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Review of Construction Business Intelligence Research

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Abstract: With the 4th industrial revolution, many advanced information technologies are being applied to the area of construction engineering and project management. These applications are usually focusing on design, construction and operation stage and are producing many meaningful fruits. Even though these studies are very important for the development of the construction industry, this study insists that the other stage perspective such as construction business also should be emphasized. Because business phase has significant impacts on the success of a construction project as well as design, construction and operation phase. So, this study reviewed the intelligent-approach papers in planning and marketing, estimation and bid, contract and claim, and project financing fields. This study provides some insights such as values, difficulties, limitations and future directions of business intelligence application.

Key words: Construction business, Intelligent construction, Data science, Information technology

1. INTRODUCTION

The beginning of the fourth industrial revolution was declared by Klaus Schwab at the World Economic Forum in 2016. It has become a global trend and terms like ‘big data’, ‘artificial intelligence’, ‘machine learning’ have overflowed all around the world. With the exponential growth of data availability and computing power, data-driven analytics have become possible to produce meaningful insight and to be applied for solving real-life problems [1]. Along with the increased research attention on the fourth industrial revolution techniques, governments have established national-level action plans to support the innovative growth of industries as well as private companies have made massive investments on related projects [2]. The construction industry also has been responding to the fourth industrial revolution by technology transformation from analog to digital along the value chain of construction projects. Boston Consulting Group (BCG) categorized digital technologies in construction industry into four groups as the user interfaces and applications, software platform and control, digital-physical integration layer, and sensors and equipment [3]. However, applications of these technologies usually have been focused on design, construction and operation stage. Even though these studies are very important for the development of the construction industry and are producing many meaningful fruits, the other stage perspective such as construction business also should be emphasized more. This business phase has significant impacts on the success of a construction project as well as design, construction and operation phase [4]. Therefore, this study aims to review construction business intelligence research in early stage of construction project as planning and marketing, estimation and bid, contract and claim and project financing to suggest directions towards effective business intelligence application in the construction domain.

2. LITERATURE REVIEW

This study reviewed academic papers related to business intelligence in early stage of construction project using the state-of-the-art techniques as shown in Table 1. Abbreviations frequently used in this study are at the end of the paper.

Table 1. Summary of reviewed papers in the construction domain

Field	Topic	Methodology	Data source	Reference
Planning & Marketing	Cost index estimation	LS-SVM, DE	Open data	[5]
	Project portfolio management	NLP	Interview	[6]
	Bid/no-bid	SVM	Survey	[7]
	Big data collection	WC, TM	WWW	[8]
	Go/no-go decision	NN	-	[9]
Estimation & Bid	Cost performance prediction	SVR	Survey	[10]
	Cost estimation	GRNN	Private	[11]
	Cost estimation	ANN	World bank	[12]
	Profitability prediction	SVM	Open data	[13]
	Cost estimation	GRNN, MLF	Public	[14]
	Cost estimation	MLP	Survey	[15]
	Cost estimation	MLP, RBF	Public	[16]
	Duration estimation	MLP	Public, Survey	[17]
	System framework	Big data	-	[18]
	Bid competitiveness	GA, ANN	Public	[19]
	Bid mark-up size	ANN	Survey	[20]
	Risk assessment	TM, SVM	Public	[21]
	Risk assessment	TM	Private	[22]
	Contractor default prediction	ESVM	Open data	[23]
	Financial distress prediction	SFNN	Open data	[24]
	Financial distress prediction	SVM, ANN, NB, KNN	Open data	[25]
	Business failure prediction	Big data, ANN	Open data	[26]
	Collusion detection	ANN	Public, Journal	[27]
Contract & Claim	Litigation outcome prediction	SVM, NB, NN	Public	[28]
	Legal knowledge extraction	TM, SVM, NB,	Public	[29]
	Escalation claim outcome prediction	MLP, GFF	-	[30]
	Claim outcome prediction	MLP, GFF	-	[31]
	Poisonous clauses extraction	TM	Private	[32]
	Contract analytics and monitoring	TM	Private	[33]
Project Financing	Financial optimization for PPP project	GA	-	[34]
	Risk analysis in PPP project	ANN, MCS	-	[35]
	Financing optimization	GALP	-	[36]

2.1. Planning and Marketing

In the present study, planning and marketing phase of construction project refer to market prediction, country selection, go/no-go decision and early screening of bad project. Cheng et al. suggested a hybrid intelligence approach for construction cost index estimation of Taiwan construction market [5]. They used 17 cost index influencing factors related to economic, financial, stock market and energy which can be acquired from open data source. In this study, the hybrid of LS-SVM and DE showed better performance than other machine learning techniques such as evolutionary support vector machine inference and backpropagation neural network. Costantino et al. developed a project selection model in view of project portfolio management using ANN [6]. They assessed critical success factors of 150 Italian projects cases by expert interview. Then they employed MLP to classify project success or failure. Sonmez and Sozgen developed a bid decision-making model for offshore oil and gas platform fabrication projects based on the SVM method [7]. They used a five-point scale to assess eight variables which have impact on bid/no bid decision. In this study, SVM method outperformed NN and conventional regression method. Moon et al. developed a document management system in order for information acquisition of international construction [8]. They proposed automatic data collection method using the WC technique from Korean construction-related websites. Then they employed NLP and TM techniques to develop the document management system which provides information of target country in the form of search engine using tagged keywords. Utama et al. suggested a go/no-go decision support model for international construction project based on a hybrid of NN and fuzzy theory [9]. They applied learning process of NN in tuning the membership function used in the fuzzy theory. The suggested model was developed based on the simulated cases of Indonesian contractors.

Many researchers have studied the marketing field in the international construction domain; mainly topics related to market selection [37-43] and entry strategy [44-49]. Nevertheless, most previous studies related to marketing are limited in employing intelligent approaches such as big data and AI. In contrast to the construction sector, marketing field of other business sector are undergoing dramatical paradigm shift with a large amount of consumers' information as big data and advanced data science tools and techniques [50]. Development of digital technologies changed business ecosystem, which targets unspecified individuals, from offline to online and from analog to digital [51]. Against this backdrop, the social media analytics and intelligence research have been developed, which aims to extract insight and inherent information from consumer's data using the WC, opinion mining, content analysis, network analysis, topic extraction [52]. For example, Samsung Electronics analyze social media to investigate what characteristics its consumers have and what are current issues related to its products, and it changes marketing strategies in real time to satisfy consumers' needs [53].

2.2. Estimation and Bid

This study reviewed papers related to project performance prediction, bid competitiveness analysis, risk analysis based on bid-related documents, prediction of financial crisis of contractor and collusion detection during tender process. Project performance prediction is not a new subject. A number of research papers have continuously suggested performance prediction model, mainly cost estimation, with limited available information based on statistic approach or case study. With the development of data science techniques, recently published papers have attempted to improve the estimation capability of previously suggested models by applying advanced methodologies and algorithms such as artificial intelligence. Son et al. suggested a cost performance prediction model that can be applied in the planning stage based on the SVR with PCA [10]. The scope of this study was limited to commercial building projects and they used 84 building projects executed in Korea. They performed a questionnaire survey, which consists of project information including cost overrun ratio and 64 variables of project definition ration index for building projects introduced by the Construction Industry Institute (CII). Yip et al. predicted the maintenance cost of construction equipment based on the GRNN model and compared it with conventional Box-Jenkins time series model [11]. Data for the maintenance cost of construction equipment were collected from a contractor across to different operational divisions respectively. This study concluded that although traditional time series approaches can analyze overall trend and fluctuation patterns, and historical changes over time, non-linear neural network model showed better performance in multivariate modeling because of reflecting dynamic relations between object-related variables. Cirilovic et al. targeted road rehabilitation and reconstruction projects in Europe and Central Asia for cost estimation using projects data from the World Bank study [12]. They compared ANN and MRA approaches, and ANN model outperformed MRA model. Zhang et al. developed a prediction model for forecasting profitability of 489 Chinese construction companies listed on China's A-shares using the PCA and SVM [13]. They used six profitability indicators; return on assets, return on equity, return on capital, earnings per share, profit margin from main business, and return on sales. In addition, this study compared the SVM model with the NN model. They argued that the SVM model showed better performance at predicting profitability than the NN model when analyzing with small samples.

Dursun and Stoy developed a conceptual cost estimation model in pre-planning phases based on the multistep ahead approach using LR, GRNN and MLF methods with 657 building project cases from Germany [14]. The data was collected from the cost information center of the German Chamber of Architects. This study used predicted values of building-element quantities as additional step compared to the conventional single-step ahead approach, and they concluded that quality and quantity of available information has more significant impact on cost estimation than which methodology is used. Marzouk and Elkadi focused on estimating water treatment plants costs executed in Egypt based on the factor analysis and MLP [15]. They identified 33 cost variables through literatures and expert interviews, and collected 160 questionnaires which assessed the impact of the variables. They developed eight NN models combining training types (batch / online / mini batch), optimization algorithm (scaled conjugate gradient / gradient descent), and number of hidden layers (one / two). As a result, a model that consists of one hidden layer using batch training type and gradient descent optimization algorithm showed the lowest MAPE. Bayram et al. compared conventional cost estimation method used in Turkey with MLP and RBF methods and they identified the radial basis function method was superior with the lowest variance with actual values [16]. Nani et al. applied MLP method to estimate duration of bridge construction projects in Ghana [17]. They collected 30 historical data and 100 questionnaires related to bill of quantity from government institution of Ghana. Unexpectedly, the performance of regression and ANN model were not so different in this study.

For bid competitiveness analysis from contractor's perspective, Zhang et al. introduced a system framework that evaluates tender price of construction project using big data [18]. This study focused on big data collection rather than detailed methodologies at the data science perspective. They suggested three types of cost data collection sources; accumulated research cases of the team on practical projects, agreement signed with companies, and agreement with the government construction project management departments. Chou et al. suggested a project award price prediction model using hybrid AI techniques [19]. Based on the GA basically, non-linear regression and ANNs were combined, and they presented 13 prediction models using various parameter values. They collected bid invitation documents and bid award data from government procurement system and Taiwan public construction commission. The result of this study revealed that ANN based models show higher performance than conventional methods for realistic simulations. Polat et al. compared performance of ANN and MRA techniques in estimating bid mark-up size of public construction projects [20]. They used questionnaire survey and collected 80 cases from 27 Turkish contractors. As a result, there was only slight difference in model performance between ANN and MRA models. From the risk analysis perspective, Lee and Yi studied on risk assessment in bidding phase [21]. They developed a project uncertainty prediction model in the bidding process based on integration of unstructured text data and structured numerical data. They collected bidding information of public infrastructure projects ordered by the California Department of Transportation. This study applied the TM technique for extracting risk-related terms from bidding documents in order to improve the accuracy of the risk prediction model which used only the numerical data. In this study, the SVM outperformed other classification models such as ANN, KNN, and NB. Son and Lee developed schedule delay risk estimation model for offshore oil and gas EPC projects using TM technique [22]. They used the scope of work in contract and lessons learned documents written by a private contractor for 13 actual cases. After determining critical terms which have significant impact on schedule delay, they extracted the critical terms through the NLP and developed a regression model to estimate schedule delay considering risk.

There are researches performed in view of the owner and investor's perspective, mainly focusing on the contractor's financial distress prediction. Tserng et al. introduced a prediction model for default of construction contractors in the United States of America (USA) using the ESVM [23]. Target companies for analysis were total of 1,422 construction contractors listed on the New York Stock Exchange, American Exchange, and Nasdaq. Financial data were collected from the Compustat Industrial database and the Center for Research in Securities Prices (CRSP), and a total of 20 input variables were used, which are categorized as liquidity, leverage, activity, and profitability. They employed the ESVM because defaulted events show extreme distribution characteristics, which produce sample selection biases during the learning process. Chen proposed a hybrid model combining three algorithms of self-organizing feature map optimization (SOMO), fuzzy logic control (FLC), and hyper-rectangular composite neural network (HRCNN) to predict financial failure of construction companies in Taiwan [24]. They used 1,615 datasets for data analysis, which consist of quarterly financial reports of 42 companies for 11 years. Choi et al. developed a prediction model for financial distress of contractors in Korean construction industry using ensemble learning [25]. They collected financial status data of contractors such as financial statements and credit ratings from Korean credit rating agencies. Then, this study developed an ensemble classifier using the six classifiers, namely, SVM, NB, ANN, C4.5, LR and KNN. Alaka et al. suggested failure prediction framework of construction firms in UK based on big data analytics and ANN. In this study, they relatively focused on framework architecture for handling large amount of data with short computing time than data analysis [26]. The topic predicting latent corporates which are exposed to financial crisis has been studied widely in other sectors too, especially in the banking sector [54]. Furthermore, Anysz et al. suggested collusion detection model during tender procedures using ANN classifier [27]. They used 249 tender records of public projects collected from Poland Public Procurement Bulletin and European journal TED (Tenders Electronic Daily). The object of this model is to classify public tender procedures as ‘Free from collusion’, ‘Collusion suspected’, and ‘Collusion highly expected’.

2.3. Contract and Claim

In the light of business management in early stage of construction project, contract and legal documents analysis have been studied. Especially, with the development of NLP and TM techniques, studies based on unstructured text data have been presented recently. Mahfouz and Kandil developed a litigation outcome prediction model using three ML techniques, namely SVM, NB and NN classifiers [28]. They gathered 400 construction precedent cases from the federal court of New York through a web database. They identified 15 significant factors affecting litigation outcome as input attributes of ML models. In this study, the SVM based model outperformed other ML models with 98% of accuracy. In addition, Mahfouz et al. suggested another ML based classifiers using textual unstructured data that determines whether judgement of court would favor to owner or contractor from construction contract [29]. They collected a total of 600 actual legal cases through the same approach used in [28]. For the classifier, they developed legal factor extraction model from textual document using TM techniques for handling unstructured data and the Term-Frequency mechanisms for weighting word tokens. In this study, the NB model had better performance than SVM, decision tree and projective adaptive resonance theory. Chaphalkar and Sandbhor suggested outcome of escalation claims prediction model using NN approach [30]. They used 419 claims arisen in the Indian construction industry. They studied 10 major factors influencing the arbitral decision making for outcome of claim, then the factors were converted into binary format as input attributes of NN models according to whether the factor exist in contract or not. Furthermore, Chaphalkar et al. extended the previous study of [30] to various types of claims [31]. Based on 831 cases resolved by arbitration in the Indian construction industry, they identified 16 intrinsic factors caused claim and used the factors as input attributes of NN model. They developed two NN based models employing MLP and GFF. Lee et al. introduced a rule-based NLP model that automatically extract poisonous clauses from a contract of international construction project [32]. They developed preprocessing rules, syntactic rules, and semantic rules to identify risk-related clauses based on the International Federation of Consulting Engineers (FIDIC) standard contract conditions. Marzouk and Enaba proposed contract analytics and monitoring model based on TM [33]. The suggested model extracts important terms from contract, retrieve similar cases and correspondence of employer and visualize previously extracted contract-related information for managerial purpose. They implemented a case study executed in Egypt in order for the model validation.

2.4. Project Financing

Publication of academic papers related to the public-private partnership (PPP) project has increased constantly and research on economic feasibility and capital structure has been the one of popular topics of PPP studies [55]. Most previous studies investigated economic viability and value for money (VFM) employing option pricing theory mainly, however, not many studies have been searched applying advanced data science techniques. Iyer and Sagheer suggested a financial optimization model for PPP project based on GA method considering not only viability of capital structure but also bid winning potential [34]. Based on 13 project characteristics of BOT road project, the proposed model suggested optimal equity and grant ratio to maximize return on equity and bid-winning probability. Shahrara et al. employed ANN to estimate expected fee for build-operate-transfer (BOT) project during concession periods. Because the purpose of this study is to calculate appropriate fee with respect to surrounding conditions, they created 1,871 scenarios using MCS rather than collecting actual data [35]. Alavipour and Arditi suggested a financing optimization model integrated with time-cost tradeoff analysis based on the GALP, which is an integration of GA and linear programming [36]. This model considered not only several financing alternatives such as short-term loan, long-term loan, and line of credit but also time-cost tradeoff and the finance-based scheduling problems.

3. DISCUSSION

Conventional statistic approaches are limited to solve real world problems because of assumptions of linearity, normality, independence among variables [56]. To overcome such limitations, data mining and AI techniques have been employed oftentimes recently. Compared with traditional methods, ANNs have advantages in applying practice because not only input data do not have to satisfy various assumptions but also ANNs are more resistant to noise and errors in the data set [12]. In other sectors, many studies employed advanced data science techniques to support establishing business strategies, for example, electricity price forecasting [57; 58], shared bicycle demand prediction [59], natural gas consumption estimation [60], aircraft spare parts demand forecasting [61], agricultural grain commodities prediction [62], medical costs inflation rate forecasting [63], and so on. With respect to recent trend of applying advanced data science techniques, research related to business phase of the construction project also has been widely performed, especially in predicting or estimating project performance. However, business intelligence based on data-driven analysis is difficult in construction domain because of unique characteristic of the construction industry such as uniqueness of product, limited number of customers, order-based market, long lead time from project start to finish, a small amount of accumulated data. In addition, the TM technique, which aims to extract meaningful information such as patters, trends, or relationships from textual unstructured data, has recently received attention along with the development of big data and data science. There is a tremendous amount of textual data on the WWW and many industrial sectors seek to analyze such open data for supporting their business, especially in marketing phase using social media analytics. However, it is limited to collect data from the WWW in construction business because customers of construction project are not unspecified individuals, but relatively small number of clients. In addition, although a large portion of corporate information is in textual data format [64], limited accessibility to sensitive business documents of public and researchers in the construction domain makes difficult to perform research using practical textual data. Data availability is especially important when applying the fourth industrial revolution techniques. Nevertheless, the research in construction sector usually suffer from lack of data [65; 66]. Against these backdrops, the authors of present paper recommend directions towards effective business intelligence application in the construction sector as follow; First, BIM based information management platform for business phase is necessary. BIM is one of the promising information management tools to innovate construction business and improve productivity through embracing digitalization [67]. However, BIM related research and development has mainly focused on project execution phase for integrating design and construction information. Its value chain should be extended to early stage of construction project for business management and supporting decision making [68]. Accumulating and analyzing various data for business phase such as construction market information, clients and competitors information, tender information for new projects and feasibility studies documents would be provide meaningful insight towards better business. Second, industry-academic cooperation should be activated more. Many companies, especially small-medium construction companies, are insufficient in knowledge management. Corporations usually lack manpower and time to invest in data analysis for extracting meaningful insight although they have practical data, whereas academics suffer from lack of practical data for investigation due to confidentiality. Industry-academic cooperation for business intelligence research and development would be win-win strategy for innovation of construction industry and business management in the fourth industrial revolution era.

4. CONCLUSION

This study briefly reviewed academic literature related to construction business intelligence in planning and marketing, estimation and bid, contract and claim and project financing fields over ten years. Although the fourth industrial revolution techniques considerably impact the research of construction domain, it seems one step behind than other sectors because of unique characteristics of construction industry. This study focused on briefly summarizing what purpose existing literature had, which advanced data science technology has been employed, and where the researchers collected data from. Detailed explanation will be presented at the ICCEPM 2020 conference.

ABBREVIATION

AI	Artificial Intelligence
ANN	Artificial Neural Network
BIM	Building Information Modeling
C4.5	Commercial version 4.5
DE	Differential Evolution
ESVM	Enforced Support Vector Machine
GA	Genetic Algorithm
GALP	Genetic Algorithm Linear Programming
GFF	General Feedforward
GRNN	General Regression Neural Network
KNN	K-Nearest Neighbors
LR	Linear Regression
LS-SVM	Least Squares Support Vector Machine
MAPE	Mean Absolute Percent Error
MCS	Monte-Carlo Simulation
MLF	Multilayer Feedforward
MLP	Multilayer Perceptron
MRA	Multiple Regression Analysis
NLP	Natural Language Processing
NN	Neural Network
PCA	Principal Component Analysis
RBF	Radial Basis Function
SVM	Support Vector Machine
SVR	Support Vector Regression
TM	Text Mining
WC	Web Crawling
WWW	World Wide Web

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