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Research article

Incorporating inflation rate in construction projects cost: Forecasting model

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ABSTRACT

Over time, the change in the inflation rate causes cost overruns by deviating the prices of goods and services in construction projects that require practitioners to make budgeting revisions. Hence, this study aims to develop a construction rates forecasting model that can incorporate the changing impact of the inflation rate on construction rates and predict the prices in a particular year, which can be adjusted when developing the Bill of Quantities. Following the time series analysis standards, a mathematical model was developed using MATLAB for forecasting. Construction rates, building prices, labour wages and machinery rates were forecasted from 2020 to 2025 based on the data collected from 2013 to 2019. Akaike information criterion was used to validate the self-developed construction rate forecasting model. It was revealed that the model yielded better results when the construction rates were compared with the autoregressive integrated moving average time series model results. The rates forecasting model may be used for any construction project where rates are affected by the inflation effect.

1. Introduction

The construction industry is one of the greatest contributors to society's development; however, it continues to struggle under one of the biggest constraints, i.e., cost overrun [1]. Cost overrun phenomena charge additional money and are a strong project failure indicator [2]. Generally, a cost overrun on project completion occurs due to negligence in handling the associated risks at the implementation level [3]. Cost overrun risk is always present in every construction project and continues to concern the stakeholders. The rate of cost overrun varies in project type; however, an estimated range lies from 21% to 55% [4–6]. The major impact of cost overrun can be attributed to the price changes of essential resources, i.e., materials, labour and machinery. Hence, accurate measurement of these resources in project cost is important [7–9], and these resources must be handled in the initial planning phase [10].

Understanding the future behaviour of the data is important in the economic, finance and business sectors [11]. Forecasting through the time series analysis technique was considered because the inflation rate is dynamic. Various famous time series techniques available to forecast the data, such as autoregressive (AR), exponential smoothing (ES), moving average (MA), a combination of AR and MA, known as the ARMA model and with the integration parameters involved, the autoregressive integrated moving average (ARIMA) model [12,13]. Time series analysis, established by Box and Jenkin, has been used widely in research. Univariate discrete is the starting point of time series analysis where a stochastic model describes how the series evolves. Based on this concept, forecasting is performed in the serial data points and has several assumptions, such as the finite linear function is z_t with independent noise of

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random variables. In the autoregressive model, the assumption of z_t is a continuous variance of the mean provided by the linear pattern of the preceding z's. This model can be considered for the stationary data series. In the case of non-stationary data, a differencing parameter is introduced until the data become stationary. This observable fact is the Autoregressive Integrated Moving Average (ARIMA) process, the ARIMA time series model [14,15].

ARIMA gained popularity because of its linear model characteristic for forecasting economic time series [16,17]. In addition to ARIMA, artificial neural networks (ANNs) have also been used for their elastic and effective computational operations for the complex relationships in the economic time series [18,19]. However, studies have shown a mixed overview on the choice of ARIMA and ANN; therefore, both have been adopted in the forecasting techniques [20]. ARIMA model has shown remarkable performance in the accuracy and precision of forecasting future values. The ARIMA model has been developed by introducing advanced machine learning algorithms that refine the forecasting [12].

Another famous time series model is exponential smoothing (ES) [21]. ES is a simple yet effective forecasting tool [22] that immediately forecasts discrete time series. This time series is popular due to its ease of forecasting and reliability [23]. ES helps smoothen the original series whose moving average does comply with the time series analysis for future forecasting. In ES, consideration is given to recent values in comparison to distant values [24,25]. ES is preferable on ARIMA for short-term forecasting due to consideration of seasonality [26]. In ES, three basic models are preferred: trend-corrected ES [27], Simple ES [28] and Holt Winters' model [29]. These models have distinctive features, including the assumption of time series on unobserved components (seasonality, growth and level) and the adaptation of these components with the changes in the market [30]. Based on the previous progress of Ord, Koehler [31], a statistical framework in ES was formulated by Hyndman, Koehler [26]. The framework functions with stochastic models and allows computation of the smoothing parameters of likelihood estimates.

One of the reasons for resource price deviations leading to cost overrun is the inflation rate. Fluctuations in the inflation rate cause prices to change annually, leaving a blackhole for stakeholders to fill until project completion [32]. Inflation in the economic world is becoming inevitable, leaving adverse effects on industries and the economy [33,34]. The effects of the inflation rate have reached beyond the construction industry and have also started to influence a country's economy [35,36]. Experts have attempted to control the inflation rate by introducing various policies; however, the issue remains complex because of the non-stagnant nature of money [37–39]. Table 1 lists the countries where construction projects are affected by resource price deviation as influenced by the inflation rate.

Generally, the reserve amount, known as the contingency cost, is kept in the project budget by the owner or related funding agencies to deal with the unforeseen risks that increase real project costs [56,57]. The contingency cost burdens the project owner because of the requirement to allot an extra amount to the actual project cost. Accounting for the effects of the cost overrun factors in the initial budget estimation calculation is necessary for a project. Hence, developing an estimation model that can incorporate the changing effects of the resources before submitting the Bill of Quantities is important [32]. Preparing a project budget is a challenge for the contractor and the owner, and estimations should control for critical factors [3].

The volatile effect of the inflation rate has had adverse effects on the entire construction industry. Owners who avoid paying for increased project costs leave contractors with no other option but to compromise on quality, which decreases project productivity. Foreseeing the long-term changing effect of the inflation rate, which ultimately causes cost overrun in a construction project, has also been a challenge for stakeholders. The inflation rate is one of the most critical factors of cost overrun in construction projects worldwide, but its severity is still undetermined by stakeholders. The above-mentioned case clearly describes the need to incorporate the inflation rate in construction rates during budget finalisation. However, current forecasting models cannot incorporate the precise influencing criteria of the inflation rate on each construction rate. Therefore, in this study, a construction rate forecasting model was developed by incorporating the impact of the inflation rate on the construction rates, i.e., building materials prices, labour wages and machinery hire rates. Time series analysis was used because it is a popular forecasting technique. Artificial intelligence (AI) tools can predict costs.

In contrast, the developed model adjusts the amount of influence that the inflation rate has on the construction rates. Managing an inflation rate that deviates from the project budget is not an effortless task, and adjustments to the budget can be a challenge. This

Table 1
Cost overrun due to inflation in various countries.

S. No	Country	Cost Overrun		
		Material	Labour	Machinery
1	Malaysia	[40,41]	[42,43]	[44]
2	Pakistan	[45]	–	–
3	United Kingdom	[46]	–	–
4	United States	[47]		
5	Egypt	[48]	–	–
6	India	[49]		–
7	Afghanistan	[50]		
8	Uganda	[51]	–	[51]
9	Nigeria	[52]	–	–
10	Zambia	[53]		
11	Vietnam	[54]		–
12	Palestine	[55]	–	–

study provides a benchmark for construction industry stakeholders to adopt the construction rate forecasting model to avoid excessive cost liability. No model can incorporate the inflation rate influence in estimating the project cost, raising the need for this model. The main contributions of this study are as follows:

1. A mathematical construction rate forecasting model to deal with one of the major concerns of the construction industry, project cost overrun, has been proposed.
2. The forecasted construction rates can be embedded into the Bill of Quantities before the tender allotment.
3. The construction industry stakeholders can forecast future rates in the present year and make the necessary adjustments to avoid a project being cost overrun.

This study is organised to include the analysis and discussion of the construction rates forecasting outcome. First, the inflation rate was predicted using Eviews software, which was incorporated into forecasting the construction rates based on the self-developed model. Time series analysis was also used to forecast the construction rates to compare with the self-developed model based on Akaike's Information Criterion (AIC). This validation technique was utilised for building material prices, and the percentage deviation validation technique for labour wages was optimised. No validation was performed for machinery hire rates because of fewer observations and the unavailability of the current year's data.

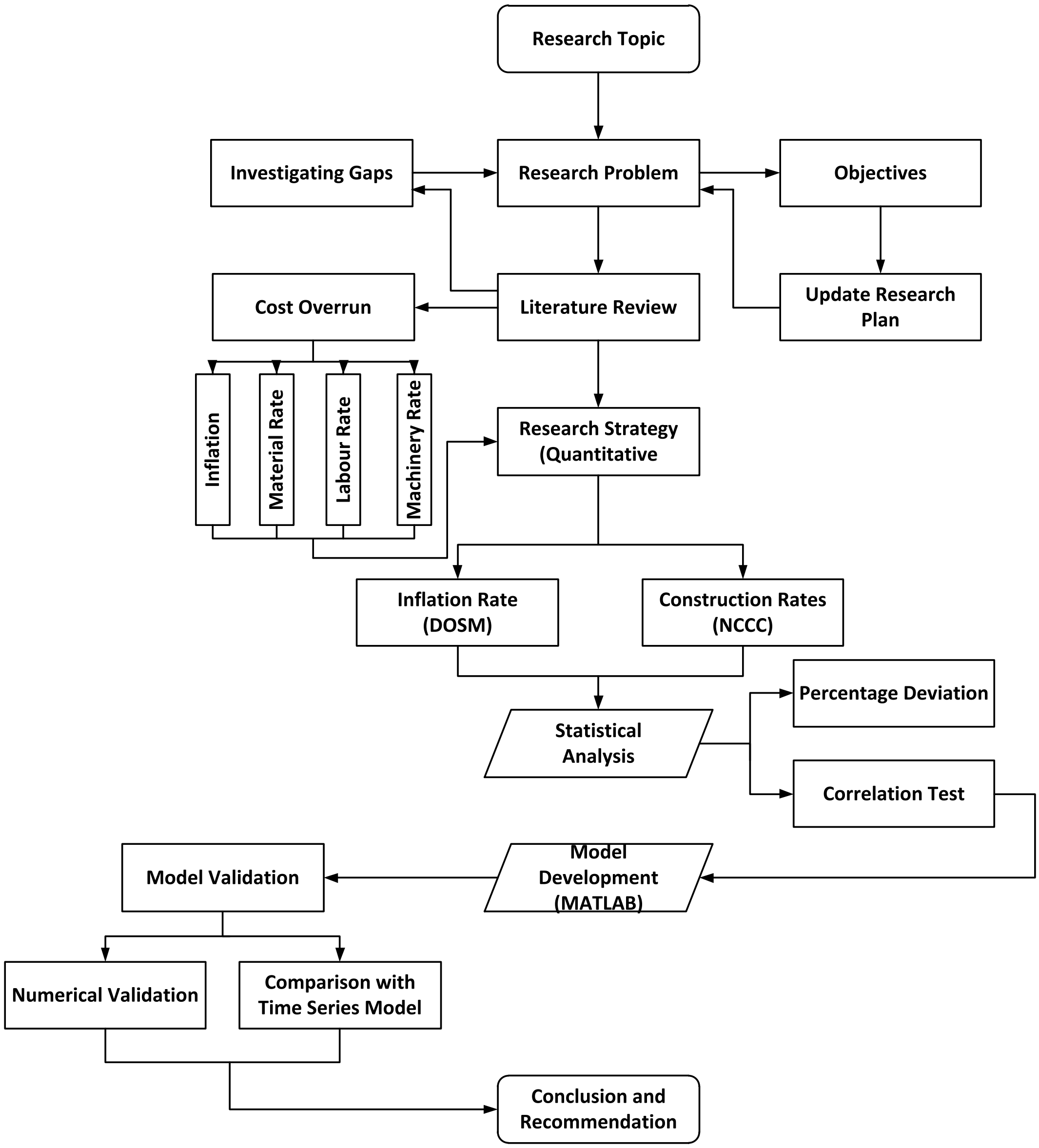

Fig. 1. Research flowchart.

2. Methodology

This study is an extensive version of the previous studies, where the relationship of construction rates, i.e., building materials prices [41], labour wages [43] and machinery hire rates [44] were evaluated with the inflation rate. The data were collected from the Government Departments of Malaysia, including the Construction Industry Development Board (CIDB) and the Department of Statistics Malaysia (DOSM) for 2013–2019. The relationship was evaluated using the Spearman correlation test with the value incorporated within the developed model for each construction rate. Thus, the thrust of the relationship can easily be evaluated. A correlation parameter was introduced in the ES equation model by investigating the relationship and its impact. A detailed research flow, which combines previous studies' strategies, is presented in Fig. 1.

2.1. Forecasting model development

2.1.1. Self-developed forecasting model

A literature review shows that no forecasting model can incorporate fewer observations and no study has investigated the behaviour of variables and ultimately forecast future values. Four mathematical equations that can forecast future rates were developed. The modifications were brought by altering the existing ES model (Equation (1)), a type of time series model.

Exponential smoothing (ES) model

$$F_{t+1} = \alpha\, A_t + (1-\alpha)\, F_t, \tag{1}$$

where F = forecast, A = Actual value (dependent variable), α = Smoothing Constant, t = time.

Based on ES, the modified equations (2)–(5) are as follows:

First equation

$$F_{t+1} = \alpha\, Y_t + (1-\alpha)\, F_t + [r\,(X_t)] + \varepsilon, \tag{2}$$

Second equation

$$F_{t+1} = \alpha\, Y_t + (1-\alpha)\, F_t + [r\,(X_t)], \tag{3}$$

Third equation

$$F_{t+1} = \alpha\, Y_t + (1-\alpha)\, F_t + \alpha\,(X_t) + \varepsilon, \tag{4}$$

Fourth equation

$$F_{t+1} = \alpha\, Y_t + (1-\alpha)\, F_t + \alpha\,(X_t), \tag{5}$$

where Y = dependent variable, X = independent variable, ε = linear error, r = correlation coefficient, α = 0.2, t = time, F = forecasting.

In the first equation, a linear error was introduced with the inclusion of correlation coefficient level and independent variable. Only the correlation coefficient level and the independent variable were introduced in the second equation. In the third equation, the correlation coefficient was replaced with the alpha with the inclusion of linear error. In the fourth equation, alpha was introduced along with the independent variable.

The forecasting analysis of one variable (lorry) by ES equation and the four developed equations are discussed in Tables 2–6.

To access the best forecasting equation among the four, the mean square error (MSE) and mean absolute percentage error (MAPE) were calculated using Equations (6) and (7) by putting a construction rate (lorry). The results are discussed in Table 7.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Yi - \widehat{Yi}\right)^2, \tag{6}$$

Table 2
Forecasting analysis of ES equation.

Year	Lorry Rates (Y)	Forecasting	Error	Error 2
2013	12500	14895.86		
2014	12,550	14416.69	−1866.69	3,484,515.56
2015	12,600	14043.35	−1443.35	2,083,255.10
2016	16900	13754.68	3145.32	9,893,045.09
2017	15444	14383.74	1060.26	1,124,144.72
2018	16573.67	14595.79	1977.88	3,911,991.62
2019	17703.33	14991.37	2711.96	7,354,729.35
2020	15533.76	15533.76	0.00	0.00
2021	15533.76	15533.76	0.00	0.00
2022	15533.76	15533.76	0.00	0.00
2023	15533.76	15533.76	0.00	0.00
2024	15533.76	15533.76	0.00	0.00
2025		15533.76		

Table 3
Forecasting analysis of the first equation.

Year	Inflation Rate (X)	Lorry Rates (Y)	Predicted (Y)	Residual	Forecasting	Error	Error 2
2013	2.11	12500	14965.68	−2465.68	14895.86		
2014	3.14	12,550	13912.09	−1362.09	11949.65	600	360,422.54
2015	2.1	12,600	14975.91	−2375.91	10705.61	1894	3,588,731.02
2016	2.08	16900	14996.37	1903.63	8707.22	8193	67,121,578.69
2017	3.8	15444	13236.98	2207.02	12248.07	3196	10,213,944.56
2018	1	16573.67	16101.10	472.57	15091.84	1482	2,195,833.18
2019	1.02	17703.33	16080.64	1622.69	15860.13	1843	3,397,388.14
2020	2.67	17850.80	14396.60	3454.21	17850.80	0.00	0.00
2021	1.91	21303.29	15165.41	6137.88	21303.29	0.00	0.00
2022	1.64	27439.94	15446.06	11993.88	27439.94	0.00	0.00
2023	1.89	39432.76	15194.19	24238.57	39432.76	0.00	0.00
2024	2.51	63670.12	14557.87	49112.25	63670.12	0.00	0.00
2025		112780.76			112780.76	0.00	0.00

Table 4
Forecasting analysis of the second equation.

Year	Inflation Rate (X)	Lorry Rates (Y)	Forecasting	Error	Error 2
2013	2.11	12500	14895.86		
2014	3.14	12,550	14415.33	−1865	3,479,452.22
2015	2.1	12,600	14040.24	−1440	2,074,303.26
2016	2.08	16900	13750.85	3149	9,917,177.00
2017	3.8	15444	14379.34	1065	1,133,503.92
2018	1	16573.67	14589.83	1984	3,935,631.18
2019	1.02	17703.33	14985.95	2717	7,384,137.89
2020	2.67	15528.77	15528.77	0.00	0.00
2021	1.91	15527.06	15527.06	0.00	0.00
2022	1.64	15525.83	15525.83	0.00	0.00
2023	1.89	15524.77	15524.77	0.00	0.00
2024	2.51	15523.56	15523.56	0.00	0.00
2025		15521.95	15521.95		

Table 5
Forecasting analysis of the third equation.

Year	Inflation Rate (X)	Lorry Rates (Y)	Predicted (Y)	Residual	Forecasting	Error	Error 2
2013	2.11	12500	14965.681	−2465.681	14895.86		
2014	3.14	12,550	13912.094	−1362.094	11951.43	599	358,289.98
2015	2.1	12,600	14975.91	−2375.91	10709.68	1890	3,573,327.20
2016	2.08	16900	14996.368	1903.632	8712.25	8188	67,039,245.20
2017	3.8	15444	13236.98	2207.02	12253.85	3190	10,177,068.27
2018	1	16573.67	16101.1	472.57	15099.66	1474	2,172,709.64
2019	1.02	17703.33	16080.642	1622.688	15867.23	1836	3,371,260.01
2020	2.67	17857.34	14396.59517	3460.747526	17857.34	0.00	0.00
2021	1.91	21318.62	15165.41128	6153.212214	21318.62	0.00	0.00
2022	1.64	27472.22	15446.06426	12026.15574	27472.22	0.00	0.00
2023	1.89	39498.70	15194.18918	24304.51082	39498.70	0.00	0.00
2024	2.51	63803.59	14557.86653	49245.72347	63803.59	0.00	0.00
2025		113049.82			113049.82		

where n = number of data points, Yi = observed values, $\widehat{Y}\ i$ = predicted values.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|, \tag{7}$$

where n = number of times the summation iteration happens, A_t = actual value, F_t = forecast value.

Based on the results, the lowest values for MSE and MAPE were from the fourth and second equations. However, the fourth equation was rejected because it did not incorporate the level of relationship among the variables. The second equation was chosen for further assessment as the correlation coefficient (r) is involved. As discussed, correlation relationships have five levels. The second equation can incorporate the correlation level, and the future rates can be predicted based on the results. By adopting the second equation, the existing deficiency of the ES model can be eliminated which does not incorporate autocorrelations.

Table 6
Forecasting analysis of the fourth equation.

Year	Inflation Rate (X)	Lorry Rates (Y)	Forecasting	Error	Error 2
2013	2.11	12500	14895.86		
2014	3.14	12,550	14417.11	−1867	3,486,091.22
2015	2.1	12,600	14044.31	−1444	2,086,043.43
2016	2.08	16900	13755.87	3144	9,885,545.05
2017	3.8	15444	14385.11	1059	1,121,241.53
2018	1	16573.67	14597.65	1976	3,904,653.24
2019	1.02	17703.33	14993.05	2710	7,345,594.02
2020	2.67	15535.31	15535.31	0.00	0.00
2021	1.91	15535.85	15535.85	0.00	0.00
2022	1.64	15536.23	15536.23	0.00	0.00
2023	1.89	15536.56	15536.56	0.00	0.00
2024	2.51	15536.94	15536.94	0.00	0.00
2025		15537.44	15537.44		

Table 7
MSE and MAPE.

Forecasting Equations	First Equation	Second Equation	Third Equation	Fourth Equation
MSE	14479650	4654034	14448650	4638195
MAPE	10%	7.19%	10%	7.18%

2.1.2. Time series forecasting model

Comparisons with existing forecasting models are necessary to check the accuracy of the self-developed forecasting model. In this study, three construction rates were taken: building materials prices, labour wages and machinery hire rates, but only building materials prices data was available monthly. Because the existing time series model cannot make predictions based on a small number of observations, therefore, the forecasting of building materials prices data was performed based on the autoregressive integrated moving average (ARIMA) time series model. Once the forecasting of the monthly data of building materials prices was completed, it was converted into annual data for comparison with the data generated by the self-developed forecasting model. Before performing any time series analysis, four data components need to be examined: trend, seasonality, cyclical and irregular. The trend can be upward or downward in a linear or nonlinear pattern. Seasonality is a short-term regular pattern that can be over a year or months. Cyclical also has a regular pattern, but its pattern is in the long term. Irregular is unpredictable because of frequent variations in the data by an influential factor.

2.1.2.1. ARIMA model. ARIMA is one of the most popular techniques in time series analysis for forecasting. It is the combination of three major components: autoregressive (AR), integrated (I) and moving average (MA). AR and MA individually can also forecast the data; however, their accuracy is not absolute. The autoregressive moving average model has also been utilised, but introducing the integrated variable makes the results more promising. Thus, the ARIMA model was used to forecast the monthly building materials price data in this study. Performing ARIMA can be achieved in two ways: one is a traditional programming method, and the other is utilising the built-in software. The number of variables was high; thus, software was chosen for the analysis.

2.1.2.2. EViews software. EViews is a statistical package utilised for econometric analysis, mainly incorporated with time series. For the study's purpose, EViews Student Version Lite (V-11) was used for the analysis. EViews has a built-in option to perform ARIMA time series analysis where the p, d and q values are selected automatically based on the best combination of the model. The AR value is represented by p, the I value is represented by d, known as differencing, and the MA value is represented by q. Moreover, in SAR and SMA, S represents the seasonality in the data.

2.1.3. Model validation

Model validation in conducting analysis using two models. This study used Akaike's Information Criterion (AIC) to validate both models. The lower the AIC value, the better the forecasting model. The AIC, using Equation (8) can be calculated as follows:

$$AIC = -2\ln(L) + 2K \tag{8}$$

where L = maximum value of the likelihood function for the model and K = number of independent values. By default, the K value is 2, and the addition is based on the number of independent variables. In this case, the number of independent variables was 1, i.e., the inflation rate, and therefore, the K value was taken as 3.

Building materials prices model validation, labour wages and machinery hire rates were also validated by percentage deviation calculation.

3. Results and discussion

3.1. Construction rates forecasting

The self-developed forecasting model (second equation) was applied to all construction rates. The forecasting of the construction rates was made from 2020 to 2025.

3.1.1. Inflation rate forecasting

The independent variable should be forecasted first to enable the self-developed forecasting model to work. The EViews software was used to forecast the inflation rate, as shown in Fig. 2. The inflation rate data were taken from 1980 to 2019 for forecasting purposes. Data from 1980 to 2010 were considered as train, and data from 2011 to 2019 were considered as a test. To forecast the inflation rate, 25 ARIMA models were simulated, as shown in Fig. 3, where ARMA model (2,2)(0,0) was the most suitable model based on the lowest AIC value, as shown in Table 8. When selecting the ARIMA model parameters, the maximum differencing was kept as 2, and the maximum AR and MA values as 4.

3.1.2. Building materials prices forecasting

The building materials prices were forecasted using the second equation and incorporating the forecasted inflation rate, as shown in Table 9. The table shows that most materials types displayed an increasing trend, indicating that material prices will go higher.

The first forecasted value for 2013 was computed by taking the average value of the dependent variable (building material) because the required F was not available at the initial stage. In this case, the literature supports taking the average or initial value as the first F value. Once the end of 2019 is reached in the dependent variable, an average value of the forecasted values from 2013 to 2019 was taken to forecast the later years. The role of the correlation coefficient is significant because it indicates the thrust of the relationship. Positive and negative relationships influence the forecasted rates.

Moreover, if the relationship is strong, the inclination or declination behaviour of the forecasting will also be high. For the materials where the relationship of the inflation rate with materials prices is weak or moderate, the inclination or declination behaviour of the forecasting value will also be weak or moderate. A comparison was made with the existing ARIMA model, a time series model, via EViews to prove the effectiveness of the self-developed model.

3.1.2.1. ARIMA forecasting for building materials prices. A high number of observations are required to perform the ARIMA forecasting. However, the monthly data on the building materials prices and the inflation rate were also available, making it easier to conduct the analysis. The monthly inflation rate was initially forecasted via EViews by performing the Automated Arima Forecasting function. The output is shown in Fig. 4.

The inflation rate values were taken as the independent variable. Later forecasting was conducted for the individual building materials. The building materials prices data were taken from January 2013 to December 2019 for forecasting purposes, where data from January 2013 to June 2018 were considered as train and data from July 2018 to December 2019 were considered as a test. The maximum differencing value was taken as 2, AR as 4, MA as 4, SAR as 2 and SMA as 2. Various forecasting models were generated, and the best one was chosen for each material, as shown in Table 10.

3.1.2.2. Validation of building materials models. To validate the self-developed and ARIMA models of each building material price, AIC was calculated and presented in Table 11.

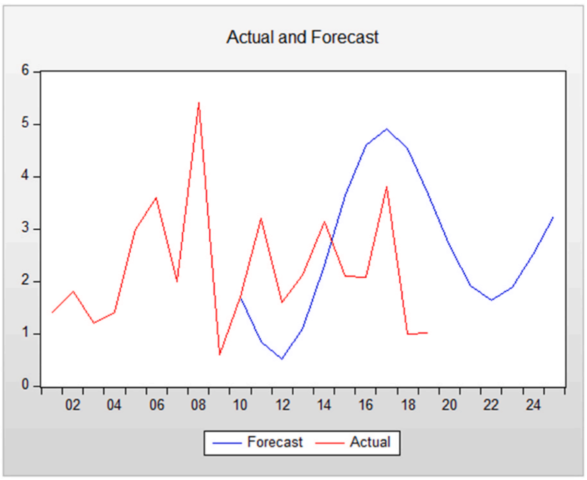

Fig. 2. Inflation rate forecasting.

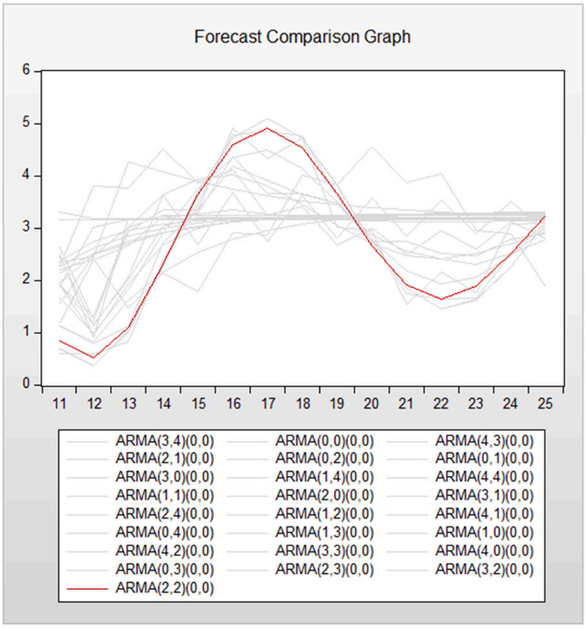

Fig. 3. ARIMA model comparison.

Table 8
Forecasting model AIC values.

S. No	Model	AIC
1	(2,2) (0,0)	3.929456
2	(3,2) (0,0)	3.985367
3	(2,3) (0,0)	3.985724
4	(0,3) (0,0)	4.033902
5	(4,0) (0,0)	4.043242
6	(3,3) (0,0)	4.051557
7	(4,2) (0,0)	4.054188
8	(1,0) (0,0)	4.061613
9	(1,3) (0,0)	4.068897
10	(0,4) (0,0)	4.072887
11	(4.1) (0,0)	4.075969
12	(1,2) (0,0)	4.076764
13	(2,4) (0,0)	4.09399
14	(3,1) (0,0)	4.102562
15	(2,0) (0,0)	4.117855
16	(1,1) (0,0)	4.121832
17	(4,4) (0,0)	4.128053
18	(1,4) (0,0)	4.133878
19	(3,0) (0,0)	4.147293
20	(0,1) (0,0)	4.151659
21	(0,2) (0,0)	4.151845
22	(2,1) (0,0)	4.178257
23	(4,3) (0,0)	4.341339
24	(0,0) (0,0)	4.351245
25	(3,4) (0,0)	4.400444

Table 11 shows that all the AIC values of the self-developed model are lesser than the ARIMA model, proving that the model yields the best alternative for forecasting. The main benefit of this model is that it provides forecasting even for a smaller number of observations. Most importantly, the self-developed model incorporates the relationship behaviour of the independent and dependent variables based on the correlation, which has a major impact.

3.1.3. Labour wages forecasting

Labour wages were also computed from the self-developed model. The forecasting results are shown in Table 12. The model adopts the same strategy of calculating future wages as described above. Initially, the correlation coefficients of all the wages required to forecast the values from 2020 to 2025 were computed.

Table 9
Forecasted building materials prices.

Building Materials Prices		Forecasted Rates (RM)					
S. No	Category of Material	2020	2021	2022	2023	2024	2025
1.1	Ordinary Portland Cement, 50 kg bag	21.74	23.70	24.73	25.42	26.22	27.43
1.2	Ordinary Portland Cement in Bulk	299.18	306.19	310.77	314.00	316.70	319.37
2.1	Granite Aggregate 3/4″	37.93	37.98	38.00	38.01	38.04	38.08
3.1	Normal River Sand- Ex	37.79	36.92	36.41	36.07	35.72	35.27
3.2	Fine River Sand for Plastering -Ex	39.82	39.15	38.75	38.48	38.22	37.88
3.3	Normal Mining Sand	34.72	34.23	33.95	33.75	33.56	33.30
3.4	Fine Mining Sand for Plastering	37.56	36.40	35.75	35.32	34.85	34.20
4.1	Mild Steel Round Bar R10, MS146	2410.25	2404.00	2399.50	2396.26	2393.94	2392.32
4.2	Mild Steel Round Bar R12, MS146	2444.99	2437.40	2431.95	2428.02	2425.20	2423.22
4.3	Mild Steel Round Bar R16, MS146	2402.20	2389.75	2380.99	2374.71	2370.05	2366.47
4.4	High Tensile Deformed Bar-Y10, MS146	2326.20	2318.75	2313.44	2309.61	2306.83	2304.83
4.5	High Tensile Deformed Bar-Y12, MS146	2304.92	2296.93	2291.23	2287.12	2284.15	2282.00
4.6	High Tensile Deformed Bar-Y16, MS146	2195.16	2190.00	2186.26	2183.55	2181.65	2180.39
4.7	High Tensile Deformed Bar-Y20, MS146	2176.05	2169.31	2164.44	2160.91	2158.42	2156.73
4.8	High Tensile Deformed Bar-Y25, MS146	2176.05	2169.31	2164.44	2160.91	2158.42	2156.73
4.9	High Tensile Deformed Bar-Y32, MS146	2176.05	2169.31	2164.44	2160.91	2158.42	2156.73
4.10	BRC A6, MS145	61.56	59.10	57.69	56.73	55.74	54.43
4.11	BRC A7, MS145	83.10	81.32	80.25	79.52	78.82	77.97
4.12	BRC A8, MS145	109.85	107.58	106.21	105.27	104.37	103.30
4.13	BRC A9, MS145	137.39	134.74	133.11	131.98	130.94	129.73
4.14	BRC A10, MS145	170.18	166.94	164.90	163.47	162.21	160.84
5.1	Ready Mix Concrete - Normal Mix - Grade15, Granite	183.64	186.19	187.71	188.75	189.76	191.00
5.2	Ready Mix Concrete - Normal Mix - Grade 20, Granite	190.31	193.08	194.74	195.88	196.97	198.31
5.3	Ready Mix Concrete - Normal Mix - Grade 25, Granite	201.38	204.00	205.57	206.65	207.69	208.95
5.4	Ready Mix Concrete - Normal Mix - Grade 30, Granite	212.45	215.11	216.71	217.80	218.85	220.12
5.5	Ready Mix Concrete - Normal Mix - Grade 35, Granite	222.72	225.30	226.84	227.89	228.91	230.16
6.1	Common Clay Bricks - Pallet	34.91	33.40	32.61	32.09	31.47	30.52
6.2	Cement Sand Bricks - Pallet	24.60	22.95	22.12	21.57	20.89	19.82
7.1	Interlocking Concrete Tiles - Standard Duotone Colour 420 mm × 330 mm	90.79	90.25	89.98	89.81	89.59	89.23
7.3	MS Decking - Ajiya AP Rib Hi-Tensile G26, 0.47 mm TCT, Clean Colourbond (Commercial)	46.50	44.33	43.16	42.39	41.50	40.21
7.4	MS Decking - Ajiya AP Rib Hi- Tensile G24, 0.53 mm TCT, Clean Colourbond (Commercial)	55.95	53.94	52.87	52.16	51.33	50.12
7.5	MS Decking - Ajiya Euro Step Roofing M350 G28, 0.40 mm TCT, Clean Colourbond	40.07	37.96	36.84	36.10	35.23	33.96
7.6	MS Decking - Ajiya Euro Step Roofing M350 G26, 0.47 mm TCT, Clean Colourbond	52.88	50.54	49.20	48.30	47.36	46.12
7.11	Corrugated Roofing Sheet-76mm Double Width, 1065 mm × 2440 mm x 4 mm (Hume/Malex/UAC)	22.85	20.81	19.72	19.01	18.17	16.92
8.4	Plain Homogeneous Floor Tiles, Standard light Colour, 300 mm × 300 mm x 8 mm - Grade 1	52.87	52.03	51.60	51.31	50.97	50.43
8.6	Glazed Ceramic Wall Tiles, Standard light Colour, 200 mm × 250 mm x 6 mm - Grade 1	68.34	66.79	65.94	65.37	64.74	63.86
9.1	Plain Cellulose Fibre Ceiling Sheet,610 mm × 1220 mm x3.2 mm (UAC/ MALEX/HUME)	40.28	39.75	39.51	39.36	39.13	38.75
9.2	Plain Cellulose Fibre Ceiling Sheet,610 mm × 1220 mm x 4.5 mm (UAC/ MALEX/HUME)	69.12	67.26	66.27	65.61	64.85	63.74
9.3	Plain Gypsum Board, 610 mm × 1220 mm x 9.5 mm, (Boral/Armstrong)	54.82	52.67	51.46	50.65	49.78	48.59
10.4	PVC Pressure Pipes Class D Grey Colour - 50 mm Diameter (paling), MS628	33.76	32.65	31.96	31.47	31.04	30.55
10.5	PVC Pressure Pipes Class E Grey Colour - 25 mm Diameter (paling), MS628	13.29	12.47	11.99	11.66	11.33	10.93
10.7	HDPE Pipe PN 16–25 mm Diameter, MS 1058	141.33	139.16	137.90	137.05	136.18	135.08
10.8	HDPE Pipe PN 16–50 mm Diameter, MS 1058	469.54	465.09	462.12	460.02	458.32	456.74
11.1	Polyethene water tank (Polytank), Circular- 200 gallons, MS 1225-weida equivalent	193.00	183.74	177.44	172.95	169.44	166.40
11.5	Water Closet Western Type- WC 644, white colour without cistern, claytan	184.34	180.68	178.24	176.51	175.11	173.81
11.7	Urinal Bowl, santana 320 c/w hanger, flange, ceramic waste & cleaning set, Johnson-Suisse	504.50	497.14	492.17	488.64	485.84	483.35
11.8	Stainless Steel Sinks - Single Bowl Single Drainer- Lay On Type, 42″ × 18″	96.36	93.77	92.25	91.22	90.19	88.88
12.1	Paint-ICI dulux standard colour-Undercoat speed	100.56	102.26	103.17	103.76	104.46	105.50
12.2	Paint-ICI dulux standard colour-external acrylic emulsion, weathershield	193.37	184.27	178.16	173.82	170.35	167.20
12.7	Paint-Nippon standard colour-timber/wood, timber finish	108.59	105.72	103.94	102.71	101.59	100.32
12.12	Paint - ICI Dulux Standard Colour Gloss Oil-based, Gloss Finish (5L)	117.59	115.17	113.85	112.98	111.99	110.57
13.1	Square hollow sections-12mm × 12 mm x 1.0 mm (0.357 kg/m)	3164.91	3149.87	3139.46	3132.01	3126.35	3121.73
13.2	Square Hollow Sections - 50 mm × 50 mm x 3.0 mm (4.38 kg/m)	3232.01	3225.95	3221.72	3218.69	3216.42	3214.61
13.3	Square Hollow Sections - 150 mm × 150 mm x 4.0 mm (20.20 kg/m)	3309.30	3311.54	3313.00	3314.02	3314.88	3315.73
13.4	Universal beams-102mm × 102 mm x 8.76 mm (19.35 kg/m)	2941.63	2964.46	2980.47	2991.96	3000.51	3007.17
13.5	Universal beams-400mm × 400 mm (2.17 kg/m)	3152.22	3186.83	3211.24	3228.78	3241.71	3251.52

(continued on next page)

Table 9 (*continued*)

Building Materials Prices		Forecasted Rates (RM)					
S. No	Category of Material	2020	2021	2022	2023	2024	2025
13.6	Equal angles-38mm × 38 mm x 3.8 mm (2.17 kg/m)	2636.51	2644.35	2649.73	2653.57	2656.53	2659.04
13.7	Equal angles-50mm × 50 mm x 4 mm (3.06 kg/m)	2559.78	2576.86	2588.82	2597.39	2603.79	2608.82
14.1	Plywood-shuttering board, 4 x 8 × 12 mm	48.65	47.15	46.37	45.87	45.25	44.29
15.1	GMS Heavy Hardwood, Balau 1	4942.11	4931.14	4923.39	4917.82	4913.72	4910.62
15.2	GMS light Hardwood, Dark Red Meranti	3181.03	3175.37	3171.37	3168.50	3166.38	3164.79
15.3	GMS Medium Hardwood, Kapur	3291.38	3279.85	3271.69	3265.82	3261.51	3258.29
15.4	Scantling Medium Hardwood, Kapur	3149.67	3137.38	3128.67	3122.42	3117.83	3114.40
16.1	Clear Float Glass 5 mm Thk, Local/Imported	54.38	52.21	50.99	50.17	49.29	48.09
16.3	Tinted Float Glass 6 mm Thk, Local/Imported, Inclusive of Cutting	66.76	64.62	63.41	62.61	61.74	60.55
17.1	CL03-Duraset brand residential grade 3 cylindric knob sets - PRIVACY-CL0363010	45.24	46.68	47.54	48.13	48.70	49.40
17.2	CL03-Duraset brand residential grade 3 cylindric knob sets - PATIO-CL0363020	48.76	50.47	51.45	52.12	52.80	53.69
17.3	CL03-Duraset brand residential grade 3 cylindric knob sets - PASSAGE-CL0363030	44.15	43.57	43.29	43.12	42.87	42.45
17.4	Concorde 102 mm × 76 mm x 2.0 mm SS hinge SUS 304	24.46	23.66	23.25	22.99	22.66	22.14
17.5	CL03- Duraset Brand Residential Grade 3 Cylindric Knob sets - ENTRANCE - CL0363000	49.96	52.07	53.31	54.16	55.00	56.06

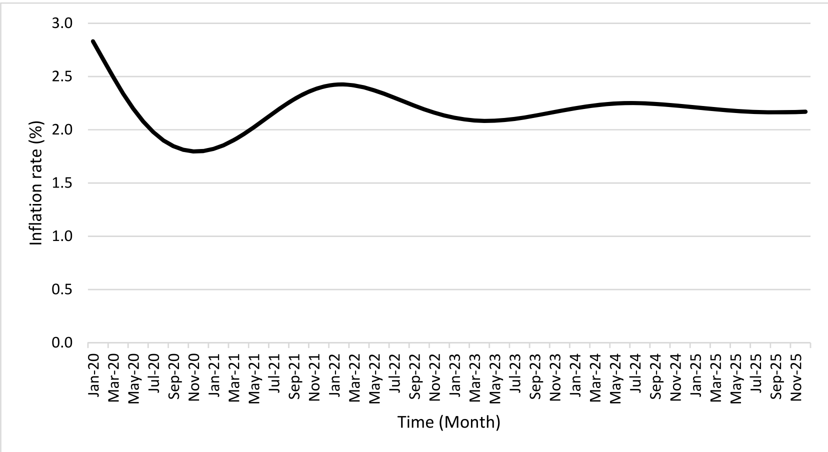

Fig. 4. Inflation rate forecasting (month-wise).

Table 10
ARIMA model for individual materials.

S. No	ARIMA Model	S. No	ARIMA Model	S. No	ARIMA Model	S. No	ARIMA Model
1.1	(1,0) (0,0)	**1.2**	(1,0) (0,0)	**2.1**	(2,1) (0,0)	**3.1**	(1,0) (0,0)
3.2	(1,0) (0,0)	**3.3**	(2,1) (0,0)	**3.4**	(1,0) (0,0)	**4.1**	(1,1) (0,0)
4.2	(1,1) (0,0)	**4.3**	(2,1) (0,0)	**4.4**	(1,1) (0,0)	**4.5**	(1,1) (0,0)
4.6	(1,1) (0,0)	**4.7**	(1,1) (0,0)	**4.8**	(1,1) (0,0)	**4.9**	(1,1) (0,0)
4.10	(2,2) (0,0)	**4.11**	(2,2) (0,0)	**4.12**	(2,2) (0,0)	**4.13**	(1,2) (0,0)
4.14	(0,0) (0,0)	**5.1**	(2,1) (0,0)	**5.2**	(1,0) (0,0)	**5.3**	(1,0) (0,0)
5.4	(2,1) (0,0)	**5.5**	(1,0) (0,0)	**6.1**	(1,0) (1,1)	**6.2**	(1,0) (0,0)
7.1	(2,1) (1,1)	**7.3**	(0,0) (0,0)	**7.4**	(0,0) (0,0)	**7.5**	(2,2) (0,0)
7.6	(0,0) (0,0)	**7.11**	(0,1) (0,0)	**8.4**	(1,1) (0,0)	**8.6**	(1,0) (0,0)
9.1	(3,2) (1,1)	**9.2**	(2,2) (0,0)	**9.3**	(0,0) (0,0)	**10.4**	(2,3) (0,0)
10.5	(0,3) (0,0)	**10.7**	(0,0) (0,0)	**10.8**	(0,0) (1,1)	**11.1**	(0,0) (0,0)
11.5	(0,1) (0,0)	**11.7**	(0,0) (0,0)	**11.8**	(0,0) (1,1)	**12.1**	(4,3) (0,1)
12.2	(0,0) (0,0)	**12.7**	(2,2) (0,0)	**12.12**	(2,1) (0,0)	**13.1**	(0,0) (0,0)
13.2	(0,3) (0,0)	**13.3**	(0,3) (0,0)	**13.4**	(0,1) (0,0)	**13.5**	(0,0) (0,0)
13.6	(1,0) (0,0)	**13.7**	(1,0) (0,0)	**14.1**	(2,1) (0,0)	**15.1**	(0,0) (0,0)
15.2	(0,0) (0,0)	**15.3**	(4,4) (1,0)	**15.4**	(2,1) (0,0)	**16.1**	(0,0) (0,0)
16.3	(0,0) (0,0)	**17.1**	(1,0) (0,0)	**17.2**	(1,0) (0,0)	**17.3**	(1,3) (0,0)
17.4	(0,0) (0,0)	**17.5**	(1,0) (1,1)				

Table 11
AIC validation.

S. No	ARIMA AIC	Self-Model AIC	S. No	ARIMA AIC	Self-Model AIC	S. No	ARIMA AIC	Self-Model AIC
1.1	1.734	−0.882	**1.2**	8.379	−9.311	**2.1**	4.788	0.034
3.1	5.168	−1.430	**3.2**	5.068	−1.014	**3.3**	5.256	−0.800
3.4	5.116	−1.175	**4.1**	12.599	−13.967	**4.2**	12.361	−14.048
4.3	12.639	−14.155	**4.4**	12.900	−13.679	**4.5**	12.901	−14.137
4.6	12.798	−13.461	**4.7**	12.798	−13.931	**4.8**	12.798	−13.931
4.9	12.798	−13.931	**4.10**	5.015	−3.055	**4.11**	5.475	−2.571
4.12	5.929	−3.926	**4.13**	6.269	0.422	**4.14**	−3.322	0.133
5.1	6.663	−5.453	**5.2**	6.679	−5.598	**5.3**	6.885	−5.862
5.4	7.079	−6.119	**5.5**	6.904	−5.805	**6.1**	3.344	0.101
6.2	2.936	0.152	**7.1**	2.510	−1.907	**7.3**	3.643	−1.255
7.4	−5.086	−0.941	**7.5**	−4.768	−1.212	**7.6**	2.494	−2.427
7.11	−4.832	−0.829	**8.4**	−4.526	0.795	**8.6**	5.225	−1.999
9.1	−4.404	1.113	**9.2**	−5.005	−1.030	**9.3**	3.426	−1.901
10.4	−4.346	−1.450	**10.5**	0.450	0.848	**10.7**	4.664	−2.739
10.8	6.546	−7.774	**11.1**	−2.449	−10.764	**11.5**	5.611	−6.634
11.7	7.191	−9.538	**11.8**	3.983	−3.221	**12.1**	4.618	−1.532
12.2	−1.538	−10.679	**12.7**	4.782	−4.485	**12.12**	−4.730	−2.088
13.1	11.226	−13.254	**13.2**	10.599	−11.448	**13.3**	10.106	−10.317
13.4	10.508	−14.476	**13.5**	11.742	−16.589	**13.6**	10.909	−13.325
13.7	11.298	−14.831	**14.1**	3.701	−1.021	**15.1**	13.086	−14.897
15.2	11.008	−12.388	**15.3**	−5.035	−14.992	**15.4**	11.913	−15.277
16.1	3.174	−2.349	**16.3**	4.031	−1.873	**17.1**	4.521	−1.520
17.2	4.726	−1.992	**17.3**	4.335	2.276	**17.4**	−2.862	2.430
17.5	5.935	−2.968						

3.1.3.1. Validation of labour wages model. The fewer observations for each labour wages category makes it impossible to compare labour wages forecasted values with any other forecasting model. Therefore, the forecasted labour wages with the actual labour wages data published in 2020 were compared, and the percentage deviation was calculated. The results are shown in Table 13.

Table 13 shows the overall deviation between the forecasted and actual labour wages in 2020. An overall deviation of 5.69% occurred, indicating that the forecasted wages are near the published wages. The effects of the COVIID-19 pandemic were not considered, which could impact the actual rates in 2020.

3.1.4. Machinery hire rates forecasting

Machinery hire rates were also computed from the self-developed model, and the forecasting results are shown in Table 14. The model adopts the same strategy of calculating future wages as described above. Initially, the correlation coefficients of all machinery hire rates, which were required to forecast the values from 2020 to 2025, were computed.

In the case of machinery hire rates, the forecasted rates with the actual rates could not be validated due to the data's unavailability. However, by looking at the upward scenario, it can be concluded that the model can forecast the rates near the existing rates. Field verification by a semi-structured interview was also performed. Most of the stakeholders with various industry working experiences agreed with the forecasting model's formulation and endorsed its workability for real-time construction projects. The demographic profile of the experts is shown in Table 15.

4. Discussion

Cost overrun in the construction industry has existed for decades, and the issue persists even with various reforms. One of the major reasons for its persistence is the inflation rate, which completely deviates from the construction rates. However, most project budget preparations do not incorporate the inflation rate. Therefore, this study proposed a forecasting model that can understand the changing behaviour of the inflation rate over time. Another issue aside from the absence of a construction rate forecasting model is that all pre-existing forecasting model requires a high number of observations to make forecasts. However, a self-developed model can perform forecasting even with fewer observations. The trend of the forecasted values is highly dependent on the relationship between the inflation rate and construction rates. The workability of the self-developed model can be achieved during the project budget preparation and development of the Bill of Quantities. By putting the construction and inflation rates in the model, a forecasted value for any particular year can be taken, which can then be incorporated into the budget estimation. The model can yield better results for projects with long duration because those projects have longer exposure to the changing behaviour of the inflation rate. Although the analysis was conducted on Malaysia's construction rates, the model applies to the construction industry of any country where the inflation rate deviates from the rates and causes cost overrun.

5. Limitations of study

This study has several limitations:

Table 12
Forecasted labour wages.

Labour Wages		Forecasted Rates (RM)					
S. No	Category of Labour	2020	2021	2022	2023	2024	2025
Construction Workers Group							
10131	General Construction Worker - Building, Local (Helper)	64.50	63.06	62.26	61.73	61.14	60.32
10132	General Construction Worker - Building, Foreign (Helper)	53.05	52.10	51.55	51.18	50.79	50.29
10211	Concretor, Skilled, Local	90.59	90.60	90.63	90.65	90.65	90.63
10212	Concretor, Skilled, Foreign	72.19	70.91	70.18	69.69	69.18	68.50
10221	Concretor, Semi-skilled, Local	68.08	66.50	65.61	65.01	64.37	63.51
10222	Concretor, Semi-skilled, Foreign	58.48	57.15	56.40	55.89	55.36	54.64
10311	Bricklayer, Skilled, Local	98.95	99.07	99.15	99.20	99.25	99.28
10312	Bricklayer, Skilled, Foreign	76.58	75.80	75.38	75.09	74.78	74.32
10321	Bricklayer, Semi-skilled, Local	71.05	69.30	68.35	67.72	67.01	65.99
10322	Bricklayer, Semi-skilled, Foreign	58.66	56.80	55.80	55.13	54.37	53.29
10411	Plasterer, Skilled, Local	111.13	111.97	112.44	112.75	113.10	113.57
10412	Plasterer, Skilled, Foreign	84.38	83.18	82.52	82.08	81.60	80.92
10421	Plasterer, Semi-skilled, Local	76.80	75.03	74.07	73.43	72.71	71.68
10422	Plasterer, Semi-skilled, Foreign	64.24	63.06	62.39	61.95	61.47	60.81
10511	Tiler, Skilled, Local	121.98	122.12	122.16	122.17	122.24	122.40
10512	Tiler, Skilled, Foreign	94.65	94.91	95.00	95.05	95.17	95.42
10521	Tiler, Semi-skilled, Local	90.13	88.93	88.27	87.83	87.34	86.65
10522	Tiler, Semi-skilled, Foreign	70.96	69.63	68.87	68.36	67.82	67.09
10611	Barbender, Skilled, Local	108.06	108.94	109.39	109.68	110.05	110.62
10612	Barbender, Skilled, Foreign	83.11	83.28	83.37	83.43	83.50	83.61
10621	Barbender, Semi-skilled, Local	80.63	79.89	79.43	79.11	78.82	78.50
10622	Barbender, Semi-skilled, Foreign	63.39	62.75	62.39	62.14	61.88	61.53
10711	Carpenter - Formwork, Skilled, Local	104.51	105.07	105.44	105.70	105.92	106.13
10712	Carpenter - Formwork, Skilled, Foreign	79.59	78.52	77.96	77.59	77.16	76.50
10721	Carpenter - Formwork, Semi-skilled, Local	77.53	76.61	76.12	75.80	75.42	74.87
10722	Carpenter - Formwork, Semi-skilled, Foreign	63.58	63.86	64.04	64.17	64.27	64.38
10811	Carpenter - Joinery, Skilled, Local	126.45	128.30	129.33	130.01	130.77	131.82
10812	Carpenter - Joinery, Skilled, Foreign	94.02	94.46	94.68	94.82	95.00	95.30
10821	Carpenter - Joinery, Semi-skilled, Local	83.86	83.18	82.82	82.59	82.31	81.88
10822	Carpenter - Joinery, Semi-skilled, Foreign	65.49	63.59	62.55	61.86	61.08	59.98
10911	Roofer, Skilled, Local	108.12	108.94	109.43	109.76	110.09	110.50
10912	Roofer, Skilled, Foreign	84.85	84.85	84.82	84.79	84.79	84.85
10921	Roofer, Semi-skilled, Local	79.76	78.81	78.31	77.97	77.58	77.02
10922	Roofer, Semi-skilled, Foreign	60.88	58.68	57.47	56.66	55.77	54.50
11011	Steel Structure Fabricator, Skilled, Local	118.59	119.36	119.86	120.21	120.51	120.81
11012	Steel Structure Fabricator, Skilled, Foreign	92.83	93.56	93.94	94.19	94.49	94.93
11021	Steel Structure Fabricator, Semi-skilled, Local	87.00	87.11	87.20	87.28	87.31	87.31
11022	Steel Structure Fabricator, Semi-skilled, Foreign	69.37	69.11	68.96	68.86	68.76	68.62
11111	General Welder, Skilled, Local	125.28	127.54	128.90	129.84	130.73	131.80
11112	General Welder, Skilled, Foreign	97.52	99.12	100.04	100.67	101.31	102.15
11121	General Welder, Semi-skilled, Local	87.64	87.59	87.64	87.69	87.66	87.49
11122	General Welder, Semi-skilled, Foreign	72.04	72.10	72.16	72.21	72.23	72.21
11211	Plumber - Building & Sanitary, Skilled, Local	114.01	114.66	115.11	115.43	115.67	115.88
11212	Plumber - Building & Sanitary, Skilled, Foreign	90.51	90.23	90.06	89.95	89.84	89.70
11221	Plumber - Building & Sanitary, Semi-skilled, Local	82.61	81.64	81.13	80.79	80.39	79.79
11222	Plumber - Building & Sanitary, Semi-skilled, Foreign	64.91	62.67	61.45	60.64	59.73	58.42
11311	Plumber - Reticulation, Skilled, Local	113.78	113.87	113.96	114.02	114.05	114.05
11312	Plumber - Reticulation, Skilled, Foreign	89.04	88.86	88.73	88.64	88.58	88.53
11321	Plumber - Reticulation, Semi-skilled, Local	82.88	81.95	81.47	81.15	80.77	80.18
11322	Plumber - Reticulation, Semi-skilled, Foreign	69.86	69.17	68.79	68.54	68.26	67.86
11421	Building Wiring Installer, Semi-skilled, Local	98.62	98.91	99.11	99.26	99.37	99.45
11422	Building Wiring Installer, Semi-skilled, Foreign	79.40	79.55	79.65	79.72	79.78	79.83
11511	Electrical Wireman PW2, Skilled, Local (per day)	135.46	137.89	139.34	140.34	141.30	142.48
11512	Electrical Wireman PW2, Skilled, Foreign (per day)	105.80	107.32	108.20	108.80	109.40	110.18
11611	Electrical Wireman PW4, Skilled, Local (per day)	159.48	160.72	161.51	162.06	162.54	163.06
11612	Electrical Wireman PW4, Skilled, Foreign (per day)	121.84	122.36	122.67	122.88	123.09	123.35
11711	Scaffolder - Prefabricated, Skilled, Local	99.75	100.32	100.69	100.95	101.16	101.38
11712	Scaffolder - Prefabricated, Skilled, Foreign	82.03	82.07	82.10	82.11	82.13	82.14
11721	Scaffolder - Prefabricated, Semi-skilled, Local	75.66	75.92	76.10	76.23	76.33	76.40
11722	Scaffolder - Prefabricated, Semi-skilled, Foreign	62.51	62.04	61.78	61.61	61.42	61.14
11811	Scaffolder - Tubular, Skilled, Local	103.07	102.66	102.48	102.36	102.19	101.89
11812	Scaffolder - Tubular, Skilled, Foreign	81.55	81.23	81.06	80.95	80.82	80.61
11821	Scaffolder - Tubular, Semi-skilled, Local	78.75	78.08	77.74	77.52	77.25	76.83
11822	Scaffolder - Tubular, Semi-skilled, Foreign	60.64	59.17	58.38	57.86	57.26	56.37
11911	Painter - Building, Skilled, Local	101.22	100.58	100.26	100.05	99.79	99.37
11912	Painter - Building, Skilled, Foreign	81.56	81.35	81.24	81.16	81.08	80.96

(*continued on next page*)

Table 12 (*continued*)

Labour Wages		Forecasted Rates (RM)					
S. No	Category of Labour	2020	2021	2022	2023	2024	2025
11921	Painter - Building, Semi-skilled, Local	76.37	75.90	75.66	75.50	75.30	74.99
11922	Painter - Building, Semi-skilled, Foreign	61.31	60.96	60.77	60.65	60.51	60.29
12031	General Construction Worker - Civil, Local	74.84	74.23	73.89	73.67	73.42	73.07
12032	General Construction Worker - Civil, Foreign	54.80	53.70	53.10	52.71	52.26	51.59
Plant and Machine Operators Group							
20111	Excavator Operator, Skilled, Local	126.20	124.79	123.89	123.26	122.71	122.15
20122	Excavator Operator, Semi-skilled, Foreign	103.07	101.95	101.20	100.67	100.24	99.84
20211	Pile Rigger, Skilled, Local	120.43	119.12	118.26	117.66	117.16	116.66
20212	Pile Rigger, Skilled, Foreign	93.57	92.10	91.16	90.49	89.92	89.34
20221	Pile Rigger, Semi-skilled, Local	84.13	81.63	80.20	79.23	78.22	76.90
20222	Pile Rigger, Semi-skilled, Foreign	66.17	63.73	62.33	61.39	60.40	59.10
20311	Off Road Truck Operator, Skilled, Local	110.50	108.67	107.56	106.80	106.07	105.21
20312	Off Road Truck Operator, Skilled, Foreign	86.47	85.69	85.20	84.86	84.55	84.22
20321	Off Road Truck Operator, Semi-skilled, Local	75.14	74.18	73.66	73.31	72.92	72.35
20322	Off Road Truck Operator, Semi-skilled, Foreign	60.08	58.63	57.85	57.32	56.73	55.88
20411	Backhoe Loader Operator, Skilled, Local	118.88	117.23	116.15	115.39	114.75	114.12
20412	Backhoe Loader Operator, Skilled, Foreign	92.27	91.00	90.19	89.63	89.14	88.61
20511	Roller Operator, Skilled, Local	105.56	103.94	102.99	102.34	101.70	100.89
20512	Roller Operator, Skilled, Foreign	89.26	88.73	88.37	88.11	87.91	87.74
20521	Roller Operator, Semi-skilled, Local	74.95	73.81	73.17	72.74	72.28	71.63
20522	Roller Operator, Semi-skilled, Foreign	57.55	56.18	55.46	54.98	54.43	53.60
20611	Roller/Compactor Operator, Skilled, Local	104.45	103.61	103.05	102.66	102.33	102.01
20612	Roller/Compactor Operator, Skilled, Foreign	86.58	86.19	85.90	85.68	85.54	85.47
20621	Roller/Compactor Operator, Semi-skilled, Local	72.63	71.26	70.51	70.01	69.45	68.65
20622	Roller/Compactor Operator, Semi-skilled, Foreign	61.87	61.32	61.00	60.79	60.57	60.27
20711	Scrapper Operator, Skilled, Local	110.21	108.92	108.15	107.62	107.11	106.48
20712	Scrapper Operator, Skilled, Foreign	88.21	87.23	86.63	86.22	85.83	85.36
20721	Scrapper Operator, Semi-skilled, Local	75.92	74.62	73.92	73.46	72.93	72.15
20722	Scrapper Operator, Semi-skilled, Foreign	62.12	60.71	59.93	59.41	58.83	58.02
20811	Motor Grader Operator, Skilled, Local	111.51	109.83	108.79	108.08	107.42	106.65
20812	Motor Grader Operator, Skilled, Foreign	91.21	89.61	88.63	87.96	87.33	86.59
20911	Wheel Loader Operator, Skilled, Local	118.07	116.71	115.83	115.21	114.69	114.17
20912	Wheel Loader Operator, Skilled, Foreign	96.16	94.74	93.82	93.18	92.63	92.06
20921	Wheel Loader Operator, Semi-skilled, Local	81.55	78.82	77.27	76.22	75.12	73.64
20922	Wheel Loader Operator, Semi-skilled, Foreign	68.29	66.41	65.33	64.60	63.84	62.84
21011	Paver Operator, Skilled, Local	123.20	121.78	120.82	120.14	119.60	119.13
21012	Paver Operator, Skilled, Foreign	101.70	100.17	99.13	98.39	97.81	97.31
21021	Paver Operator, Semi-skilled, Local	84.22	81.69	80.23	79.24	78.22	76.89
21022	Paver Operator, Semi-skilled, Foreign	71.62	70.02	69.06	68.41	67.77	67.00
21111	Mobile Crane Operator, Skilled, Local	151.92	152.18	152.28	152.33	152.44	152.66
21112	Mobile Crane Operator, Skilled, Foreign	120.37	120.71	120.81	120.86	121.02	121.39
21121	Mobile Crane Operator, Semi-skilled, Local	109.18	108.32	107.79	107.43	107.09	106.70
21122	Mobile Crane Operator, Semi-skilled, Foreign	83.33	82.59	82.16	81.85	81.56	81.21
21211	Crawler Crane Operator, Skilled, Local	140.21	139.61	139.24	138.99	138.76	138.47
21212	Crawler Crane Operator, Skilled, Foreign	109.29	109.23	109.15	109.09	109.08	109.12
21221	Crawler Crane Operator, Semi-skilled, Local	101.58	101.04	100.78	100.62	100.39	100.00
21222	Crawler Crane Operator, Semi-skilled, Foreign	78.70	77.85	77.39	77.08	76.73	76.24
21311	Tower Crane Operator, Skilled, Local	156.58	154.73	153.56	152.73	152.02	151.25
21312	Tower Crane Operator, Skilled, Foreign	121.90	120.36	119.40	118.74	118.14	117.46
21321	Tower Crane Operator, Semi-skilled, Local	113.06	110.45	108.86	107.76	106.73	105.53
21322	Tower Crane Operator, Semi-skilled, Foreign	84.79	82.92	81.83	81.09	80.34	79.37
21411	Forklift Operator, Skilled, Local	100.09	97.49	95.91	94.81	93.79	92.60
21412	Forklift Operator, Skilled, Foreign	83.88	82.41	81.44	80.76	80.19	79.64
21421	Forklift Operator, Semi-skilled, Local	76.49	74.16	72.78	71.84	70.91	69.76
21422	Forklift Operator, Semi-skilled, Foreign	64.14	62.33	61.24	60.49	59.77	58.91
21511	Slinger/Dogger, Skilled, Local	105.34	103.60	102.47	101.67	101.00	100.35
21512	Slinger/Dogger, Skilled, Foreign	89.85	88.18	87.09	86.33	85.69	85.05
21521	Slinger/Dogger, Semi-skilled, Local	80.76	78.82	77.65	76.84	76.08	75.15
21522	Slinger/Dogger, Semi-skilled, Foreign	66.10	64.44	63.44	62.75	62.09	61.31
IBS Installer Group							
30111	IBS Precast Concrete Installer, Skilled, Local	105.68	104.94	104.51	104.22	103.93	103.54
30121	IBS Precast Concrete Installer, Semi-skilled, Local	76.97	75.05	74.01	73.32	72.54	71.41
30211	IBS Lightweight Panel Installer, Skilled, Local	107.32	107.88	108.14	108.31	108.54	108.94
30221	IBS Lightweight Panel Installer, Semi-skilled, Local	80.76	80.04	79.63	79.36	79.07	78.66
30311	Lightweight Blockwall Installer, Skilled, Local	103.78	103.10	102.71	102.44	102.17	101.80
30321	Lightweight Blockwall Installer, Semi-skilled, Local	77.01	75.16	74.15	73.48	72.73	71.64
30411	System Formwork Installer, Skilled, Local	108.79	108.83	108.86	108.88	108.89	108.90
30421	System Formwork Installer, Semi-skilled, Local	80.53	78.86	77.93	77.31	76.64	75.70

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Table 12 (*continued*)

Labour Wages		Forecasted Rates (RM)					
S. No	Category of Labour	2020	2021	2022	2023	2024	2025
30511	Roof Truss Installer (Timber), Skilled, Local	104.44	105.00	105.29	105.49	105.72	106.05
30521	Roof Truss Installer (Timber), Semi-skilled, Local	75.84	75.39	75.17	75.03	74.84	74.54
30611	Roof Truss Installer (Light Gauge Steel), Skilled, Local	105.29	105.49	105.59	105.65	105.73	105.88
30621	Roof Truss Installer (Light Gauge Steel), Semi-skilled, Local	81.95	82.36	82.58	82.72	82.89	83.16

1. Selangor region, the hub of construction in Malaysia, was selected as the study area, but the construction rates are most likely to be the same in all regions.
2. The data from the previous seven years were examined to identify the relation between price increases and inflation.

6. Conclusion

In this study, a construction rate forecasting model was developed to examine the inflation rate relationship with the construction rates. A model was developed to predict future construction rates based on the influential rate of inflation rate. The number of observations of building materials prices data were higher and thus were also forecasted using Time Series Analysis, the ARIMA model. The forecasting was made from 2020 to 2025 with a self-developed and ARIMA models, validated via AIC. The values revealed that the self-developed model performed better than the ARIMA model. The developed dynamic construction rate forecasting model integrates past construction rates with the inflation rate and foresees the rate deviation over time. Therefore, its practical implementation should be made at the initial stage of a project while setting up the project budget which will save the efforts of adjusting the contingency cost. The model can be utilised in any country's construction industry with similar project cost overrun issues due to the inflation rate.

Even with several limitations applied, the contribution of this work is effective to the body of knowledge. This study provides insights into model development by emphasising the connectivity of the inflation rate with the construction industry in affecting its performance. Besides, a mathematical construction rate forecasting model has been proposed to deal with one of the major concerns of the construction industry. In a nutshell, this study contributes to theoretical and practical knowledge. As a theoretical contribution, the studied analysis provides a benchmark for future researchers to pursue the case more deeply and evaluate the other hidden factors that can impact the project budget. The developed model can further be modified upon assessing the relationships of the construction industry. While as a practical contribution, this study provides a mathematical construction rate forecasting model which can predict future prices, that can be embedded into the Bill of Quantities before the tender allotment. The construction industry stakeholders can foresee the future rates in the present year and make the necessary adjustments to avoid a project being cost overrun.

The following future directions are proposed:

1. The developed dynamic forecasting model integrates past construction rates with the inflation rate and foresees rate deviation over time. Therefore, practical implementation should be performed at the initial stage of a project while setting up the project budget to minimise efforts of adjusting the contingency cost.
2. Other forecasting techniques can also be used to draw a comparison to predict the construction rates based on the influence of the inflation rate.
3. Other influential factors, such as oil prices, should be examined to observe the influence of construction rates in deviation.

Funding

Not applicable.

Data availability

1. Sharing research data helps other researchers evaluate your findings, build on your work and to increase trust in your article. We encourage all our authors to make as much of their data publicly available as reasonably possible. Please note that your response to the following questions regarding the public data availability and the reasons for potentially not making data available will be available alongside your article upon publication.

Has data associated with your study been deposited into a publicly available repository?

Ans: No.

CRediT authorship contribution statement

Muhammad Ali Musarat: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Wesam Salah Alaloul:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization. **M.S. Liew:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Funding acquisition.

Table 13
Labour wages validation.

S. No	Forecasted	Actual	S. No	Forecasted	Actual	S. No	Forecasted	Actual
Construction Workers Group								
10131	64.50 5.73%	68.20	**10132**	53.05 3.68%	55.00	**10211**	90.59 4.32%	94.50
10212	72.19 18.44%	85.50	**10221**	68.08 16.04%	79.00	**10222**	58.48 15.60%	67.60
10311	98.95 11.67%	110.50	**10312**	76.58 3.16%	79.00	**10321**	71.05 6.97%	76.00
10322	58.66 10.13%	64.60	**10411**	111.13 0.34%	111.50	**10412**	84.38 1.45%	85.60
10421	76.80 4.82%	80.50	**10422**	64.24 5.55%	67.80	**10511**	121.98 10.67%	135.00
10512	94.65 −4.91%	90.00	**10521**	90.13 4.29%	94.00	**10522**	70.96 −6.85%	66.10
10611	108.06 −1.90%	106.00	**10612**	83.11 −10.96%	74.00	**10621**	80.63 12.87%	91.00
10622	63.39 −2.82%	61.60	**10711**	104.51 8.12%	113.00	**10712**	79.59 18.11%	94.00
10721	77.53 16.09%	90.00	**10722**	63.58 0.03%	63.60	**10811**	126.45 0.43%	127.00
10812	94.02 −1.61%	92.50	**10821**	83.86 21.64%	102.00	**10822**	65.49 11.46%	73.00
10911	108.12 1.74%	110.00	**10912**	84.85 −1.01%	84.00	**10921**	79.76 5.32%	84.00
10922	60.88 11.70%	68.00	**11011**	118.59 3.72%	123.00	**11012**	92.83 −7.90%	85.50
11021	87.00 −10.92%	77.50	**11022**	69.37 −4.13%	66.50	**11111**	125.28 −6.13%	117.60
11112	97.52 −14.88%	83.00	**11121**	87.64 −7.57%	81.00	**11122**	72.04 −10.88%	64.20
11211	114.01 −2.20%	111.50	**11212**	90.51 −7.20%	84.00	**11221**	82.61 −4.37%	79.00
11222	64.91 0.14%	65.00	**11311**	113.78 −0.24%	113.50	**11312**	89.04 −5.66%	84.00
11321	82.88 −7.10%	77.00	**11322**	69.86 −7.54%	64.60	**11421**	98.62 0.90%	99.50
11422	79.40 −4.78%	75.60	**11511**	135.46 2.34%	138.64	**11512**	105.80 1.65%	107.55
11611	159.48 8.88%	173.65	**11612**	121.84 −7.33%	112.91	**11711**	99.75 2.05%	101.80
11712	82.03 10.32%	90.50	**11721**	75.66 −0.21%	75.50	**11722**	62.51 15.18%	72.00
11811	103.07 −1.52%	101.50	**11812**	81.55 −4.36%	78.00	**11821**	78.75 2.23%	80.50
11822	60.64 6.53%	64.60	**11911**	101.22 8.67%	110.00	**11912**	81.56 1.76%	83.00
11921	76.37 4.75%	80.00	**11922**	61.31 5.21%	64.50	**12031**	74.84 17.58%	88.00
12032	54.80 14.26%	62.62	**20111**	126.20 6.54%	134.45	**20122**	103.07 −5.79%	97.10
20211	120.43 −0.77%	119.50	**20212**	93.57 1.52%	95.00	**20221**	84.13 23.02%	103.50
20222	66.17 24.67%	82.50	**20311**	110.50 17.19%	129.50	**20312**	86.47 1.19%	87.50
20321	75.14 16.44%	87.50	**20322**	60.08 20.67%	72.50	**20411**	118.88 13.26%	134.65
20412	92.27 13.14%	104.40	**20511**	105.56 12.45%	118.70	**20512**	89.26 13.49%	101.30
20521	74.95 23.28%	92.40	**20522**	57.55 13.82%	65.50	**20611**	104.45 11.05%	116.00
20612	86.58 3.95%	90.00	**20621**	72.63 25.98%	91.50	**20622**	61.87 5.86%	65.50
20711	110.21 16.32%	128.20	**20712**	88.21 16.76%	103.00	**20721**	75.92 21.18%	92.00
20722	62.12 15.90%	72.00	**20811**	111.51 11.38%	124.20	**20812**	91.21 3.61%	94.50
20911	118.07 5.79%	124.90	**20912**	96.16 8.46%	104.30	**20921**	81.55 16.50%	95.00
20922	68.29	69.00	**21011**	123.20	138.00	**21012**	101.70	108.30

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Table 13 (*continued*)

S. No	Forecasted	Actual	S. No	Forecasted	Actual	S. No	Forecasted	Actual
	1.04%			12.02%			6.49%	
21021	84.22	103.90	**21022**	71.62	80.00	**21111**	151.92	151.50
	23.37%			11.70%			−0.28%	
21112	120.37	110.80	**21121**	109.18	123.50	**21122**	83.33	76.00
	−7.95%			13.12%			−8.79%	
21211	140.21	153.30	**21212**	109.29	108.00	**21221**	101.58	112.50
	9.34%			−1.18%			10.75%	
21222	78.70	73.00	**21311**	156.58	188.70	**21312**	121.90	134.00
	−7.24%			20.51%			9.92%	
21321	113.06	135.50	**21322**	84.79	101.50	**21411**	100.09	106.10
	19.85%			19.71%			6.00%	
21412	83.88	77.00	**21421**	76.49	84.50	**21422**	64.14	67.50
	−8.21%			10.47%			5.24%	
21511	105.34	106.34	**21512**	89.85	88.00	**21521**	80.76	88.19
	0.95%			−2.06%			9.20%	
21522	66.10	69.00	**30111**	105.68	110.50	**30121**	76.97	81.50
	4.38%			4.56%			5.88%	
30211	107.32	97.50	**30221**	80.76	83.00	**30311**	103.78	103.50
	−9.15%			2.77%			−0.27%	
30321	77.01	83.00	**30411**	108.79	103.50	**30421**	80.53	83.00
	7.78%			−4.87%			3.07%	
30511	104.44	132.00	**30521**	75.84	91.00	**30611**	105.29	114.00
	26.39%			19.99%			8.27%	
30621	81.95	84.00						
	2.51%							
Overall Deviation = 5.69%								

Table 14
Forecasted machinery hire rates.

Machinery Hire Rates		Forecasted Rates (RM)					
S. No	Category	2020	2021	2022	2023	2024	2025
1.1	Hydraulic Excavator. Komatsu, PC200-7	9483.03	9421.04	9377.15	9345.59	9322.46	9305.17
1.2	Hydraulic Excavator, Komatsu, PC300-7	16555.17	16511.96	16481.43	16459.49	16443.36	16431.2
1.3	Hydraulic Excavator, Komatsu, PC400LC-7	24505.25	23985.24	23615.78	23349.83	23156.12	23013.53
1.4	Hydraulic Excavator, Hitachi, ZAXIS 120	8538.666	8429.148	8351.581	8295.79	8254.943	8224.455
1.5	Tracker Excavator, Sumitomo, SH120-3	8518.022	8407.708	8329.552	8273.333	8232.194	8201.531
2.1	Bulldozer, Komatsu, D65E-12	14429.55	14266.63	14150.87	14067.54	14006.85	13962.18
3.1	Motor Grader, Caterpillar, 140H Standard	14766.79	14394.45	14129.95	13939.56	13800.85	13698.66
4.1	Lorry, Hino, BDM 10000 kg	15528.77	15335.96	15199.14	15100.68	15028.82	14975.62
4.2	Lorry, Hino, BDM 20000 kg	21409.77	21114.5	20904.79	20753.85	20643.85	20562.73
4.3	Lorry, Nissan, BDM 3000 kg	12597.74	12372.62	12212.81	12097.8	12013.91	11951.91
4.4	Lorry, Nissan, BDM 5000 kg	14425.89	14093.58	13857.55	13687.66	13563.85	13472.59
4.5	Lorry, Nissan, BDM 10000 kg	16455.81	16225.91	16062.75	15945.33	15859.66	15796.28
5.1	Mobile Crane, Kato, NK200H II	12066.1	11851.29	11698.57	11588.62	11508.62	11449.9
5.2	Mobile Crane, Kato, NK450B	23287.36	22846.82	22533.83	22308.53	22144.43	22023.59

Table 15
Demographic profile of respondents.

Respondent	Qualification	Year of Experience	Organisation Type	Business Nature
1	B.Sc Civil Engineering	10	Private	Contractor
2	B.Sc Civil Engineering	10	Public	Client
3	B.Sc Electrical Engineering	8	Private	Consultant
4	B.Sc Civil Engineering	16	Private	Client
5	PhD in Civil Engineering	29	Public	Client
6	PhD in Civil Engineering	18	Public	Academic
7	B.Sc Civil Engineering	26	Private	Contractor
8	PhD in Civil Engineering	22	Public	Consultant
9	B.Sc Civil Engineering	40+	Private	Client
10	B.Sc Civil Engineering	31	Private	Client
11	B.Sc Civil Engineering	3	Private	Client
12	B.Sc Civil Engineering	3	Private	Client
13	B.Sc Civil Engineering	14	Private	Client
14	B.Sc Civil Engineering	20	Private	Client

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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List of Abbreviations

Abbreviation	*Definition*
ES	Exponential Smoothing
AR	Autoregressive
MA	Moving Average
ARMA	Autoregressive Moving Average
I	Integrated
ARIMA	Autoregressive Integrated Moving Average
ANN	Artificial Neural Network
MSE	Mean Square Error
MAPE	Mean Absolute Percentage Error
r	Correlation Coefficient
SAR	Seasonal Autoregressive
SMA	Seasonal Moving average
AIC	Akaike's Information Criterion

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