International Journal of Structural Civil Engineering and Management
Volume 2, Issue 02, 2026

A literature study on building price forecasting models

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

Research Article
Received: 27-02-2026 Revised:02-04-2025 Accepted:10-04-2026 Published:25-04-2026

ABSTRACT

Using a three-stage evaluation procedure, this study summarises a list of forecasting models that have been utilised in the construction sector in the past. The research focuses on publications published between 2012 and 2022 (all included), with a total of 34 documents chosen for further examination. The findings show that the number of publications varied between 2012 and 2016, with a notable uptick after 2016. The rising interest in this issue is shown by the distribution line from 2016 to 2020. The building cost index, shifting material prices, and overall construction expenses were all major issues for the researchers. The vector error correction model, the artificial neural network, and the autoregressive integrated moving average were the three most common forecasting models used in the previous literature. Predictions relied heavily on time series and ML methods. The hybrid model could be a useful tool for researchers looking to enhance the precision of their predictions in future investigations. The consequences of natural catastrophes should also be considered in subsequent research. Researchers and industry practitioners may use this study's findings to choose an appropriate forecasting model and put accurate prediction into practice.

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 consumers' choices to buy (Mahoto et al., 2021). Setting the right pricing for each product is crucial for a firm, since profitability is heavily dependent on sales % (Mahoto et al. 2021). According to Nguyen et al. (2019), several industries have made it a high priority to forecast product pricing changes in recent years. According to Vijh et al. (2020), managers may benefit from activity predictions while making decisions, developing strategies, and trying to maximise earnings while minimising losses. Furthermore, consumers may be able to get the things they need at a reasonable price with the use of forecasts (Nguyen et al. 2019).

A large amount of construction materials is used by the quick construction of new structures due to urbanisation and population increase, particularly in developing nations (Kisku et al. 2017). The bulk of a construction project's budget usually goes into resource expenses, which include things like materials, labour, and equipment. According to Shiha et al. (2020), one of the main reasons why construction cost overruns happen is because of fluctuations in material costs. Sustainable development is anticipated to be attained via the use of recycled goods in the building sector. Recycled concrete and other environmentally friendly goods are priced at or above their original counterparts due to the high expense of recycling treatment. Establishing a recycling market and promoting sustainable development might be helped by predicting the price of sustainable resources. Consequently, it is essential for all parties involved, such as principals, contractors, and suppliers, to anticipate changes in prices and devise methods that would provide profits (Jiang et al. 2013). However, it could be difficult to estimate a product's pricing since the price might be affected by a lot of different things and could go up and down. As an example, stock prices can be influenced by political situations, the global economy, and company performance (Vijh et al., 2020), while agricultural product prices can be affected by weather, plant diseases, customer demands, and the competitive environment (Drachal, 2019). Market and political factors impact the building industry's material price fluctuations (Jiang et al. 2013). Furthermore, prior research has shown that material cost changes are strongly correlated with political and economic instability (Shiha et al. 2020).

The purpose of this research is to evaluate the existing literature in order to provide a synopsis of the many forecasting models that have been used in the construction industry in the past. Researchers and practitioners in the field may use this paper's findings to choose an appropriate forecasting model and put it into practice for more accurate product pricing estimate.

Literature review

A major focus of study in recent decades has been on predicting product price trends (Yu and Yan 2020). Swei et al. (2017), cement (Afolabi and Abimbola 2022, Velumani and Nampoothiri 2018), steel (Shiha et al. 2020), asphalt (Faghih and Kashani 2018, Mir et al. 2021), wood (Banas and Utnik-Banas 2021), and many more construction materials were studied. In order to

foretell how much a product will cost in the future, forecasters often look at both past and present data (Nguyen et al. 2019). Furthermore, prior research has investigated the changes in building expenses (Velumani and Nampoothiri 2019, Jiang and Liu 2014, Petroutsatou et al. 2012), supplies used (Beljkaˇs et al. 2020, Ali et al. 2019), and property valuation (Chen et al. 2022, Tchuente and Nyawa 2022). The complexity, incompleteness, and ambiguous nature of these data sets, however, makes prediction all the more challenging (Yu and Yan 2020).

Tseng et al. (2018) compiled a wealth of research on the topic of forecasting model selection. The housing market, for example, makes extensive use of the hedonic pricing model (Yim et al. 2014). Machine learning algorithms have shown to be quite successful in making predictions (Mahoto et al. 2021). According to Singhal and Swarup (2011), an Artificial Neural Network (ANN) model has the potential to forecast market behaviours by analysing past prices, volumes, and other data. A number of time series methods, such as the Autoregressive Integrated Moving Average (ARIMA) (Tseng et al. 2018), are often used in traditional forecasting models. Different data sets tend to elicit different opinions on which forecasting models are better and how well they perform (Ayodele Ariyo et al. 2014). Researches are anxious about picking the right prediction model (Tseng et al., 2018), however there aren't enough studies that have looked at construction forecasting models in depth.

Procedure for doing research

Finding research gaps, establishing a new theoretical framework, and providing a state-of-the-art understanding of a certain research issue are all possible outcomes of a systematic literature review (Paul and Criado 2020). Following the outline provided by Osei-Kyei and Chan (2015), this research used a three-stage review method. Exhibited in Figure 1 is the study's research framework.

Step one included searching the Scopus database for research that has built forecasting models. In particular, Scopus is a popular literature search engine compared to Web of Science and Google Scholar due to the breadth of publications it includes (Falagas et al. 2008). According to Joshi (2016), Scopus is the best database since it is constantly updated with new citations and abstracts from literature. Compared to Web of Science, it is easier to use and allows for more targeted searches (Weron 2014). First, "Price"; second, "Prediction," "Estimation," "Forecast," or "Price model"; and third, "construction" were all included in the "title/abstract/keyword" section of Scopus. Publications published throughout the years 2012–2022, inclusive, were the only ones considered for this investigation. Technology has been a game-changer in the construction business, turning it into a high-tech powerhouse in the last decade. New forecasting methodologies are always emerging, and using new technology makes price forecasts more accurate. Writings from the last decade capture the spirit of the industry's evolution and provide a detailed account of current events. 'Article' and 'Review' were the document kinds. 'Book,' 'chapter,' 'conference paper,' 'editorial,' 'letter,' 'note,' and'short survey' were not included in the document categories examined in this research. Only the English language was allowed. Six hundred twelve documents were found. Here are the search codes: (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’))

Stage 2 included creating a visual evaluation to weed out papers with abstracts and titles that didn't pertain to the forecasting models. At this point, the writers checked the 612 papers that were found for anything that could be relevant to construction price forecasts by looking at the titles and abstracts. The document would not be included if either the title or the abstract did not include these keywords. Sixty-three papers were chosen. Full texts of the 63 papers were subjected to yet another round of visual assessment. Finally, 34 documents were selected for further analysis in stage 3. Table 1 shows the 34 publications that used various forecasting methods.

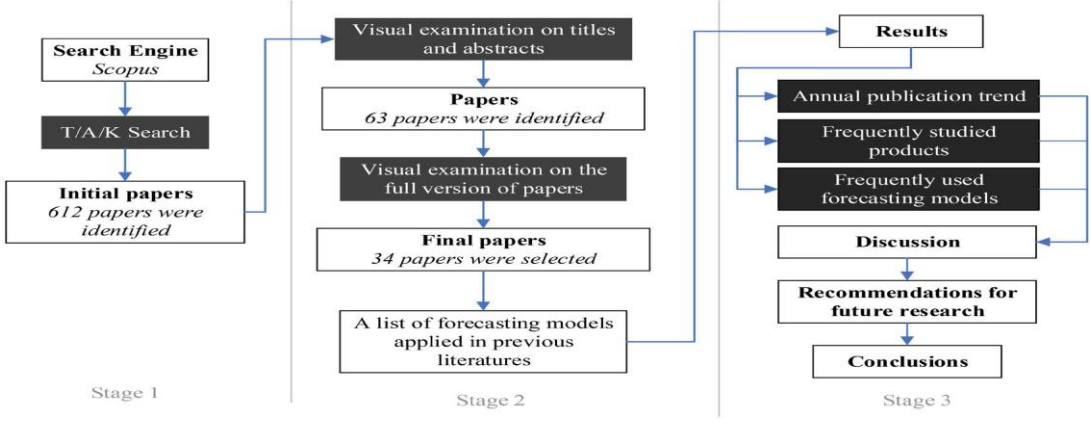


Figure 1. Research framework of this study.

Results and discussion

Publication trend

Publications covering the subject of construction sector pricing projections have been trending upwards, as seen in Figure 2. This statistic specifically only shows the years that the 34 papers that were chosen for publication were published. While this evaluation may fall short of providing a complete bibliography, it does provide a synopsis of the relevant literature as well as recommendations for further study. Figure 2 shows that there has been a large rise in the number of publications since 2016. In 2020, there were seven publications, up from one in 2016. From 2012 to 2016, the number of publications published each year was lower, however at least one paper was published every year.

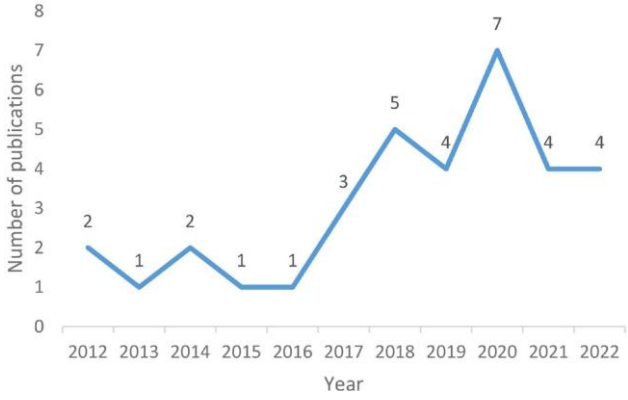


Figure 2. Annual publication trend.

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 displays the frequency of several expected item types in prior literatures. Out of all the documents, thirteen pertain to material pricing, six to the construction cost index, five to building cost, four to housing price, three to product consumption, two to the amount of the bid award, and one to labour cost.

Figure 3 shows that earlier research placed an emphasis on building material price prediction. This category was rated first and occurs thirteen times in the 34 publications that were chosen. The price of building materials is a big issue for everyone involved since unexpected changes in the market or unforeseen circumstances on the job site might drive up the cost of materials and delay project completion (Mir et al. 2021). A crucial factor in determining the success of a construction project, material cost accounts for 25% of the entire project cost (I¸sıkda˘g et al. 2023). Each location has its own set of pricing, and the cost of a

local variables may influence a certain commodity. For instance, material supply might be disrupted and costs could rise as a result of strikes and natural catastrophes. Every year, building material costs are adjusted to account for inflation. However, this process

Interest in this area is expected to rise between 2016 and 2020, as shown by the distribution line. This can be because there is a greater diversity of product attributes and the market structure is more complicated. More accurate models are needed for bigger and more complex data sets (Petropoulos et al. 2022). The rise in publishing numbers may be attributable, in part, to the fact that analytical abilities have been enhanced and adjacent subjects have been piqued by advances in computers. Publications before to 2016 also mostly dealt with building expenses. With regard to the six publications in question, four of them projected

may lead to erroneous material estimate and frustration for those involved (Muhammad Ali et al. 2021). An accurate prediction of future changes in material costs is crucial for developing suitable strategies throughout the ten-ders and implementation phases (Velumani and Nampoothiri 2018). A review of relevant literature was conducted to ascertain the prices of various building materials, such as asphalt, cement, concrete, steel, lumber, and bitumen. Another issue was the cost of raw materials, which includes things like iron ore and crude oil, which may have a significant impact on the final price of a product (Mir et al. 2021). Several nations' exports are dependent on the uneven distribution of energy and raw material commodities; this might affect international commerce and lead to conflicts (Drachal 2021). Due to its widespread usage as a source of energy and transportation, crude oil price fluctuations have the potential to have a substantial effect on economies throughout the globe (Wang et al. 2020). Worldwide GDP may fall by 0.2 percent if oil prices were to rise by 10% (Miao et al. 2017). Governments, businesses, and people alike are so interested in reliable crude oil price forecasts (Wang et al. 2020). The projection is difficult to produce because of many outside influences, such as the COVID-19 pandemic's unknown outcomes (Wu et al., 2021) and the intricate interplay between politics and the economy (Wang et al., 2020).

Second and third, with totals of 6 and 5, respectively, were the construction cost category and the construction cost index (CCI). According to I¸sıkda˘g et al. (2023), almost 90% of construction projects have cost overruns, meaning that actual expenses end up being higher than projected. Since correct construction cost

estimates are critical for early-stage planning, risk assessment, and decision-making, related parties put in a lot of effort to get them right (Jiang et al. 2022). Cost estimates for building projects are notoriously difficult to establish due to the inherent uncertainty of the process (Petroutsatou et al. 2012). For example, differ- ences, price increases, and unknown ground conditions are prevalent (Petroutsatou et al. 2012). According to Jiang et al. (2022), CCI has the potential to be used for calculating construction costs, which would simplify the process of prediction and provide both short-term and long-term cost changes. Labour expenses and the cost of certain building supplies are the inputs used to determine CCI (Jiang et al. 2022). Market trends, cost comparisons, cost plans, tender preparation, and investment planning are all possible uses for CCI (Moon and Shin 2018).

The value of real estate was forecast in four separate pieces. The cost of housing is a major issue for the general population as, for many, buying a house represents a major financial commitment (Tchuente and Nyawa 2022). As Shi et al. (2021) point out, the financial system is directly affected by changes in property values, and a thriving housing market is strongly linked to economic development. Both macro (such as the economy, population, and family income) and micro (such as neighbourhood characteristics) factors were considered by Chen et al. (2022) when examining the factors that influence home prices. Homebuyers may gain leverage in negotiations if sellers were aware of price swings, and sellers could avoid the hazards of over- or underestimating their market value if they did (Tchuente and Nyawa 2022). Consumption of construction materials, award price, and future labour expenses were also anticipated in previous research. Predicting building expenses requires accurate estimates of future material consumption and manpower costs. In particular, the hourly wages of construction workers in the US more than quadrupled between 1995 and 2016 (Faghih et al. 2021). Construction cost variations caused by shifts in worker pay have the potential to disrupt cash flow, reduce profits, and postpone or even halt projects (Faghih et al. 2021). Furthermore, for the government to allocate scarce resources effectively, it is critical to predict the demand for building supplies in the future (Jiang and Liu 2014). According to Jiang and Liu (2014), contractors may obtain a competitive edge and set optimum prices by predicting their material use. It is possible to utilise the data to place an offer (Beljkaˇs et al. 2020). It is possible for contractors to get contracts by generating profit-and cost-accounting forecasts (Chou et al. 2015). According to Chou et al. (2015), there is a risk of losing the contract if one bids too high and loses profit if one bids too low in competitive bidding.

Frequently used models

This article categorises forecasting models into four groups: (1) traditional methods, which include the hedonic price model, regression analysis, and time series analysis; (2) machine-learning algorithms, which include ANN and support vector machine, among others; (3) hybrid methods; and (4) others, which include methods that aren't mentioned in the

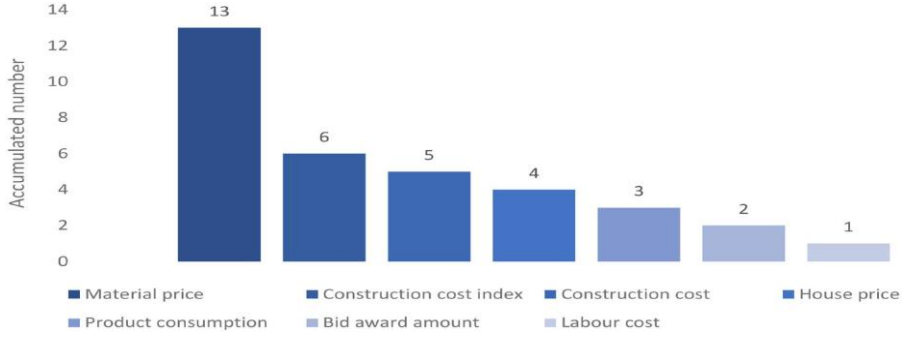


Figure 3. Categories of predicted products in previous literatures.

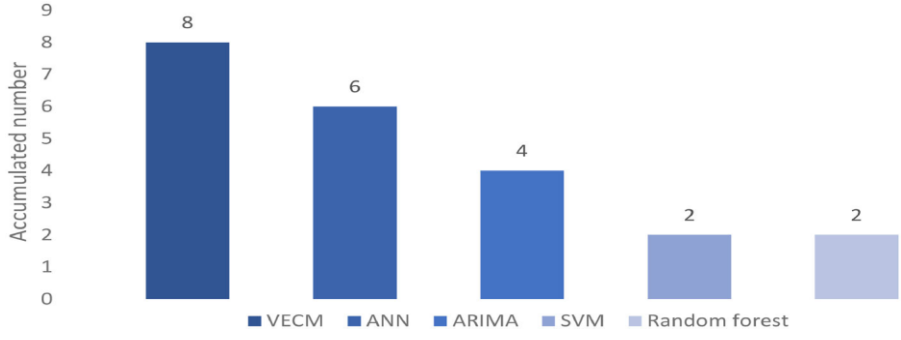


Figure 4. Accumulated number of forecasting models used in previous literatures.

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 fur- ther discussed and compared.

Vector error correction model (VECM)

A method for examining variable dynamics and including an adjustment process to long-term equilibrium, VECM combines the vector autoregressive model with cointegration limitations (Jiang et al. 2013). According to Shao et al. (2019), this approach has extensive use in economic and financial research. If the time series data is not steady, VECM is the way to go (Pradhan and Bagchi 2013). The procedure consists of five steps: (1) selecting dependent and independent variables and collecting historical data for prediction; (2) analysing the bidirectional or unidirectional relationships between variables using Granger causality; (3) testing the stability of the data with a cointegration test; (4) making predictions and analysing their accuracy; and (5) evaluating the impacts of independent variables using impulse response and variance decomposition analysis (Lee et al. 2019). Prior research in multivariate time series analysis has established VECM as a reliable model for making predictions (Lee 2019, among others. The VECM method may capture the links between dependent variables and a variety of independent factors, in contrast to the univariate time series analysis method that uses just the target variable's time series data for prediction (Lee et al. 2019). It is possible to use VECM to forecast material prices since the model relies on time series data and material prices are characterised by their time-dependence. For example, Faghih and Kashani (2018) anticipated the immediate and far future costs of asphalt, cement, steel, and other construction materials using VECM. According to Faghih and Kashani (2018), a collection of variables, including future material prices, time series data of material prices, and GDP, CPI, and WTI crude oil price, were considered independent variables. A number of macroeconomic factors were studied by Jiang et al. (2013) to determine their correlations with building costs. According to Jiang et al. (2013), the long-term building price is governed by national income, population, and interest rate, whereas short-term construction costs are strongly tied to population increase.

Artificial neural network (ANN) model

ANN model consists of three layers: input layer (such as attrib- utes 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 inter- connected with artificial neurons capable of storing and process- ing 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 interdependen- cies between variables (Singhal and Swarup 2011). Besides, com- pared 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 han- dle 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 advan- tages make the ANN-based model suitable for complex price forecasting and have contributed to the model's growing promin- ence in research (Singh et al. 2017). However, the problem of underfitting or overfitting could be caused by increased complex- ity 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 (Ö mer Faruk 2010). Nonlinear data sets limit the applica- tion of ARIMA (Ö mer 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 sci- entific 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 per- formance 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

In earlier works, several models for making predictions were suggested. Since it is not always easy to determine whether real-world time series are linear or nonlinear, it might be challenging to choose an appropriate forecasting model for certain commodities in practice (Zhang 2003). The time-dependent character of material pricing has led to the widespread adoption of time-series techniques (such as VECM and ARIMA) for predicting building material costs (Table 1). In order to forecast the future trend of a dependent variable, time-series methods look at its past values together with the equivalent data of other independent variables (Hwang et al. 2012). Predicting energy prices is fraught with uncertainty due to their extreme volatility (Gao and Lei 2017). Predicting future raw material costs was the subject of many papers. For example, according to Safari and Davallou (2018), the political climate, economic development, and labour market circumstances are among the several variables that affect the price of crude oil. Relationships were often captured by collecting and analysing time series, such the monthly reported oil price. There are a number of potential explanatory factors that might be considered. As an example, in order to quantify the dynamics of supply and demand, we looked at coal output in the US, total consumption, and inventories (Drachal 2021). Some research used ARIMA, a conventional statistical model based on linear assumptions, to forecast building material prices and expenses. The building business pays close attention to long-term predictions because, according to Lee et al. (2019), earnings are higher during the operating period than during the construction phase. Capital expenditures, such as the purchase of land and equipment, might benefit from long-term predictions, while product development could make better use of medium-term predictions (Lam and Oshodi 2016). However, it may be difficult to make accurate long-term projections due to the fact that prediction errors grow as prediction periods go longer (Lee et al. 2019). To be more precise, VECM is versatile enough to be utilised for both short- and long-term estimations, while ARIMA models work well for predictions made in the near future. The time series characteristics also play a role in deciding which model to use. The ARIMA model is often used for time series prediction when it is linear and stationary (Valenzuela et al. 2008). Data that is not steady over time should be processed using VECM (Pradhan and Bagchi 2013). Predictions of building material prices, construction costs, and CCI were made using machine learning approaches (ANN, random forest, and GRNN) (Table 1). A number of variable elements may influence the real-world situation, which means it may be dynamic. Factors that influence building costs include material, personnel, equipment, project duration, kind, and location (Rafiei and Adeli 2018). Machine learning methods take into account a number of variables and make use of time-series data to foretell potential outcomes. Finding an appropriate model to deal with the time series' defects is crucial, since there is a large variety of machine learning models (Ahmed et al. 2010). Figure 4 shows that ANN is one of the most popular models. Potential applications include the forecasting of difficult situations that now cannot 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.

handled using standard procedures (Ghatak and Ghatak 2018). The capacity of this model to predict economic circumstances and financial data causes it to grow rapidly (Tseng et al. 2008). Considering all the status and connections in time series data is impossible for a single model because to the complexity of real-world issues, according to Safari and Davallou (2018). Consequently, CCI and building cost predictions were made using hybrid models.

For the purpose of predicting future home values, the hedonic pricing model was considered alongside time-series and machine-learning models (Table 1). The hedonic pricing model has its roots in Lancaster's (1966) theory and has been widely used to study the correlations between neighbourhood, home size, number of rooms, parking, and location with property values (Limsombunchai 2004). With the hedonic pricing model, we can see why certain qualities are more highly valued than others and how

the housing market (Zhang and Dong 2018, Tam et al. 2022, Owusu-Ansah 2011, Lu 2018, Chen 2017, Cebula 2009), to a large degree (Yim et al. 2014). In addition, according to Tam et al. (2022), one may utilise the hedonic pricing model to determine how much each attribute influences the cost of other goods. The government is kept informed of public concerns via the exploration of predicted items in the construction business. These items include changes in the pricing of building materials, product consumption, and housing prices. The practical application of the findings is anticipated to aid in the selection of an appropriate forecasting approach and the commencement of accurate product price estimation.
This research included a number of models for making predictions. There are benefits and drawbacks to every model. All other techniques could not be captured by a single model. The use of hybrid approaches, which integrate many models, is on the rise in the scientific community. According to Liu et al. (2021), different models have their own strengths, weaknesses, and areas of emphasis. To improve forecasting accuracy, hybrid models might combine these models' strengths. In particular, hybrid models allow for the inclusion of several structural features (Ribeiro and Oliveira 2011). If researchers want to find a way to make better predictions in the future, they may look at hybrid models.
Now is a time of enormous unpredictability, with global wars, bushfires, and the COVID-19 pandemic all posing threats that can cause material prices and building costs to fluctuate significantly. Forecasting and quantifying these uncertainty is of utmost importance (Petropoulos et al. 2022). As an example, the COVID-19 pandemic prompted the suspension of many social and economic activities throughout the globe, which in turn altered consumer habits and contributed to volatile markets (Zhou et al. 2021). As the illness spreads, it has a tremendous effect on the building sector. Delays in construction, income loss, declining productivity, and a lack of skilled workers were felt by most UK construction enterprises (Ogunnusi et al. 2021). Many building projects were halted or postponed during the pandemic as a result of decreased investment due to economic downturns and uncertainty (Alsharef et al. 2021). Raw material costs have risen and supply chain disruptions have occurred as a consequence of the worldwide decline in industrial output (Alsharef et al. 2021). The rise in material prices also makes it harder to pay contractors on time, which in turn disrupts cash flow and reduces productivity (Alsharef et al., 2021). Also, raw material prices—including oil, gas, and coal—are heavily impacted by the Russia-Ukraine war, which disrupts the supply of Russia's primary exports (Mardones 2023). Natural catastrophes, particularly severe weather events, are expected to occur more often in the future, leading to higher demands for manpower and resources during reconstruction as well as higher reconstruction costs (Kim et al. 2021). Material prices are expected to rise significantly due to the increasing demand (D€ohrmann et al. 2017). Reducing market fragility, understanding the implications of comparable occurrences, and developing adequate measures might be achieved by studying the responses of financial markets to disasters, such as COVID-19, foreign wars, and natural disasters. In future research, it may be necessary to consider the effects of these events on the construction industry.

Conclusion

In recent decades, forecasting product price trends has emerged as a prominent area of study. The majority of a construction project's budget goes into resources, and one of the biggest reasons for budget overruns is the unpredictable cost of building materials. Principals, contractors, and suppliers are all involved parties, therefore it's critical for them to predict how prices will rise and fall and come up with good strategies to maximise earnings. But you can have a hard time predict how much a thing will cost since there are a lot of variables that might affect it. Researchers are quite concerned about choosing the right prediction approach. Articles published between 2012 and 2022 (inclusive) were the focus of this paper's thorough literature evaluation. Additional analysis was performed on 34 documents.

We looked at the trend in publications on important subjects, goods that are often predicted, and forecasting techniques that are often employed. Although there were less publications covering this subject between 2012 and 2016, the distribution line showing an increase in interest from 2016 to 2020 was indicative of this trend. Seven publications will have been published by 2020, up from one in 2016. This can be because there is a wider variety of products on the market and the market structure is becoming more complicated. Researchers were also quite worried about CCI, building expenses, and material price fluctuations. In particular, the success or failure of a project is strongly correlated with the cost of building materials. Evaluating potential risks, making decisions, and planning the first stages all depend significantly on CCI and building cost estimates. In earlier research, the VECM, ANN, and ARIMA models were often used for forecasting. Nevertheless, prior literature offers varying opinions on the performance and supremacy of forecasting models, particularly when it comes to distinct data sets. Various models' applications were thoroughly examined. The bulk of the categories used time series and machine learning approaches. These included construction costs, product consumption, building material prices, CCI, home prices, and bid award amount. Predictions of building costs and CCI were made using hybrid models, whereas predictions of home prices were made using the hedonic pricing model. The hybrid model has the potential to be a research tool in future investigations. approach that might increase the accuracy of forecasts by combining the best features of many models. Market fragility might be mitigated, the effects of comparable events could be understood, and appropriate measures could be developed if we understood how financial markets responded to calamities like COVID-19, global wars, and natural disasters. Future research may have to account for how these occurrences have affected the construction industry. Academics may use this study's results to better understand construction price forecasts and use them to inform future studies in this field. Few in-depth evaluations of forecasting models used in the construction sector have been published, despite the fact that prior studies have focused on finding the best forecasting model to use. In order to help fill this knowledge vacuum, this work performed a thorough literature analysis to compile a list of forecasting models utilised in the construction sector. The practical implications of this study's results include potential

improvements to launch accurate estimate and new understandings of model selection. Furthermore, professionals in the field may be able to use the results to enhance their strategic planning and decision-making processes.

References

Abimbola O. and Afolabi AO. 2022. Implementation of a web-based system for cement price prediction using machine learning. Accessed May 12, 2023. IJECE. 12(5): 5214-5225. Published in 2010, by Ahmed NK, Atiya AF, Gayar NE, and El-Shishiny H. doi: 10.11591/ijece.v12i5. Time series forecasting using machine learning models: an empirical comparison. Economic Review, 29(5-6): 594-621. "Akkurt S, Tayfur G, Can S. 2004." (doi: 10.1080/07474938.2010.481556). Cement compressive strength prediction using a fuzzy logic model. Cemetery Research. 34(8): 1429-1433. Published online: doi: 10.1016/j.cemconres.2004.01.020.

In 2010, Alex DP, Al Hussein M, Bouferguene A, and Fernando S. published.... Model for cost assessment using artificial neural networks: water and sewer installation services provided by the city of Edmonton. Journal of Construction Engineering and Management, 136(7), 745–756. this article's DOI is 10.1061/ (ASCE)CO.1943-7862.0000184.

In 2019, Ali, Kalantari, Ahmadi, and Eslami published a study. The instance of bitumen consumption as a test case for a versatile genetic algorithm-fuzzy regression method for prediction. Clinical Infectious Diseases. 19(1):71-88. 10.1108/CI-11-2017-0089 is the DOI.

In 2021, the authors Alsharef, Banerjee, Uddin, Albert, and Jaselskis published a paper. Effects of the COVID-19 Pandemic on the American Construction Sector at the Outset. International Journal of Environmental Research and Public Health. Article published in 2014 by Ayodele Ariyo, Aderemi Oluyinka, and Charles Korede with the DOI 10.3390/ijerph18041559. Analysis of ARIMA and ANN models for stock price prediction compared with artificial neural networks. "Journal of Applied Mathematics" (2014): 1–7. DOI: 10.1155/2014/614342.

Ebrahimipour V., Azadeh A., Moghaddam M., Khakzad M., 2012. An technique for improving oil price estimates and forecasting that combines a flexible neural network with fuzzy mathematical programming. Doi: 10.1016/j.cie.2011.06.019. Computer Engineering Journal, 62(2), 421–430.

In 2021, Banas and Utnik-Banas published a study. Testing a short-term wood price forecasting model using an exogenous variable and seasonal autoregressive moving averages. Regarding Policy Economics, 131:102564(1–10). 102564, doi: 10.1016/j.forpol.2021.10260.

The year 2020 was commemorated by Beljkaˇs Zˇ, Kneˇzevi'c M, Ruteˇsi'c S, and Ivaniˇsevi'c N. Utilisation of AI to predict the amount of concrete and reinforcing needed to build integrated bridges. Advances in Civil Engineering, 2020, 1–8. doi: 10.1155/2020/8645031.

Ashuri B. and Cao Y. 2020. Long short-term memory for highway building cost index volatility prediction. Publication information: Journal of Management Engineering, volume 36, issue 4, pages 25–28, doi: 10. 1061/(ASCE)ME.1943-5479.0000784.

In 2009, Cebula R. How the hedonic pricing model was used to analyse the Savannah real estate market and the historic core of the city. Journal of Regulation Studies, Volume 39, Issue 1, Pages 9–22, DOI: 10.52324/001c.8197.

In 2022, Chen, Liu, Arribas-Bel, and Singleton published a paper. Evaluate the usefulness of user-created maps of cityscapes for home value prediction. Urban and Landscape Planning 226: 104486. 104486. doi: 10.1016/j.landurbplan.2022.

In 2017, Chen WY... Environmental externalities of urban river pollution and restoration: a hedonic study in Guangzhou (China). Environmental and Urban Planning 157: 170–179. The publication's DOI is 10.1016/j.landurbplan.2016.06.110.

Wu Y-W, Cheng M-Y, and Hoang N-D 2013. Estimating the building cost index using a hybrid intelligence technique based on LS-SVM and Differential Evolution: a case study from Taiwan! Journal of Automotive Structures, 35: 306-313. The publication's DOI is 10.1016/j.autcon.2013.05.101.

It was 2015. Chou J-S, Lin C-W, Pham A-D, Shao J-Y. Enhanced AI algorithms for project award price prediction. Published in Autom. Constr., volume 54, pages 106–115, doi: 10.1016/j.autcon.2015.02.006.

Authors: Dorfmann, Gu€rtler, and Hibbeln. 2017. The impact of natural disasters on the expenses of reconstruction: insured loss inflation. The citation is from the Journal of Risk Insurance, volume 84, topics 851–879. Reference: 10.1111/jori.12134.

In 2019, Drachal K. Agricultural commodity price analysis using novel Bayesian model combination strategies. Article published in Sustainability (Basel, Switzerland) on 11/19/2005 with the DOI 10.3390/su11195305.

Using Bayesian dynamic finite mixtures, Drachal K. (2021) predicts the prices of certain energy commodities. Resource Economics, 99, 105283. Publication date: 10.1016/j. eneco.2021.105283.

Uɔgurlu B., Ediger VS¸, Akar S. 2006. Using a combination of ARIMA and comparative regression, we can predict Turkey's fossil fuel output. The Energy Policy. the number of pages from 34 to 3846. this article's DOI is 10.1016/j.enpol.2005.08.023.

As of 2019, Elfahham Y. Building cost index estimation and forecasting using the use of neural networks, time series, and regression. "Alexander Engineering Journal" (58(2):499–506), with the DOI 10.1016/j.aej.2019.05.002.

With contributions from SAM Faghih, Y. Gholipour, and H. Kashani, 2021. Framework for time series analysis of building labour costs forecasts. Journal of Civil Engineering (KSCE) 25(8): 2809– 2823. Article DOI: 10.1007/s12205-021-1489-4.

In 2018, Faghih SAM and Kashani H. Using a vector error correction model to predict the cost of building materials. J. Constr. Eng. Manage. 144(8):12–15. doi: 10.1061/(ASCE)CO.1943–7862.001528.