Literature Review of the applications of Artificial Intelligence (AI) in Construction Project Management

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Abstract

The application of Artificial Intelligent (AI) has increased in the field of construction project management in recent years, mostly due to the development of high-performance computer or robot and the potential to improve construction management efficiency. To achieving a comprehensive understanding of the research work on this subject, this paper conducts a literature view and content analysis of existing literatures on AI application in construction project management field focusing on the last decade. The authors selected the articles based on different category of AI technology and published journals with an impact factor higher than 1.0. The search resulted in 68 articles, which were then categorized into five categories to systematize the research conducted over the years. They are construction productivity management, construction safety and health management, construction performance management, construction claims and litigations, and construction logistics and site planning. The authors then analyze the selected articles that are most representative and influential from each category based on their citation and pertinence to their field. This review concluded the current trends of AI application in construction project management and further identified the gaps and limitations of the existing studies which could lead the direction of future research.

Keywords

Artificial Intelligent, Construction Project Management, Neural Network, Computer Vison, Productivity Management, Safety, Construction Performance

1. Introduction

Comparing with the manufacture industry, construction industry as one of the pillar industries has its own characteristics. Due to the nature of construction industry and its tasks, it is highly competitive, risk-averse, very complex tasks, unique to each individual project, heuristic problem-solving need. In respond to these unique features, it has become critical to improve the performance, safety and sustainability of construction in general. To successfully accomplish a construction project, project management plays a critical role. To manage a construction project in a high efficient manner, construction managers and management teams have already developed and drawn on the experience of many different theories and techniques. For this reason, Artificial Intelligence (AI) starts to catch construction professionals' attention and soon becomes a suitable tool in recent years to benefit construction project management.

AI techniques has already been adopted in many fields, such as face recognition, fraud detection, detect vehicle and pedestrian, on-line product recommendation and advertisement. In general, AI is the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. The term is frequently applied to the project of developing systems endowed with the intellectual processes characteristic of humans, such as the ability to reason, discover meaning, generalize, or learn from past experience. It contains a wide range of disciplines and techniques, such as Machine Learning, Neural Network and Deep Learning. While there are many other research activities have conducted comprehensive reviews on AI techniques for construction application (Moselhi *et al.*, 1991; 1992; Chan *et al.*, 2009; Brilakis, 2012; Seo *et al.*, 2015), they either focus on a specific AI technique or a specific aspect of application field instead of providing an overview of AI applications in construction management. With the aim of providing the readers with comprehensive and sufficient knowledge of the current literatures and usages of AI in construction project management, we review herein the existing research in AI in construction management.

This study reviews current literature on AI applications in construction management: 1) to reveal the current trend of AI techniques; 2) to understand how these techniques are applied to address specific construction management related problems; 3) to identify commonly found research challenges and limitations; and 4) to provide innovative ideas, perspectives, and approaches that may help future studies.

2. Methodology

The literature search of AI application in construction project management was part of a comprehensive study of AI applied in general construction fields. This part mainly discussed the methodology of comprehensive literature search of AI application in all the fields in construction and its results that included the 68 papers used in this study of summarizing the implementation of AI in construction project management. Since no similar job has been done before, the comprehensive literature research reviewed publications on construction-related AI research until 2017 in use of the quantitative method of bibliometric analysis, with no fixed start date selected.

In the first step of this bibliometric analysis, we started with a key word search in Web of Science (WoS) database. "Construction" is used with "Artificial Intelligence", "Machine Learning", "Deep Learning", "Supervised Learning", "Unsupervised Learning", "Support Vector Machine", "Neural Networks", "Computer Vision", and "Natural Language Processing" together respectively as keywords in WoS "Topic". There were 2072 articles fit the selection criteria. Afterwards, an initial review was conducted to remove articles that are not in construction industry, duplicated, and do not apply AI techniques. After this first round of literature screening, 408 articles were selected. To ensure a more appealing bibliometric analysis and categorization to academic peers, articles published in journals with a WoS "5-year Impact Factor" less than 1.0 are removed, which resulted in 352 articles. To reveal the latest trend of applied AI techniques and their application fields with the bibliometric analysis, this review mainly focused on literatures published in the last 10 years between 2007 and 2017, 273 articles in 38 journals remain. This entire process along with it result is demonstrated in the following Figure 1.

After three rounds of literature screening, the following literature analysis was based on the 273 articles with higher impact that published in recent 10 years. The study first applied a generally used categorization method of bibliometric analysis on the literatures. Rather than using existing research themes or areas present in other studies for literature categorization, we proposed our own categories based on the articles' contents. Proceeding to the next step, the authors brought together the categories to restructure it into a systematic framework. Based on each article's content and domain, the selected articles are grouped into eight major categories according to their research objectives and application fields. The categorization result is shown in Table 1, along with the number of articles.

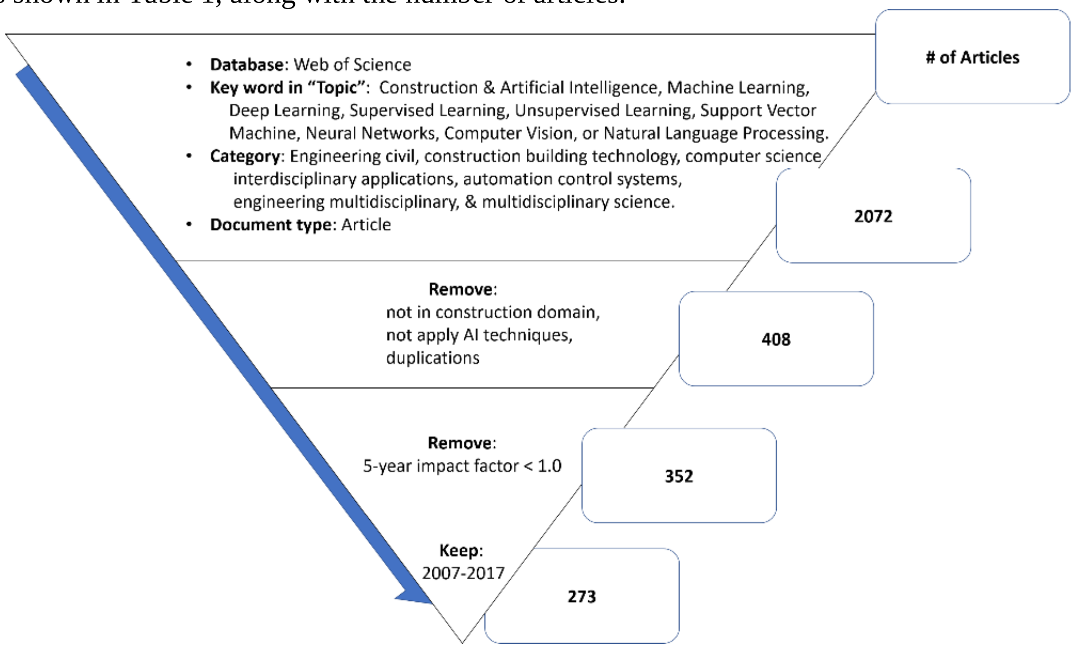

Figure 1: Literature Search and Screening Processes.

Table 1: Major Research Fields in Construction Domain Applying AI Techniques

Category	Num. of Articles
Construction Project Management	68
Construction Engineering: structure, material, and method	54
Estimation and Cost Control	42
Scheduling and Progress Control	15
Construction Business Administration	29
Construction-related Entity and Activity Recognition: imagery and sensing data	48
Project Document and Knowledge Management: textual data	21
Energy and Sustainability	8

Among the eight categories, construction project management was the primary field and the largest field of AI implementation in construction. To better explain AI could do for construction project management, this following paper focuses on the content analysis of application status, limitations and future trends of AI applications in this field. According to our selection criteria, there are 68 articles fall into the category of Construction Project Management. The articles are further developed into 6 sub-categories shown in Table 2. Among the sub-categories, "Productivity" was the most studied domain, while "Safety" becomes the most popular topic in the last three years.

Table 2: Sub-categories under Construction Project Management

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total	%
Productivity	-	5	-	3	1	3	1	-	3	3	3	20	~29%
Safety	-	-	-	-	-	-	1	1	4	7	5	18	~26%
Performance	1	2	1	3	1	1	-	-	1	-	-	10	~15%
Claims & Litigation	2	-	-	1	-	1	3	1	-	1	-	9	~13%
Logistics & Site	-	1	-	-	-	2	-	3	1	1	-	8	~12%
Other	2	-	1	-	-	-	-	-	-	-	-	3	~4%

For the 68 articles about how AI applied in construction project management, not every single one was listed in the reference list in the end of this paper. The authors only referenced articles that we have directly used or we thought provide good overviews of the literature, by referencing both classic works and more recent surveys. We sincerely apologize if any scholar may feel slighted by their omission, and we are open to any feedback where someone feels that an idea has been misattributed.

3. Content Analysis

To discuss the results and provide a more qualitative analysis of the papers that discuss how to use AI techniques to benefit construction project management, the authors of this study proposed a sub-categorization structure summarized in Table 2 and used it to format the following content analysis. In the sub-categories descriptions, we have opted to describe and analyze the most representative and influential articles of the respective sub-category based on their citation and pertinence to their field.

3.1 Construction Productivity Management

Construction productivity management is a popular subject in the field of Construction Project Management. About 30% of the literatures studied the construction productivity using AI technologies. The majority of these studies focus on the approaches of applying AI techniques to measure or predict the productivity of construction crews, construction equipment, or certain construction processes based on collected or recorded data, while others focused on how to apply computer vision (CV) and machine learning (ML) to automatically analyze on-site productivity in real time.

To ensure the on-time delivery of qualified building products to the owner and its cost, it is essential to precisely estimate construction productivity. However, current practices heavily rely on historic data collected from various resources with inconsistent measurement and operators' personal experience, which may lead to a poor productivity prediction result. To address this problem, Song and AbouRizk (2008) developed a systematic process to collect data from both historic and on-going projects to train a neural networks (NN) to estimate labor productivity of future projects. By validating their work with actual data from a steel fabrication company, they concluded that NN was an effective approach to predict labor productivity with appropriate selection of NN's parameters and the NN algorithm. However, the requirement on large amount of pre-labeled/valued data brought difficulties on data collection. To avoid this shortcoming, in some of the latest studies, the researchers focused on comparing the performance among different NN algorithms, improving NN algorithms, and finding the most effective input variables to feed into the NN algorithms. Heravi and Eslamdoost (2015) further studied Multilayer Feed-Forward Back-Propagation NN with the data collected during the process of concrete foundation installation from two power plant construction projects to predict the construction productivity. The results have shown labor competence, poor decision making and motivation of labor were identified as the most influential factors for the construction performance. Recently, El-Gohary et al. (2017) studied the influence of 19 NN input variables at both project administration/management level and construction site level. To accurately predict crew productivity, Mirahadi and Zayed (2016) combined linguistic terms along with the numerical values together as input variables for NN algorithms. A hybrid approaching was developed, in which NN processed crispy values and FUZZY provided a systematic reasoning with fuzzy numbers, to accurately predict labor productivities with both qualitative and quantitative input variables. Different from above studies focusing on the crew productivity predication and management, many other scholars have paid their attention to predict other productivity relevant factors, such as earthmoving machinery effectiveness ratio (Schabowicz and Hola, 2008), production rate in tunneling project (Lau *et al.*, 2010), and productivity loss due to change orders (Cheng *et al.*, 2015 with the help of different NN algorithms and a hybrid AI system integrated FUZZY, SVM, and GA.

Analyzing and monitoring the productivity of on-going construction activities is as important as predicting it ahead of time. To overcome the drawbacks of the extremely time-consuming manually on-site observation by construction management personnel, (semi-)automatic and (near) real-time interpretation of imagery data collected from the jobsites becomes an increasing trend. Gong and Caldas (2010) designed and developed a semi-automatic video interpretation system combining CV and ML techniques to analyze the productivity and to detect abnormal scenario of certain construction tasks, including pouring concrete, earthmoving, installing scaffold, and hoisting. Recent studies have also focused on continuously analyzing the CV and ML techniques to improve the quality of the imagery data interpretation process. By adopting an active zoom camera and placing physical markers on target construction machines, Azar (2016) established a system which could detect and track specific pre-selected machines and collected task-oriented data more precisely. Soltani *et al.* (2017) suggested that knowing the pose of certain construction equipment can lead to a more accurate estimation of the time consumption on each operation state/phase. Thus, they developed a process which determined the 2D skeleton of excavators on video frames. Another contribution of this study was that it implemented synthetic images as the training images for the ML algorithm. It may inspire other researchers who have difficulties on obtaining enough training data.

3.2 Construction Safety and Health Management

Construction industry is one of the top contributors for workplace fatalities. Many construction accidents, which lead to enormous financial losses, are caused by poor safety performance. This has motivated extensive research activities to study the causes of injuries and unsafe behaviors, and applied AI techniques to develop various real-time safety monitoring systems to improve the practices of safety management.

To prevent unsafe behaviors or accidents on construction site, the ability to identify the causes for injuries and unsafe behavior is crucial for an effective construction safety management. AI techniques have been applied in many studies to detect the factors that affected construction safety climete. Goh and Sa'adon (2015) studied cognitive factors influencing an unsafe behavior of not anchoring a safety harness while working at height. With survey data collected from 40 construction workers, they compared Multiple Stepwise Linear Regression, NN, and Decision Tree techniques to explore the most influential cognitive factors that triggered the unsafe behavior. Their analyses revealed that 1) subjective norm was the key influencer for the unsafe behavior, 2) NN and Decision Tree were more suitable techniques to evaluate construction labor's cognitive factors. Taking advantages of large amount underutilized existing construction injury reports, several studies have established AI systems to analyze causes of diverse types of accident and to identify potential risks. Tixier *et al.* (2016; 2017) employed NLP to automatically transfer the unstructured injury reports to a structured accident database with 101 fundamental construction work environment attributes per report. They also compared two Unsupervised ML techniques to model the incompatibilities among the attributes. Based on experiments, NLP has found to be an efficient technique to quickly retrieve valuable data from injury reports with a high accuracy. Bayesian Network technique was also utilized in study the existing accident reports in some recent researches. Gerassis *et al.* (2017) focused on analyzing the causes of occupational accidents in embankment construction projects. Weka, a ML software (Hall *et al.*, 2009), was adopted to analyze a database of 353 accidents and to select the key attributes in these accidents. Then, the key attributes were quantified to analyze the causes of different accidents using Bayesian Network.

Monitoring on-site safety circumstance in real time is also an essential task that can help site manager proactively prevent injuries and identify potential threatens. While combining with ML techniques, computer vision and accelerometer were found to be efficient tools to automatically recognize unsafe behaviors in real time. Kim Hongjo and his colleagues (Kim *et al.*, 2015) introduced a hybrid AI model combined with computer vision and fuzzy inference techniques to monitor struck-by accidents and to improve on-site working practices. CV techniques were used to recognize construction workers and equipment from captured videos and calculate two risk factors: proximity and crowdedness. Then, the fuzzy inference was adopted to assess the on-site safety level based on both risk factors. Besides video camera and RGB-D cameras used in computer vision, accelerometer and the heat strain were also used to capture labor's motion data in recent studies. Lim *et al.*(2015) implemented accelerometer in smart phones to collect labor's three-axis acceleration streams, and applied 579 sets of processed datasets to train a NN classifier that recognized near miss slip and trip from normal walking events. An advanced portable light-weight wearable sensing system named Inertial Measurement Units (IMU) that integrates accelerometer, gyroscope and magnetometer together was then also utilized to capture labor's motion features and monitor unsafe behaviors in the study conducted by Yang *et al.*(2016). With the motion data collected at 17 body joints by the IMU based motion sensor, Chen *et al.*(2017) built a SVM multiclass classifier to detect 6 awkward postures from normal postures. Yi *et al.*(2016) constructed a heat strain (measured by Rating of Perceived Exertion, RPE) prediction model based on back-propagation NN technique monitoring the site condition with temperature and labors heart beats to protect labors who work in hot and humid conditions.

3.3 Construction Performance Management

As a construction project proceeds, measuring construction performance can help construction management team and project owner evaluate if their objectives are met. AI has applied in this research field to monitor the project performance dynamically, to identify causes for performance failure, and to measure the performance of other related activities which may influence project success, such as rework, construction management services in design phase, and pre-project planning.

Construction site and its surrounding environment keep change as project processes; thus, a good project performance prediction system should also be able to predict the performance dynamically. Ko and Cheng (Ko and Cheng, 2007; Cheng et al., 2010; 2012) developed several hybrid AI models for the above purpose by taking the progressive environment into account. As the ability of CV that could (semi-)automatically analyze images and video been noticed in construction industry, there are also numbers of researcher considered CV as a potential tool to monitor on-site project performance in real time. Yang *et al.*(2015) reviewed previous studies on computer vision techniques in construction that have the potential be applied for performance assessment and monitoring, and outlined the research gaps and potential future research.

Instead of measuring construction performance directly, other research activities focused on the influence of certain activities on project performance and project success. Wang *et al.*(2009) established 20 performance indicators under 5 major categories for the evaluation of construction management service in design stage, and then developed a NN model to estimate owner's satisfaction degree using the indicators. Wang and Gibson (2010) investigated the relationship between pre-project planning and project performance. They applied Project Definition Rating Index score as the indicator to describe the level of pre-project planning. With this indicator, Back-Propagation NN and Linear Regression were compared to predict project cost and schedule performance. By examine the experiment results, pre-project planning measured by PDRI score has found to be positively related to project performance measured by cost and schedule growth, and NN showed a better performance over Linear Regression with their dataset collected from 140 projects.

3.4 Claims and Litigations: Occurrence and Outcome Prediction

Construction projects involve numbers of different participants with their own interest. Managing different interests and potential arguments is also an important content of construction project management. Claims and litigations may influence the success of a construction project significantly. To provide decision-support information for managing potential claims and litigations, many studies have tested various AI techniques to predict potential occurrences and results.

One of major research areas regarding AI applications in construction claims and litigations is to predict their potential occurrences. Many studies have shown the feasibility of applying AI technique to predict potential litigation. Chou and Lin (2012) and Chou *et al.*(2013) compared various ML algorithms and ensemble learning systems to predict dispute occurrence. The efficiency and effectiveness of applying AI to proactively predict potential occurrence of dispute was re-confirmed, while the performance of ensemble learning systems was tested to be more reliable than single models in terms of predicting disputes in Publish-Private Partnership projects. MLP Back-Propagation NN was also applied to predict not only the potential occurrence, but also severity of claims regarding time and cost in construction projects (Yousefi, *et al.*, 2016).

Besides predicting the occurrence of potential claims and litigations, scholars also predicted their outcomes by taking advantage of AI techniques. Successfully predicting the outcome of a litigation provides each party involved in the litigation with a strong decision-support tool to find potential resolution prior to the litigation process and even support the decision of whether or not to take the case to litigation. Chau (2007) developed a hybrid AI system combining NN with Particle Swarm Optimization to predict litigation results in construction projects. Arditi and Pulket (2009) also compared performance of Weka (Hall et al., 2009) with various ML techniques including NN, Case Based Reasoning and Boosted Decision Tree on predicting construction litigation outcomes. 38 case attributes and the litigation results extracted from 132 cases were used to train the prediction models; and then 12 cases were implied to the models to predict their litigation outcomes. The test results suggested that the hybrid model outperformed other ML techniques, while the quality of training examples contributed significantly to the predication performance.

3.5 Construction Logistics and Site Planning

Construction site layout and logistics planning is one of the essential components in construction planning, and could incomparably affect the project progress. The task of construction site layout planning is dynamic, multi-objective and uncertain as project proceeds. To deal with these characteristics, Xu and Li (2017) worked on a mathematical model with fuzzy random variables to describe a multi-objective optimization problem of minimizing the total cost of site layout while maximizing the distance between the high-risk facilities and the facilities that needed to be protected from hazard resources. Yahya and Saka (2014) tested another AI technique in the name of Artificial Bee Colony to enhance the multi-objective site layout problem of minimizing facility cost and safety hazard. Their model was tested to be robust and efficient while applied in two case studies, a residential building construction project and a private hospital construction project. To optimize the location of a tower crane in a jobsite and its operational cost, Lien and Cheng (2012; 2014) proposed an approach which integrated Bee Algorithm and Particle Swarm Optimization together. The integrated model was compared with each individual algorithm for both one crane and multiple cranes optimization problems. Results showed that the proposed integrated algorithm outperformed the other two algorithms for location optimization, but it was unable to optimize operational cost for multiple cranes. The method has also shown a superior performance for facility layout optimization comparing with several Evolutionary Algorithms.

In addition to site optimization and facility layout problems, AI techniques have also been applied to solve problems in many other fields to improve construction logistics and planning, such as material transportation system (Zeng *et al.*, 2014), construction resource localization (Soltani *et al.*, 2015) and machinery path planning system (Kuenzel *et al.*, 2015).

4. Conclusion

As seen from the precious analysis, AI application research has consistently grown in recent years since more sophisticated algorithms being proposed, more powerful hardware being invented, and more data being collected for the computer to learn. Nearly about 60% of the papers being published in the recent 5 years of the period under review, meaning that the latest five years were particularly productive in terms of applying AI relative techniques in the field of construction project management. Despite the higher number of publications in the recent years, the quality and complexity of recent papers are substantially high, meaning that AI study in construction is reaching advanced levels of maturity.

In the categorization process, the authors carefully analyzed the content of the 68 selected articles and categorized them into five different fields that AI applied in construction project management. The application field that had the highest number of published papers were: (1) Construction Productivity Management; (2) Construction Safety and Health Management; (3) and Construction Performance Management. Accordingly, these three fields can be considered as the main research trend of using AI to facilitate construction project management, with the Construction Safety and Health Management having the highest growth rate in the recent five years, main pushed by the technologies of computer vision, natural language processing and data mining.

Our analysis of existing AI application literature revealed that the subjects that can be considered as contemporary trends or as having potential are: the usage of AI to reduce safety hazard and to improve construction productivity; the development of AI-based decision support tools; create hybrid/integrate system that combines more than one AI technique for analysis purpose; increase the ability and accuracy of (semi-)automotive process of real-time construction information. However, some gaps or topics that have not been solved were identified in AI application literature as well, namely: the lack of large amount of proper training images and date for computer vision and other AI technique when they were used in construction management fields; and methods to auto process the exiting data from construction project without affect the construction action that is going on.

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