one each. Prediction of the fracture energy of asphalt mixture specimens (Majidifard *et al.*, 2019) and the flow number of dense asphalt mixtures (Mirzahosseini *et al.*, 2013) were the primary focus of the studies that used AI tools in transportation related studies.

5.2 Use of hybrid tools

Empirical methods along with modelling capabilities have become more powerful due to the challenges in the modelling of processes experienced in the nature (Yurdakul and Akdas, 2013; Momade and Hainin, 2019). Reportedly, use of AI tools are providing more accurate results in comparison to conventional regression tools used over the decades. There is no requirement for any predetermined mathematical models for their computations as they have an ability to tolerate experimental inaccuracies far better than other tools (Eldin and Senouci, 1994; Amlashi *et al.*, 2019). On the other hand, the regression modelling is based on a predefined structure of the model with a limited number of linear/non-linear equations. Recent studies have shown that applications of many regression models have limitations in obtaining an accurate regression equation. Lack of consideration of several factors by the regression model is another factor that made the regression analysis unsuitable (Yeh and Lien, 2009). Thus, various soft computing techniques (SCT) have emerged aiming at coping with these limitations, while the most prominent feature of the SCT is the ability to learn from experience and extract the knowledge contained in the experimental data (Mohammadi Bayazidi *et al.*, 2014).

To increase the accuracy of results and to use a more robust performance, many newer studies are combining two AI tools. For example: ANFIS that was first used by Takatgi and Sugeno (1985) is a fuzzy inference system implemented in the framework of adaptive networks, which has been used earlier in many studies prediction of compression coefficient of soil (Pham *et al.*, 2019), measures the adhesion/cohesion force among asphalt molecules at nanoscale level (Hassan *et al.*, 2018), prediction of vertical settlement in ERP system (Bui *et al.*, 2019) and others. FNN, which utilizes fuzzy sets and constitutes a three-layered architecture, is another example of a hybrid technique introduced in the reviewed articles. The network does not learn from examples, but through the evaluation of a special fuzzy error measure (Nauck and Kruse, 1993). The extended version incorporates fuzzy-if-then rules through the reduction of the number of nodes in the network's hidden layer. FNN has been used for various research topics, such as contractor prequalification (Lam *et al.*, 2001), to estimate contractors' mark-up (Liu and Ling, 2003), among others. Examples of other hybrid techniques that have been used in various disciplines/sub-disciplines are Support Vector Regression – Particle Swarm Optimization (SVR – PSO) (Yaseen *et al.*, 2018), SVR (Goudarzi *et al.*, 2019), multi-gene genetic programming (MGGP) (Hodhod *et al.*, 2018), Random Support Vector Regression (RSVR) (Zhang and Fang, 2019), ANN/simulated annealing (ANN/SA) (Majidifard *et al.*, 2019), weights of evidence–multivariate logistic

6. Conclusion

Several studies have reported the practicality and feasibility of the AI and predictive models in solving engineering problems. A thorough literature review was conducted on the application of AI tools in the AEC industry. A total of 165 selected journal articles related to AI applications in the AEC industry from 2014 to 2020 were robustly reviewed. The following items were extracted from the review: type of AI tools used, the major purpose of application, the geographical location where the study was conducted and the distribution of studies in terms of the outlets they are published by.

Based on the review results, the disciplines the AI tools have been used for were classified into eight major areas such as geotechnical engineering, project management, energy, hydrology, environment and transportation, while construction materials and structural engineering are the top disciplines where the AI tools were used the most. In total, 47 AI tools were identified and have been used in various AEC disciplines. Although ANN has been widely used AI tool, the researchers have used other AI tools, which shows efforts of exploring other tools for better modelling abilities. There is also clear evidence of that studies are now growing from applying a single AI tool to applying hybrid ones to create a comparison and showcase which tool provides a better result in an apple-to-apple scenario.

The findings of the study highlighted on the new trends on AI applications by different researchers. It also established a focal point for all researchers who can use this study to understand to what length the studies have been conducted. This paper can serve as a primary source for all researchers to review upon and use as a basis to understand how to carry forward the studies in application of AI tools and AEC topics such as project management, transportation, material properties, etc.

Although the study provides a snapshot of the AI studies, due to several limitations, the researchers must be cautious while implementing the research outcomes. Firstly, this study reviews the studies that are indexed by Scopus starting from 2014 and until its commencement. Secondly, although the authors have put in the best of efforts to capture each and every research paper on application of AI tools in the AEC industry; however, there will be papers that were not captured due to the keywords used for the search of literature in the start of the research. Thirdly, a co-citation network could also be established, which provides “a forward-looking assessment on document similarity in contrast to bibliographic coupling”. This remains a limitation of the research which the authors believe future reviewers can address when preparing their articles on similar/related topics.

Although AI tools have been used in wide range of disciplines, there are also other areas which future research can focus on:

- (1) Geotechnical engineering: Earth retaining structures, earthquake engineering, ground motion hazard analysis, shallow and deep foundation modelling and laboratory and field testing of soil related properties.
- (2) Project management: schedule and scope management, as well as risk and safety-related studies.
- (3) Transportation: urban transportation planning, air pollution and health-related studies as well as transportation safety and design.
- (4) Environmental studies: water resources planning and management, as well as waste-water treatment.

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Appendix

The supplementary file is available online for this article.

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