Application of Artificial Neural Networks in Construction Management

Subjects: Engineering, Civil
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Artificial neural networks (ANN) exhibit excellent performance in complex problems and have been increasingly applied in the research field of construction management (CM) over the last few decades. This paper aims to provide a comprehensive understanding of the application of ANN in CM research and useful reference for the future.Content analysis is performed to comprehensively analyze 112 related bibliographic records retrieved from seven selected top journals published between 2000 and 2020. The results indicate that the applications of ANN of interest in CM research have been significantly increasing since 2015. Back-propagation was the most widely used algorithm in training ANN. Integrated ANN with fuzzy logic/genetic algorithm was the most commonly em-ployed way of addressing the CM problem. In addition, 11 application fields and 31 research topics were identified, with the primary research interests focusing on cost, performance, and safety.

Keywords: artificial neural network ; construction management

1. Introduction

The construction industry has made a significant contribution to the development and maintenance of buildings and civil infrastructure. As a data-intensive industry, the construction industry is experiencing unprecedented growth in data volume [1]. The hidden knowledge in these data is of great significance for adopting appropriate construction approaches to improve project performance. Nevertheless, data-driven technology adoption in construction management (CM) has been relatively conservative [2]. According to the digitization report released by McKinsey, the construction industry is currently one of the worst-performing industries in terms of digitalization [3]. Meanwhile, data in the construction industry are far from being fully utilized. It is estimated that site managers waste tremendous time processing data before making a decision [4]. Machine learning, as a set of technologies that can automatically detect patterns in data, brings a significant added value to saving time and maximizing computing resources, especially when processing large amounts of data [5]. It has shown excellent performance in many continuously expanding areas of construction, such as building structure design and performance evaluation, prediction of residual value of construction equipment, and vulnerability analysis of existing buildings [6][7][8]. Therefore, intelligent technology is urgently needed, with the artificial neural network (ANN) being one of the most promising ones to handle the rapid growth of data generation in CM.

ANN is a mathematical model inspired by the biological brain to acquire the knowledge hidden in historical data for information-processing and computation purposes [9]. As a branch of artificial intelligence (AI) technology, ANN performs well in dealing with complex nonlinear problems without assuming the relationships between variables, because of the self-learning, self-organizing functions, and high-speed computing capabilities [10]. For these reasons, ANN is particularly suitable for solving practical CM problems, which is difficult for classical mathematics and traditional modeling [9]. ANN can play roles in the prediction, optimization, classification, and decision-making in the practice of CM and has been used in CM since the early 1990s [11]. For instance, Juszczyk et al. [12] proposed a predictive model for fast cost analyses and conceptual estimates in the planning stage. The crack detection method of wavelet neural network was proposed by Turkan et al. [13] to minimize the possibility of facility failure.

Since ANN is the most commonly used AI method in the architecture, engineering and construction industry [14], a growing body of literature reviewing ANN applications has been published. For instance, Sony et al. [15] systematically reviewed the application of convolutional neural networks in structural state assessment. These reviews on ANN focused on a specific application instead of targeting CM. Pan and Zhang [16] reviewed AI in CM in which ANN is mentioned limitedly in some paragraphs. Adeli [17] reviewed the application status of ANN from 1989 to 2000 in CM which was limited to research before 2000. It can be seen there is no thorough review and systematic analysis of the existing literature on ANN in CM for the past 20 years. The absence of an up-to-date systematic review on ANN in CM makes it difficult for researchers to understand the diversity and complexity of using ANN for CM.

2. Publication Trend of Research on ANN in CM from 2000 to 2020

To analyze the publication trend of ANN in CM in the past 20 years, the selected articles were profiled based on journal and publication year. It can be found that JCEM (38) and AC (34) include the most publications on this topic, accounting for 64.29% of the total, while the remaining five journals account for 35.71%. **Figure 1** shows the publication trend for ANN in CM from 2000 to 2020. It reveals an overall increase since 2000 within three years. Especially since 2015, the number of related documents has increased dramatically. This result is consistent with the application trend of data mining technology in the construction industry [18], as the construction industry has a growing need to process a large amount of heterogeneous data [19].

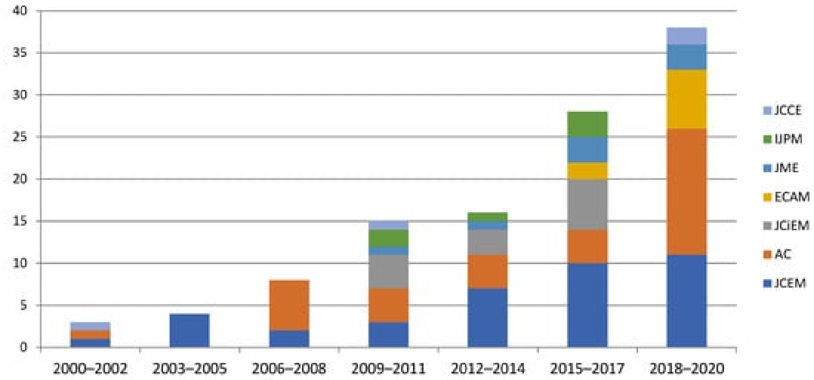

Figure 1. Publication trend of literatures on ANN in CM (2000–2020).

3. Types of ANN Applied in CM Research

Figure 2 provides the statistical result of the types of ANN used in the reviewed articles. The results show that a total of 13 types of ANN were employed in the CM research. BPNN has captured the most attention and accounts for 45.1% of the total. MLPNN and CNN both account for 13.8%. In addition, RBFNN, GRNN, and PNN have also received some attention.

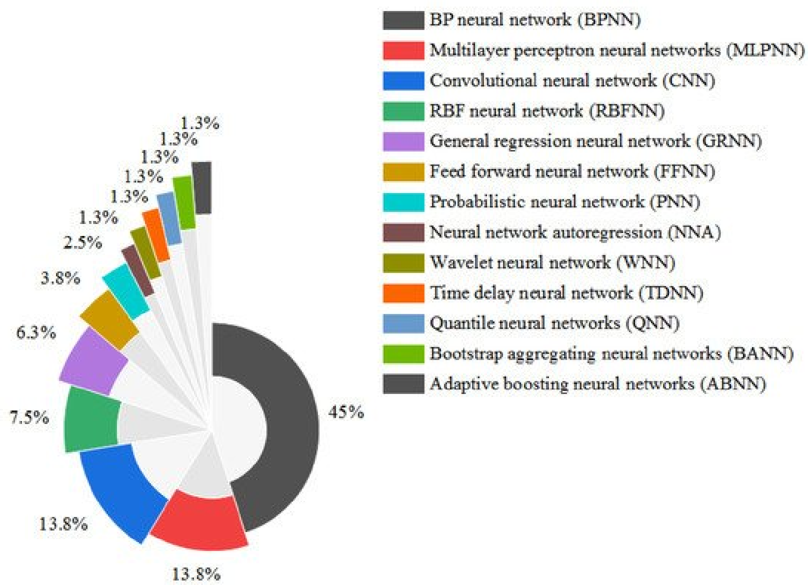

Figure 2. Types of ANNs applied in selected articles.

BPNN is a multilayer feed-forward neural network trained according to the error back-propagation algorithm. It has the general advantages of all neural networks such as self-learning and adaptive capabilities, nonlinear mapping capabilities, and high fault tolerance [20], and its own advantages, such as simplicity and good generalization capability [21]. A detailed review found that BPNN as a representative of ANN in CM has been applied to all application fields, demonstrating its absolute domination.

MLPNN is typically designed with a fully connected feed-forward-based architecture and trained by static back-propagation, LM, Gauss-Newton, or other algorithms. Its input layer contains a set of sensory nodes, and both hidden layers and the output layer contain computing nodes [22]. It has been applied to complete a wide range of classification and prediction tasks in the CM field. The CNN model achieves feature extraction through a stack of layers (such as convolution, activation, and polarization) on the input image [23]. It is one of the deep learning algorithms that has been widely used in the image field [24]. The characteristics and main research fields of BPNN, MLPNN, and CNN are listed in **Table 1**.

Table 1. Comparison of BPNN, MLPNN and CNN.

Type	Features	Weakness	Applicable Field
BPNN [10][25][26]	**Gradient descent method. Nonlinear mapping function. Self-learning and adaptive.**	**Problem of slow convergence, over-fitting, and local optima.**	**Applied to prediction and classification tasks in CM: widely used to solve problems in 11 fields; see Table 2.**
MLPNN [12][27]	**Nonlinear mapping function. Global optimization.**	**Insufficient generalization ability. Poor performance in processing multidimensional data.**	**Applied to prediction and classification tasks in CM: claim prediction, cost prediction, classification of patent screening, classification of project decision.**
CNN [15][28]	**Sparse connectivity and weight sharing. Suitable for high-dimensional data.**	**Large amount of calculation, and high requirements for input data.**	**Applied to the image field in CM: safety risk identification at construction site, sewer image defect classification, equipment tracking and monitoring.**

4. Methods Integrated with ANN Applied in CM Research

The result shows that 61% of studies established a hybrid model in which ANN is integrated with other methods to solve the problems in CM, and the number is considerably greater than that of the individual model. Researchers are adopting more and more hybrid models to improve the performance and overcome the defects of a particular method [29][30].

Figure 3 illustrates the distribution of methods/algorithms integrated with ANN more than twice in the reviewed studies. The results indicate that Fuzzy Logic (FL) (21) is used more often combined with ANN in the selected literature than the others, followed by Genetic Algorithms (GA) (15). Furthermore, case-based reasoning and long short-term memory have achieved ideal results in auxiliary ANN applications.

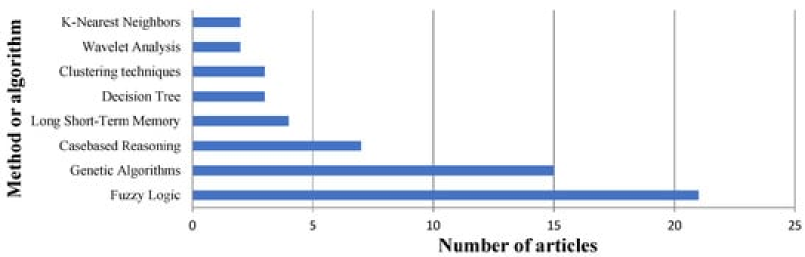

Figure 3. Methods/algorithms integrated with ANN in selected articles.

Most research on the application of individual ANN models has focused on using its capabilities to deal with highly nonlinear problems. However, the accuracy of the estimation results is not very high when dealing with uncertainty and subjectivity issues. These disadvantages can be partially overcome by integrating FL, which is a tool for representing uncertain and imprecise information [31]. FL imitates the human decision-making process in a high-level way for automated systems to describe highly complex, undefined, or difficult-to-analyze topics [32]. However, FL encounters difficulties in determining parameters. ANN was introduced to resolve this problem and to infuse into the FL a capacity for self-learning. As the actual CM problems are always complex and uncertain due to the changing nature of the construction industry [33], FNN has been widely used in CM.

GA is a stochastic search approach inspired by the natural evolution process, which involves crossover, mutation, and survival fitness evaluation. It is widely used to identify parameter values for ANN models to solve search and optimization problems. GA helps improve the convergence speed, and its mutation mechanism avoids confinement to locally optimal solutions [34]. In addition, the complementary combination of ANN, GA, and FL can maximize their respective merits [35]. When dealing with CM problems with complex, uncertain, and subjective characteristics such as dynamic project success prediction and subcontractor performance evaluation, FL is used to deal with uncertainty and approximate inference, while ANN is employed in fuzzy input-output mapping and GA is used for optimization.

5. Application Fields and Hot Topics on ANN in CM

Twelve application fields are identified, as shown in **Table 2**. Cost is the most common application field of ANN (23.21%), followed by performance (16.07%) and safety (11.60%).

Table 2. 11 application fields and 31 specific topics on ANN in CM.

Code	Application Fields	Freq./ Percentage	Specific Topics	Freq.	Percentage
1	Cost	26 23.21%	Project cost estimation	13	11.61%
			Materials prices prediction	5	4.46%
			Bid price prediction	3	2.68%
			Forecasting construction cost index	2	1.79%
			Usage and service cost estimation	2	1.79%
			Maintenance cost of equipment prediction	1	0.89%
2	Performance	18 16.07%	Corporate performance evaluation	5	4.46%
			Project performance evaluation	11	9.82%
			Industry performance evaluation	2	1.79%
3	Safety	13 11.61%	Worker safety behavior assessment	10	8.93%
			Accident analysis for construction safety	2	1.79%
			Safety climate prediction	1	0.89%
4	Quality	9 8.04%	Health monitoring of construction structure	6	5.36%
			Construction stability testing	3	2.68%
5	Resource	9 8.04%	Mechanical equipment management	3	2.68%
			Material management	2	1.79%
			Fund management	2	1.79%
			Patent technology management	1	0.89%
			Human resources management	1	0.89%
6	Risk	7 6.25%	Optimal risk allocation in projects	3	2.68%
			Multi-project resource conflict risk prediction	3	2.68%
			Prediction of financial contingency	1	0.89%
7	Contract	6 5.36%	Project dispute prediction and resolution	3	2.68%
			Prediction of project claim	3	2.68%
8	Schedule	6 5.36%	Project duration and time estimation	4	3.57%
			S-curve prediction, auxiliary schedule control	2	1.79%
9	Procurement	5/4.46%	Contractor prequalification and selection	5	4.46%

Code	Application Fields	Freq./ Percentage	Specific Topics	Freq.	Percentage
10	Environment and sustainability	4 3.57%	Energy consumption evaluation	3	2.68%
			Environment assessment	1	0.89%
11	Other	9 8.04%	Model or system development	7	6.25%
			Trend forecast	2	1.79%

Cost is the main criterion for project feasibility study and early project decision-making. Cost overruns can lead to project cancellations [36]. The highest degree of attention (23.21%) demonstrates that ANN has made progress in solving traditional cost management problems. Performance is critical to construction [37]. A total of 16.07% of studies focused on performance measurement and improvement, which is the second hottest topic after cost. According to Ayhan and Tokdemir [38], more than 1.3 million people suffer from occupational accidents in the construction industry annually. Although safety management systems have been introduced in recent decades, occupational safety is still poor [39]. **Table 2** (11.60%) indicates that safety is a major concern in the construction industry. With the application of information and sensor technology, the availability of an extensive training dataset makes ANN a promising approach in construction safety management [39]. In addition to the above three fields, quality and resources also received significant attention, and both accounted for 8.04%. All application fields and specific topics are shown in **Table 2**.

Upon further analysis, 31 specific topics about ANN in CM can be extracted from the above 11 fields. **Table 2** shows all ANN topics in CM in the selected articles and the percentage of articles on each topic. It implies that cost estimation is the most widely discussed topic (11.61%), followed by project performance evaluation (9.82%) and worker safety behavior assessment (8.93%).

For construction cost estimation, ANN is a representative method for early construction cost estimation by identifying cost influencing factors and establishing a prediction model based on historical data [21]. Juszczyk, Zima, and Lelek [12] presented an original approach of building construction cost predictive models based on ensembles of some MLPNNs. Rafiei and Adeli [40] used advanced machine learning concepts to create innovative construction cost estimation models, including an unsupervised deep Boltzmann machine learning approach and a soft-max layer three-layer BPNN. Some studies compared multiple models to find the best one, for example, comparing ANN with multiple regression analysis [41] and comparing different types of ANN [42]. ANN is recognized as one of the most common AI techniques for parametric cost modeling, so determining model parameters is the key stage of model development [43]. The selected literature has been surveyed to identify the drivers in the cost field, and **Table 3** presents important variables in main topics.

Table 3. Important variables in main cost field.

Research Topics	Input Variable	Description	References	Variable Ranking
Predicting construction cost	Total construction area	Above and below ground	[35][40][42][44]	1
	number of floors	Above and below ground, building height	[35][42][44]	2
	project locality	Project location, location index	[40][44][45]	3
	Facility	Interior decoration, electromechanical infrastructure	[35][44]	4
	Market conditions	Price at the beginning of the project, economic variables and indexes	[40][44]	5
	Site conditions	Topography, ground conditions, soil condition	[35][44]	6
Forecasting index/price	Corresponding data in previous	Material prices in the previous five days, price index of the last two quarters, etc.	[46][47][48]	1
	Macroeconomic indicators	CPI, PPI, unemployment rate, GDP, foreign reserves, lending rate, etc.	[49][50]	2

The application of ANN in project performance evaluation consists of project success evaluation and project productivity evaluation. Cheng et al. [51] developed and applied EFHNN to evaluate project success by fusing hybrid neural network, FL and GA. For evaluation of project productivity, ANN is mainly used for construction operations and the prediction of construction worker productivity. Han et al. [52] combined simulation and an ANN technique to produce more reliable prediction results for earthworks productivity. To improve the predictive performance of labor productivity, Heravi and Eslamdoost [53] proposed using Bayesian regularization to optimize BPNN. The performance of FFNN was compared with RBFNN in modeling the productivity of masonry crews by Gerek et al. [54].

ANN applications in worker safety behavior assessment include the fall prevention inspection for working at a height, unsafe behavior, and posture detection. High-altitude fall accidents are the main cause of fatalities on construction sites. Zhang et al. [55] proposed using a smartphone as a data collection tool to detect and identify near-miss falls based on ANN. This method helps to identify hazardous elements and vulnerable workers. In terms of unsafe behavior and posture detection, Patel and Jha [10] used ANN to predict employees' safe work behaviors and identified the main influencing factors of safe behaviors. Yi et al. [56] presented an early warning system as a surveillance method for working in hot and humid environments, safeguarding frontline workers' health and safety.

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