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A systematic literature review on price forecasting models in construction industry

Mingxue Ma, Vivian W. Y. Tam, Khoa N. Le and Robert Osei-Kyei

School of Engineering, Design and Built Environment, Western Sydney University, Penrith, NSW, Australia

ABSTRACT
This paper summarizes a list of previously used forecasting models in the construction industry, using a three-stage review process. Specifically, articles published between 2012 to 2022 (inclusive) are investigated, and 34 documents are selected for further analysis. The results present a fluctuating number of publications from 2012 to 2016 and a significant increase since 2016. The distribution line between 2016 to 2020 indicates the growing interests in this topic. In addition, fluctuating material prices, construction costs and construction cost index were top concerns of researchers. Previous literatures frequently employed three forecasting models: Vector error correction model, Artificial Neural Network and Autoregressive Integrated Moving Average. Time series and machine learning techniques were widely used in prediction. Future studies could consider the hybrid model as a research method to improve the forecast accuracy. Additionally, future studies should take the effects of natural disasters into account. Findings of this study are expected to help researchers and industry practitioners select a suitable forecasting model and implement precise prediction in practice.

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KEYWORDS
Price forecasting; construction; literature review

Introduction

Customers usually prefer products which could satisfy both their needs and budgets. Therefore, the price of a product could determine customers' purchase decisions (Mahoto et al. 2021). Given that the profitability of a business largely relies on the percentage of sales, it is of great importance for a business to set a proper price for each product (Mahoto et al. 2021). In recent years, predicting the price trends of products has attracted attentions from industry and is currently regarded as a top priority in many sectors (Nguyen et al. 2019). For business managers, predicting activities can contribute to decision-making, formulating business strategies, maximizing profits and minimizing losses (Vijh et al. 2020). In addition, forecasting could help customers in purchasing their required products at a suitable price (Nguyen et al. 2019).

The rapid population growth and urbanization have resulted in the construction of new buildings, which consumes a great quantity of construction materials, especially in developing countries (Kisku et al. 2017). In construction industry, resource costs (such as materials, labour and equipment) typically constitute the majority of construction project costs. Fluctuation of material prices is identified as one of the leading cause of construction cost overruns (Shiha et al. 2020). Utilizing recycled products in the construction industry is expected to attain sustainable development. Because of the high cost for recycling treatment, the price of sustainable products (such as recycled concrete) remains at or above the price of original products. Forecasting the price of sustainable materials could contribute to the establishment of the recycling market and the promotion of sustainable development. Therefore, it is crucial for related stakeholders (including principals, contractors and suppliers) to estimate future price changes and develop profitable strategies (Jiang et al. 2013). However, predicting the price of a product could be challenging, because the price might be impacted by multiple factors and subject to fluctuations. For instance, stock price is dynamic and unpredictable in nature, and they may be influenced by political conditions, global economy and business performance (Vijh et al. 2020), while weather conditions, plant diseases, customer demands, and the competitive environment might impact the price of agricultural products (Drachal 2019). In the construction industry, material prices fluctuate with market and political conditions (Jiang et al. 2013). In addition, previous literatures have revealed a strong correlation between economic and political instability and fluctuations in material costs (Shiha et al. 2020).

This paper aims to conduct a comprehensive literature review to summarize a list of forecasting models previously used in construction industry. Findings of this paper are expected to help researchers and industry practitioners in selecting a suitable forecasting model and implementing precise estimation of product prices in practices.

Literature review

Predicting the price trend of a product has become a research hotspot in last decades (Yu and Yan 2020). A great range of construction materials was investigated, including cement (Afolabi and Abimbola 2022, Velumani and Nampoothiri 2018), timber (Banas and Utnik-Banas 2021), steel (Shiha et al. 2020), asphalt

CONTACT Vivian W. Y. Tam vivianwytam@gmail.com

(Faghih and Kashani 2018, Mir et al. 2021) and concrete (Swei et al. 2017). The forecasting process usually uses historical and current data to predict the future price of a product (Nguyen et al. 2019). In addition, the dynamics of construction costs (Velumani and Nampoothiri 2019, Jiang and Liu 2014, Petroutsatou et al. 2012), material consumption (Beljkaš et al. 2020, Ali et al. 2019), and house price (Chen et al. 2022, Tchuente and Nyawa 2022) were explored in previous studies. However, these data could be complex, incomplete and fuzzy, which increase the difficulty in prediction (Yu and Yan 2020).

A great collection of previous literatures focused on selecting a suitable forecasting model to make a prediction (Tseng et al. 2018). For instance, hedonic price model is widely used in housing market (Yim et al. 2014). It has been observed that machine learning algorithms are effective forecasting methods (Mahoto et al. 2021). Artificial Neural Network (ANN) model could use historical prices, quantities and other information as inputs to predict market behaviours (Singhal and Swarup 2011). Traditional forecasting models include multiple time series methods (including Autoregressive Integrated Moving Average (ARIMA)) (Tseng et al. 2018). The views on the performance and superiority of forecasting models vary, especially for different data set (Ayodele Ariyo et al. 2014). Therefore, the selection of a proper prediction model is one major concern for researchers (Tseng et al. 2018), but there are insufficient studies that have comprehensively evaluated forecasting models used in the construction industry.

Research method

A systematic literature review could provide a state-of-art understanding of specific research topic, identify research gaps and establish a new theoretical framework (Paul and Criado 2020). This study adopted a three-stage review process, following the description of Osei-Kyei and Chan (2015). Figure 1 presents the research framework of this study.

In stage 1, the Scopus database was selected to identify studies which developed forecasting models. Specifically, Scopus is widely used for searching the literatures, because it covers a wider range of journals than Web of Science and Google Scholar (Falagas et al. 2008). Scopus is the most comprehensive database, which is continuously updated for searchable citations and abstracts of literatures (Joshi 2016). It is user-friendly and permits more precise queries than Web of Science (Weron 2014). Three groups of keywords were included in the 'title/abstract/keyword' area of Scopus: (1) 'Price'; (2) 'Prediction', 'Estimation', 'Forecast' or 'Price model'; and (3) 'construction'. The scope of the exploration was restricted to articles published between 2012 to 2022 (inclusive). Over the past decade, technology has played a significant role in transforming the construction sector into a high-tech industry. Leveraging new technologies improves the accuracy of price forecasts, and new forecasting approaches are continuously emerging. Literatures from these 10 years represent the industry's trend and describe in detail the most recent situations. Document types were 'Article' and 'Review'. It should be noted that other document types, including 'book', 'chapter', 'conference paper', 'editorial', 'letter', 'note', and 'short survey' were not reviewed in this study. Language was restricted to English only. A total of 612 documents were identified. The search codes are as below:

(TITLE-ABS-KEY ('price') AND TITLE-ABS-KEY ('construction') AND TITLE-ABS-KEY ('Prediction' OR 'Estimation' OR 'Forecast' OR 'Price model')) AND PUBYEAR > 2011 AND (LIMIT-TO (DOCTYPE, 'ar') OR LIMIT-TO (DOCTYPE, 're')) AND (LIMIT-TO (LANGUAGE, 'English'))

In stage 2, a visual examination was generated to exclude documents whose titles and abstracts were irrelevant to forecasting models. During this stage, the authors examined the titles and abstracts of the 612 identified documents, to determine if they contain content related to price forecasting in construction industry. If the document's title or abstract did not contain these keywords, it would be excluded. 63 documents were selected. Another round of visual examination on the full texts of the 63 documents was carried out. Finally, 34 documents were selected for further analysis in stage 3. Table 1 presents a list of forecasting models applied in 34 articles.

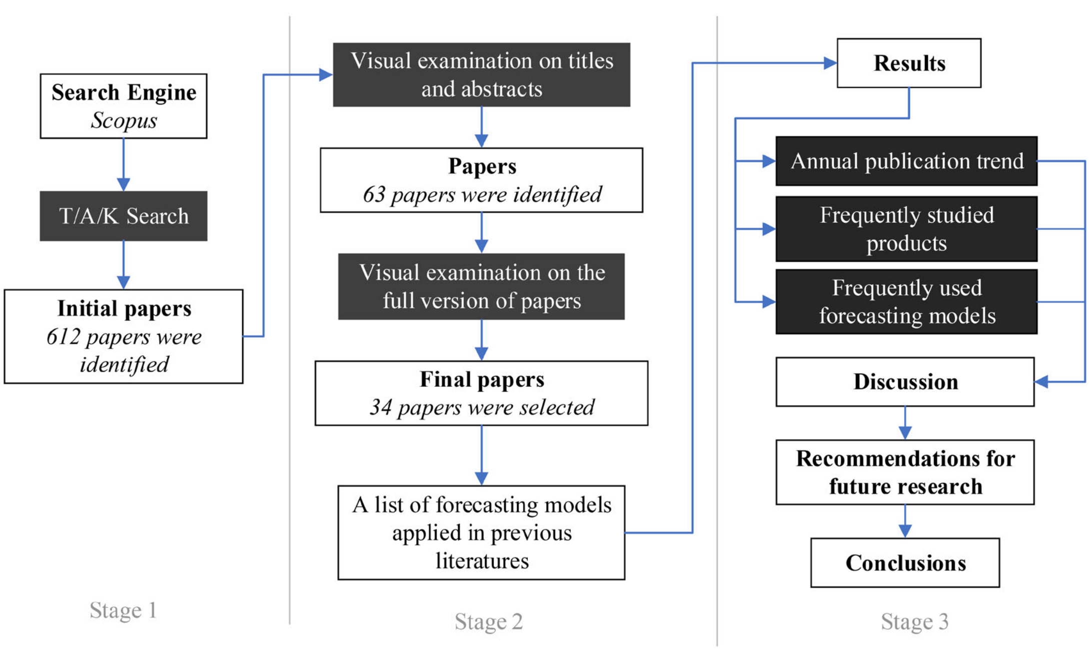

Figure 1. Research framework of this study.

Results and discussion

Publication trend

Figure 2 depicts the publication trend for topics related to price forecasts in construction industry. In particular, this figure only presents the publication years of the 34 selected articles. This review may not be able to provide an exhaustive list of relevant references, but it can provide a summary of previous literatures and suggestions for future research. Since 2016, the number of publications experienced a significant increase, reaching a peak of 7 publications in 2020 from 1 publication in 2016 (Figure 2). Although fewer papers were published annually between 2012 and 2016, at least 1 paper was published each year. The distribution line between 2016 and 2020 indicates increasing interests in this topic. This may be the result of a more complex market structure and a wider variety of product characteristics. Larger and more complicated data sets require more precise models (Petropoulos et al. 2022). Advancements in computing have improved analytical skills and sparked interests in related fields, which could contribute to the increase in publications numbers. In addition, publications before 2016 focused on construction costs. Specifically, four of the six publications forecasted

Table 1. A list of forecasting models applied in previous literatures.

Ref.	Applications		Model	Category	Reference
1	Material	Cement	Web-based learning platform	Machine-learning algorithms	(Afolabi and Abimbola 2022)
2			Artificial neural network (ANN)	Machine-learning algorithms	(Velumani and Nampoothiri 2018)
3		Construction material indices	ARIMA and Non-Linear Autoregressive Neural Network (NARNET)	Time-series models	(Işıkdağ et al. 2023)
4		Asphalt and steel	ANN	Machine-learning algorithms	(Mir et al. 2021)
5		Timber	Autoregressive integrated moving average (ARIMA), seasonal univariate (SARIMA) and seasonal bivariate with an exogenous variable (SARIMAX).	Time-series models	(Banas and Utnik-Banas 2021)
6		Building material price	Spearman correlation	Correlations	(Musarat et al. 2020)
7		Steel and cement	ANN	Machine-learning algorithms	(Shiha et al. 2020)
8		Bituminous	Vector error correction model (VECM)	Time-series model	(Swei 2020)
9		Raw materials: iron ore	VECM	Time-series model	(Lee et al. 2019)
10		Asphalt, steel and cement	VECM	Time-series model	(Faghih and Kashani 2018)
11		Raw material: crude oil	Least Absolute Shrinkage and Selection Operator (LASSO) regression method	Regression analysis	(Miao et al. 2017)
12		Concrete and asphalt	Univariate time-series techniques	Time-series model	(Swei et al. 2017)
13		Raw material: crude oil	Dynamic model averaging (DMA)	Bayesian techniques	(Naser 2016)
14	Hourly earnings of construction labour		VECM	Time-series model	(Faghih et al. 2021)
15	Construction costs		ANN	Machine-learning algorithms	(Velumani and Nampoothiri 2019)
16			Back-propagation neural network and support vector machine (SVM)	Hybrid model: machine-learning algorithms	(Rafiei and Adeli 2018)
17			VECM	Time-series model	(Jiang et al. 2014)
18			ARIMA	Time-series model	(Hwang et al. 2012)
19			General regression neural network (GRNN)	Machine-learning algorithms	(Petroutsatou et al. 2012)
20	Construction cost index		ARIMA	Time-series model	(Jiang et al. 2022)
21			Long short-term memory model (LSTM)	Machine-learning algorithms	(Cao and Ashuri 2020)
22			Autoregressive time series	Time-series model	(Elfahham 2019)
23			VECM	Time-series model	(Moon and Shin 2018)
24			K-NN and PERT models	Machine-learning algorithms	(Wang and Ashuri 2017)
25			Least Squares Support Vector Machine (LS-SVM) and Differential Evolution (DE)	Hybrid model	(Cheng et al. 2013)
26	Product consumption	Concrete	ANN	Machine-learning algorithms	(Beljkaš et al. 2020)
27		Bitumen	Genetic algorithm (GA)	Optimization algorithms	(Ali et al. 2019)
28		Aggregate	VECM	Time-series model	(Jiang and Liu 2014)
29	House price		Random forest	Machine-learning algorithms	(Chen et al. 2022)
30			Neural networks and random forest techniques	Machine-learning algorithms	(Tchuente and Nyawa 2022)
31			VECM	Time-series model	(Shi et al. 2021)
32			Hedonic price model	Traditional forecasting methods	(Wen et al. 2018)
33	Bid award amount	Engineering, procurement, and construction projects	Technical Risk Extraction and Design Parameter Extraction	Machine-learning Algorithms	(Park et al. 2021)
34		Bridge projects	ANN	Machine-learning algorithms	(Chou et al. 2015)

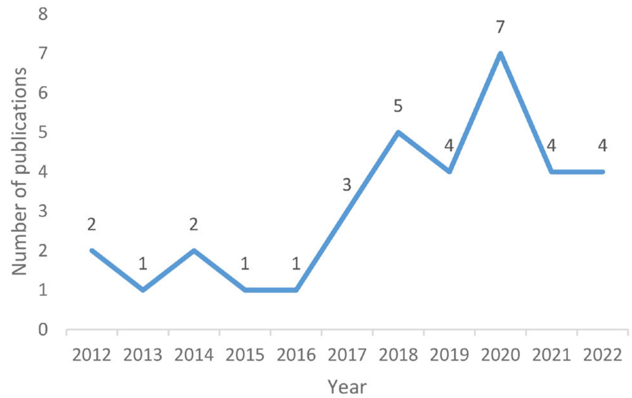

Figure 2. Annual publication trend.

construction costs. Publications after 2016 investigated multiple subdomains within the construction sector, including the costs of multiple materials, product consumption and house prices.

Frequently studied products

Figure 3 presents different categories of predicted items and their frequency in previous literatures. They are material prices (13 papers), construction cost index (6 papers), construction cost (5 papers), house price (4 papers), product consumption (3 papers), bid award amount (2 papers), and labour cost (1 paper).

According to Figure 3, prediction of construction material prices was emphasized in previous studies, since this category appears 13 times in 34 selected papers and ranked first. Construction material price is a major concern for all related parties, because price volatilities and uncertain conditions during construction process could incur extra costs which might hinder the completion of projects (Mir et al. 2021). In construction projects, material cost constitutes 25% of total project cost, which is a key component in project success (Işıkdağ et al. 2023). There are different prices for different regions, and the price of a particular commodity may be affected by local factors. For instance, strikes and natural disasters could disrupt material supply and raise prices. Due to the fluctuation of inflation rate, the annual adjustment of construction material prices could result in inaccurate material estimation and distress among stakeholders (Muhammad Ali et al. 2021). During the preparation of the tenders and execution phase, it is essential to have an accurate estimation of prospective changes in material prices, in order to formulate appropriate strategies (Velumani and Nampoothiri 2018). Price of construction materials, including cement, concrete, asphalt, steel, timber and bituminous was investigated in selected literatures. In addition, the price of raw materials (such as crude oil and iron ore) was one concern, because raw material price is one influential factor in changes of material price (Mir et al. 2021). Unequal distribution of raw materials and energy commodities makes several countries rely on exports, which could impact international trades and cause tensions (Drachal 2021). Movements in crude oil price could significantly impact world economy, because most production process relies on crude oil for energy or transportation (Wang et al. 2020). A 10% increase in oil price could reduce global Gross domestic product (GDP) by 0.2% (Miao et al. 2017). Therefore, accurate forecasting of crude oil price becomes one concern for government, industry and individuals (Wang et al. 2020). However, multiple external factors, including uncertainties from Coronavirus (COVID-19) pandemic (Wu et al. 2021) and complex politico-economic dynamics (Wang et al. 2020) makes the forecast a challenging task.

The categories of construction cost index (CCI) and construction cost ranked second and third, with accumulated numbers of 6 and 5, separately. In the construction industry, problem of cost overrun persists, with construction costs exceeding their planned costs in approximately 90% of construction projects (Işıkdağ et al. 2023). Related stakeholders spend great efforts to estimate construction costs accurately, because it is crucial in early-stage planning, risk assessment and decision making (Jiang et al. 2022). However, the unpredictability of construction process makes it difficult to predict the final construction cost (Petroutsatou et al. 2012). For instance, variations, cost escalations and unknown ground conditions are common (Petroutsatou et al. 2012). CCI could be used to calculate construction costs, simplifying the complexity of prediction and providing short- and long-term changes in costs (Jiang et al. 2022). CCI is calculated using labour costs and the prices of certain construction materials (Jiang et al. 2022). CCI could also be used to evaluate market trends, compare costs, formulate a cost plan, prepare tenders and plan investments (Moon and Shin 2018).

There were four articles predicting property prices. Housing affordability is one public concern, because purchasing a home could be one of the largest investments in most people's life (Tchuente and Nyawa 2022). A healthy housing market is closely associated with economic growth, and fluctuations in property prices have direct impacts on the financial system (Shi et al. 2021). Chen et al. (2022) analyzed determinants of house price from two perspectives: macro (including economy, population, household income) and micro (such as neighborhood characteristics). Understanding price fluctuations could not only provide homebuyers with bargaining power, but also enable sellers avoid overestimation or underestimation risks (Tchuente and Nyawa 2022).

Previous studies also predicted the consumption of construction materials, the award price and future labour costs. Estimating future material consumption and labour costs is critical in the prediction of construction costs. Specifically, hourly earnings of construction labour doubled during the period from 1995 to 2016 in the United States (Faghih et al. 2021). Movements in labour wages could cause deviations in construction costs, which could further lead to unsteady cashflow, loss in profit and delay or cancellation of projects (Faghih et al. 2021). In addition, it is of great importance for government to estimate future consumption of construction materials, in order to allocation valuable resources appropriately (Jiang and Liu 2014). For contractors, prediction of material consumption could help them develop optimal pricing strategies and gain market advantages (Jiang and Liu 2014). The information could be used to make a bid (Beljkaš et al. 2020). Contractors could win a contract by conducting predictions that account for costs and profits (Chou et al. 2015). In competitive bidding, bidding at a lower price might result in profit loss, while overestimation might lead to loss of contract (Chou et al. 2015).

Frequently used models

In this article, forecasting models are classified as follows: (1) traditional forecasting method, including hedonic price model, regression analysis and time series analysis; (2) machine-learning algorithms, including artificial neural network (ANN) and support vector machine (SVM), and etc., (3) hybrid methods; and (4) others, including methods which are not mentioned in the

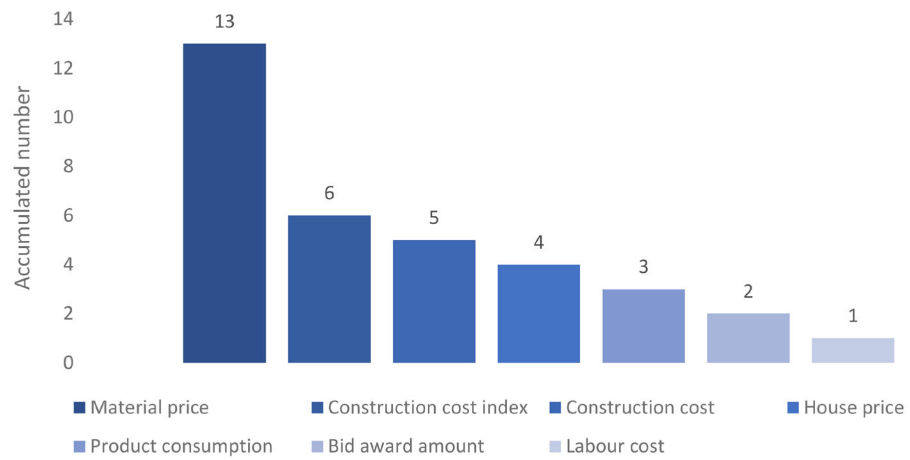

Figure 3. Categories of predicted products in previous literatures.

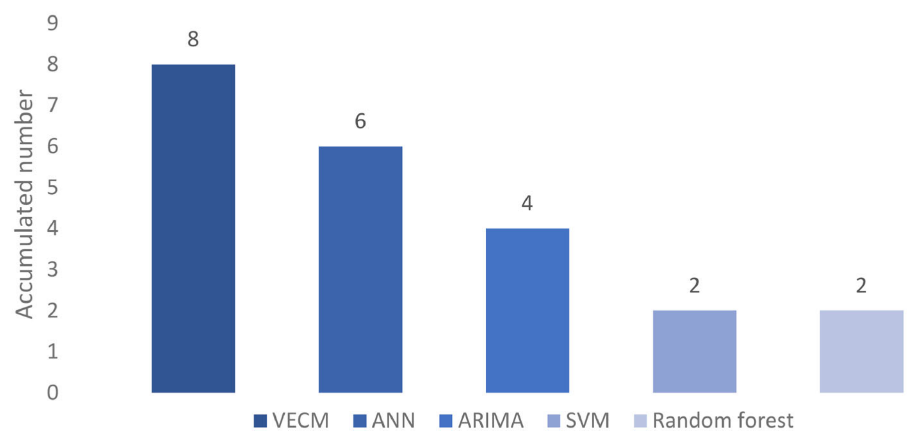

Figure 4. Accumulated number of forecasting models used in previous literatures.

previous three categories (including optimization algorithms and correlations). Selecting a suitable prediction method is imperative to generate accurate forecasts. Figure 4 presents the frequencies of each forecasting model. The most frequently used forecasting models are vector error correction model (VECM), artificial neural network (ANN) and autoregressive integrated moving average (ARIMA). These three forecasting models would be further discussed and compared.

Vector error correction model (VECM)

VECM combines vector autoregressive model and cointegration restrictions, which examines dynamics between variables and includes adjustment process to long-term equilibrium (Jiang et al. 2013). This model is widely used in financial and economic studies (Shao et al. 2019). VECM is recommended when the time series data are non-stationary (Pradhan and Bagchi 2013). Five steps are involved in the procedure: (1) selection of dependent and independent variables and collection of historical data for prediction, (2) Granger causality analysis to check the bidirectional or unidirectional relationships between variables, (3) a cointegration test to assess data stability, (4) prediction and analysis of accuracy, and (5) impulse response analysis and variance decomposition analysis to evaluate impacts of independent variables (Lee et al. 2019).

In previous studies, VECM had been verified to be an accurate forecasting model in multivariate time series analysis (Lee et al. 2019). Different from univariate time series analysis which conducts prediction by using only time series data of target variable, VECM could capture the relationships between dependent variables and a set of independent variables (Lee et al. 2019). Since VECM depends on time series data and material prices are featured for a time-dependent nature, VECM is suitable for predicting material prices. For instance, Faghih and Kashani (2018) used VECM to predict the short- and long-term prices of construction materials (including asphalt, steel, and cement). Dependent variable was future material price, while the independent variable were time series data of material price and a set of variables (including gross domestic product, consumer price index, WTI crude oil price) (Faghih and Kashani 2018). Jiang et al. (2013) investigated relationships between construction costs and a group of macroeconomic variables. While population growth is closely associated with short-term construction prices, the long-term construction price is determined by national income, population and interest rate (Jiang et al. 2013).

Artificial neural network (ANN) model

ANN model consists of three layers: input layer (such as attributes of commodities), hidden layers (it is commonly referred as 'black box'), and output layer (including the estimated price of commodity) (Limsombunchai 2004). These three layers are interconnected with artificial neurons capable of storing and processing a large amount of information (Ghatak and Ghatak 2018).

The fundamental concept of the ANN model is to use historical data to forecast future circumstances. Therefore, this model is featured as a data-driven model, and a set of known input variables should be obtained to establish a mathematical relationship between input and output data (Ghatak and Ghatak 2018). In addition, the nonlinear relationships among variables could be captured in hidden layers (Qiu and Song 2016).

ANN model could estimate the cost of a commodity based on related physical attributes and map the complex interdependencies between variables (Singhal and Swarup 2011). Besides, compared to physics-based models, one significant advantage of the ANN model is that the solution is fast and straightforward (Ghatak and Ghatak 2018). Alex et al. (2010) notified three advantages of ANN model: (1) ANN model could model the interdependencies between input data; (2) this model could handle the nonlinear relations which coexist between cost-related parameters; and (3) this model is shown to be more efficient than regression in handing incomplete data sets. These advantages make the ANN-based model suitable for complex price forecasting and have contributed to the model's growing prominence in research (Singh et al. 2017). However, the problem of underfitting or overfitting could be caused by increased complexity and reduction in degree of freedom, which negatively decreases the generation ability (Singh et al. 2017). ANN model is also criticised as a black box model, because they are unable to present an explicit relationship between inputs and outputs (Akkurt et al. 2004).

Autoregressive integrated moving average (ARIMA)

Time series analysis is a useful approach for forecasting when knowledge on the underlying data generating process is inadequate or there is no appropriate explanatory model which describes the underlying relationships between prediction and explanatory variables (Zou et al. 2007). ARIMA model is one of the most widely used time series models, because of its low research costs and high efficiency in short-term forecasting (Zou et al. 2007). ARIMA model is developed as a data-oriented approach and originated from the data structure, which adequately represents a precise data-generating process (Kohzadi et al. 1996). When there is a linear and stationary time series, ARIMA model is frequently selected for prediction, because of its high performance and robustness (Valenzuela et al. 2008). It linearly combines past value and past errors to forecast future value of a variable (Zou et al. 2007). However, the requirement for trainings in statistical analysis, knowledge of the field of application and versatile specialized computer program increases difficulty in the establishment of an ARIMA model (Ediger et al. 2006). Model parameters which could satisfy the statistical residual diagnostic checking would be chosen in the ARIMA model (Ömer Faruk 2010). Nonlinear data sets limit the application of ARIMA (Ömer Faruk 2010). Existence of linear correlation between time series values is generally assumed, despite the impracticality of linear relationships in real-world problems (Wang et al. 2013). Therefore, ARIMA model might be unable to provide satisfactory results for complex real-world problems and non-linear relationship should be defined (Wang et al. 2013).

Comparison of three forecasting models

It is of great importance to forecast prices using suitable and scientific methods. Table 2 compares three models described in previous sections (VECM ANN, and ARIMA), based on their assumptions, advantages and limitations. The views on the performance and superiority of forecasting models from previous literatures are different, especially for different data sets (Ayodele Ariyo et al. 2014). In addition, adoption of forecasting methods without consideration of case conditions and characteristics of data might lead to distortion in results (Azadeh et al. 2012). Therefore, before decisions on forecasting model, it is necessary to evaluate the availability and empirical characteristics of data.

Discussion

Plenty of forecasting models were proposed in previous literatures. However, it is often difficult to find a suitable forecasting model for certain commodities in practice, because it is hard to diagnose the linearity or nonlinearity of real-world time series (Zhang 2003). Due to the time-dependent nature of material prices, time-series approaches (VECM and ARIMA) have been widely used to predict the prices of construction materials (Table 1). Time-series approaches use historical values of a dependent variable and the corresponding data of other independent variables to predict future trend of the dependent variable (Hwang et al. 2012). The high volatility of energy prices significantly increases uncertainties in its prediction (Gao and Lei 2017). Several articles discussed the forecasting of the prices of raw materials. For instance, the price of crude oil is impacted by multiple factors, including political environment, economic growth and labour market conditions (Safari and Davallou 2018). Time series, such as the monthly reported oil price, were often collected and analysed to capture relationships. Several possible explanatory variables would be taken into consideration. For instance, in the case of coal, U.S. coal production, total consumption and stocks were taken to measure supply and demand forces (Drachal 2021). ARIMA, as a traditional statistical model, which is based on linear assumptions, was applied to predict material prices and construction costs in some studies. Long-term forecasts attract attentions from construction industry, because profits from operation phase exceed those from construction phase (Lee et al. 2019). Long-term prediction could be used for capital investments, including acquisition of land and equipment, while medium-term prediction could be useful for product development (Lam and Oshodi 2016). However, long-term estimates could be challenging, since prediction errors increase along with the length of prediction period (Lee et al. 2019). Specifically, ARIMA models are suitable for short-term forecasts, while VECM could be used in both short- and long-run estimates. In addition, features of the time series determine which model to use. When a time series is linear and stationary, ARIMA model is frequently selected for prediction (Valenzuela et al. 2008). VECM is recommended for non-stationary time series data (Pradhan and Bagchi 2013).

Machine learning techniques (ANN, random forest and GRNN) were used to predict the price of construction materials, construction costs and CCI (Table 1). The real-world problem could be dynamic and might be impacted by a set of changeable factors. For instance, material, labour, equipment, project duration, type and location are determinants of construction costs (Rafiei and Adeli 2018). Machine learning techniques consider a set of factors and use time-series data to forecast future circumstances. Different machine learning models vary widely, and it is important to find a suitable model to handle the imperfections of the time series (Ahmed et al. 2010). ANN was found to be one frequently used model (Figure 4). It could be applied to the prediction of complicated problems which are unable to be

Table 2. Models comparison.

Pricing models	Description	Inputs	Software	Assumptions	Advantages	Limitations
VECM	It could capture the relationships between dependent variables and a set of independent variables	Corresponding time series data for each variable.	Eviews, R, and MATLAB	Model coefficients are constant.	(1) It could capture the relationships between dependent variables and a set of independent variables; (2) It could avoid problems of time series destabilization and spurious regression; and (3) It could be used when the data is non-stationary.	It is unable to characterize relative potency between variables during the selected time period, which reduces reliability of results.
ANN	It is a highly complex nonlinear dynamic learning system, which can capture nonlinear modes.	(1) Independent variables (attributes of product), such as attributes of housing (size, room number, accessibility to CBD and subway station; (2) Dependent variable (price), such as unit price of housing; and (3) Time series data, such as historical daily stock prices.	R, MATLAB and Python.	No prior assumptions about the model.	(1) It has the ability to learn and to capture unknown or very hard relationships; (2) It estimates the cost of commodity considering the physical attributes; (3) It models the interdependencies between input data; (4) It handles the nonlinear relations which coexist between cost-related parameters; (5) It is shown to be more efficient than regression in handing incomplete data set; and (6) It can handle large amount of data.	(1) Forecast cost is within a limited certainty; (2) The base of cost estimation during the preliminary stages of conceptual design is on uncertainties which might be inaccurate; (3) It is featured for low accuracy, slow convergence speed and difficulty in determining the hidden layers nodes of neural network for small samples; and (4) It is unable to present an explicit relationship between inputs and outputs.
ARIMA	This method is based on analysis of historical data of price time series, following the rule that price changes with time.	Time series data, such as historical daily stock prices.	R, MATLAB, Python, Ruby, JavaScript.	The time series must be linear or near linear.	(1) Low research costs and high efficiency in short-term forecasting; and (2) Only data of the time series in question is required.	(1) It is unable to catch the non-linear relationship and might fail to provide satisfactory results for complex real-world problems; and (2) There exists difficulty in the establishment of an ARIMA model for the requirement for trainings in statistical analysis, knowledge of the field of application and versatile specialized computer program.

solved by conventional methods (Ghatak and Ghatak 2018). This model expands quickly because of its ability to forecast financial data and model economic conditions (Tseng et al. 2008). There is a consensus that single model is unable to consider all the status and correlations in time series data, because of complexity in real world problems (Safari and Davallou 2018). Therefore, hybrid models were used in prediction of construction cost and CCI.

In addition to machine-learning and time-series models, the hedonic price model was used to forecast house prices (Table 1). Hedonic price model is derived from Lancaster's (1966) proposal, which has been extensively used to investigate relationships between housing attributes (including location, house size, numbers of rooms, parking facilities and neighbourhood) and house prices (Limsombunchai 2004). Since hedonic price model could explain which characteristics are valued more or less and to what extent (Yim et al. 2014), hedonic price model has been widely applied in housing market (Zhang and Dong 2018, Tam et al. 2022, Owusu-Ansah 2011, Lu 2018, Chen 2017, Cebula 2009). Besides, the hedonic price model could be used to estimate the extent to which each characteristic impacts the price of other commodities (Tam et al. 2022).

Recommendations for future research

In last few years, price forecasting received intensive attentions. Clearly, price forecasting is essential to make marketing strategies, avoid potential risks, obtain profits and enhance management. Findings of this study could inform researchers and industry practitioners who are interested in price forecasting and provide useful contributions to practice. Specifically, frequently forecasted items in the construction industry were explored, which inform the government of public concerns, including fluctuations in prices of construction materials, product consumptions and house prices. For practice, the results are expected to help select a suitable forecasting method and launch precise estimation of product prices.

Several forecasting models were introduced in this study. Each model has its advantages and disadvantages. No individual model could represent all other methods. Hybrid methods, which combine two or more models, are gaining popularity in research. Different models have their respective advantages, limitations and focus, and hybrid models could integrate their advantages and enhance forecasting accuracy (Liu et al. 2021). Specifically, use of different structural characteristics is accepted in hybrid models (Ribeiro and Oliveira 2011). Future studies could consider hybrid models as a research method to improve forecast accuracy.

It is an era of great uncertainties, such as COVID-19, bush fires and international conflicts, which could result in substantial changes in material prices and construction costs. It is crucial to forecast and quantify these uncertainties (Petropoulos et al. 2022). For instance, the global outbreak of COVID-19 in the worldwide forced the closure of social and economic activities, which changed people's behaviour patterns and caused market instability (Zhou et al. 2021). The disease's spread has an enormous impact on the construction industry. In the United Kingdom, the majority of construction firms experienced delays in construction activities, revenue loss, a decline in productivity, and a skill shortage (Ogunnusi et al. 2021). During the pandemic, a great number of construction projects were cancelled or suspended around the world, because of economic downturns and unpredictability reduced investment (Alsharef et al. 2021). The reduction in global industrial production has resulted in supply chain disruptions and an increase in the prices of raw materials (such as timber, cement and concrete products) (Alsharef et al. 2021). Furthermore, the increase in material prices poses challenges to timely payments to contractors and causes cash flow issues and productivity losses (Alsharef et al. 2021). In addition, the Russia-Ukraine conflict interrupts the supply of Russia's main exports and greatly influences the price of raw materials, such as oil, gas, and coal (Mardones 2023). In the future, the frequency of natural disasters (including extreme weather) is anticipated to rise, resulting in increased reconstruction costs and demands for labours and materials (Kim et al. 2021). The rising demand is anticipated to result in a substantial increase in material costs (Döhrmann et al. 2017). Understanding the reactions of financial markets to catastrophes (including COVID-19, international conflicts and natural disasters) could reduce market fragility, enable us to comprehend the impacts of similar events and formulate suitable strategies. The impacts of these events on the construction sector might need to be take into account in future studies.

Conclusion

Predicting the price trend of a product has become a research hotspot in last decades. In the construction industry, resource costs typically constitute the main part of project costs, and the fluctuation of material prices is identified as one major cause of construction cost overruns. Therefore, it is crucial for related stakeholders (including principals, contractors and suppliers) to estimate future price changes and formulate appropriate strategies to increase profits. However, it may be difficult to anticipate the price of a product, because it could be impacted by multiple factors. Selecting a proper prediction method is a major concern for researchers. This paper conducted a comprehensive literature review and investigated articles published between 2012 to 2022 (inclusive). 34 documents were selected for further analysis.

The publication trend on relevant topics, frequently forecasted products and frequently used forecasting models were investigated. The results presented that although lower numbers of publications were recorded between 2012 and 2016, the distribution line between 2016 and 2020 indicated the increasing attentions received by this topic. Since 2016, the number of publications has increased to 7 in 2020 from 1 in 2016. This may be the result of a more complex market structure and a growing range of product characteristics. In addition, fluctuations in material prices, construction costs and CCI were top concerns of researchers. Specifically, the price of construction material is closely associated with the achievement of projects. Early-stage planning, risk assessment and decision making rely heavily on estimations of construction cost and CCI. Three forecasting models were frequently used in previous studies: VECM, ANN and ARIMA models. However, the views on the performance and superiority of forecasting models from previous literatures are different, especially for different data sets. Applications of different models were comprehensively discussed. Time series and machine learning techniques were used in the majority of categories: prices of construction materials, construction costs, CCI, product consumption, house prices and bid award amount. Hybrid models were used to predict construction cost and CCI, and Hedonic price model was used in forecasting house prices.

Future studies could consider the hybrid model as a research method to improve forecast accuracy, because they could integrate advantages of different models and enhance forecasting accuracy. Understanding the reactions of financial markets to catastrophes (including COVID-19, international conflicts and natural disasters) could reduce market fragility, enable us to comprehend the impacts of similar events and formulate suitable strategies. The impacts of these events on the construction sector might need to be considered in future studies. For academia, the findings of this study have the potential to enhance the understanding of price forecasting in the construction sector and have great implications for future research in this area. While previous research has concentrated on selecting the most appropriate forecasting model for making predictions, there has been a scarcity of comprehensive reviews of forecasting models employed in the construction industry. This paper conducted a systematic literature review to generate a list of forecasting models used in construction industry, which can contribute to bridging this research gap. For practice, findings of this study could provide insights for model selection and provide useful contributions to launch precise estimation. In addition, the findings could help industry practitioners to improve decision-making and formulate strategic planning.

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