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MACROECONOMIC DRIVEN CEMENT PRICE FORECASTING IN SRI LANKA USING ECONOMETRIC AND DEEP LEARNING MODELS

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ABSTRACT

Cement price stability is fundamental to the performance of the construction sector, which significantly contributes to national economic development in Sri Lanka. However, recent macroeconomic instability characterized by exchange rate depreciation, inflationary pressures, and fuel price volatility has intensified cement price fluctuations, particularly during the 2022 economic crisis. Despite the growing need for reliable forecasting tools, limited research has evaluated the combined application of econometric and deep learning models for cement price prediction in highly volatile emerging economies. This study develops and compares forecasting models using a 20-year monthly macroeconomic dataset (2006 to 2025). An Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model was established as a linear baseline, incorporating key predictors including Inflation, Exchange Rate, Diesel Price, and Global Coal Prices identified through Pearson correlation analysis. Advanced deep learning architectures, namely Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Attention-based LSTM (ATT-LSTM), were implemented to capture non-linear temporal dependencies. Model performance was evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2). Results indicate that while the GRU model achieved the highest accuracy under optimized sequence-length configurations, the LSTM demonstrated greater stability and robustness during crisis-period testing. Overall, deep learning architectures outperformed the ARIMAX baseline in capturing cement price volatility during the Sri Lankan economic crisis. These findings can support contractors, quantity surveyors, and policymakers in improving procurement planning and managing construction cost risks during periods of economic instability.

Keywords: *Cement; Construction Economics; Deep Learning; Macroeconomic Variables; Price Forecasting.*

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1. INTRODUCTION

The construction sector plays a vital role in the economic development of Sri Lanka, contributing significantly to Gross Domestic Product (GDP) and generating employment opportunities nationwide (Central Bank of Sri Lanka, 2021). Within this sector, cement serves as a foundational material that supports residential, commercial, and large-scale infrastructure projects (Petrova, 2024). Cement plays a fundamental role in construction activities, and fluctuations in cement prices directly influence investment decisions, project feasibility, and broader urban development strategies. Consequently, cement price stability is closely associated with both construction sector performance and national economic growth (Tokyo Cement Company (Lanka) PLC, 2025).

In recent years, however, Sri Lanka has experienced severe macroeconomic instability characterized by high inflation, currency depreciation, and disruptions in global supply chains (Lanka News Web, 2022). These macroeconomic shocks have intensified volatility in construction material markets, particularly affecting cement prices (Tokyo Cement Company (Lanka) PLC, 2025). Since cement production and distribution are highly sensitive to exchange rate movements, fuel prices, and global coal prices, external shocks quickly translate into domestic price fluctuations (Fortune Business Insights, 2026). As a result, contractors, project managers, and suppliers face increasing uncertainty, which often leads to budget overruns, delayed project completion, and contractual disputes (Abdelalim et al., 2024). Given these challenges, accurate forecasting of cement prices has become essential for effective procurement planning and risk mitigation within the construction industry (Ma et al., 2024).

Although forecasting techniques have evolved significantly, emerging economies such as Sri Lanka present unique modelling challenges because economic instability and crisis periods often cause sudden and unpredictable price fluctuations. Traditional econometric approaches, including regression models and statistical time-series techniques such as Autoregressive Integrated Moving Average (ARIMA), are widely used to analyse relationships between economic variables. These approaches provide interpretable relationships between macroeconomic variables and commodity prices, making them valuable tools for policy analysis (Shiha & El-adaway, 2024). However, such methods may struggle to capture complex non-linear interactions that arise during periods of extreme economic instability. In contrast, deep learning techniques are capable of modelling sequential dependencies and non-linear dynamics that conventional statistical methods may overlook (Osman & Otaibi, 2025). Therefore, integrating econometric and deep learning approaches offers a comprehensive analytical framework capable of capturing both linear macroeconomic effects and complex temporal patterns.

Despite increasing global research on construction material price forecasting, limited attention has been given to forecasting construction material prices within the Sri Lankan context. Previous forecasting studies in Sri Lanka have primarily focused on other economic sectors, including short-term electricity demand forecasting (Shiwakoti et al., 2025), tourism demand prediction (Hewapathirana, 2025), and unemployment rate modelling (Gunawardhana, 2023). These studies demonstrate that statistical and machine learning techniques have been successfully applied to economic forecasting problems in the country. However, similar analytical approaches have not been applied to modelling the price behaviour of construction materials such as cement. As a result, there remains a significant research gap in developing forecasting models for construction material prices in Sri Lanka, particularly under conditions of prolonged macroeconomic instability and economic disruptions.

To address this research gap, this study utilizes monthly cement price data from January 2006 to December 2025, covering both stable economic periods and the economic crisis of 2022. The study develops and evaluates multiple forecasting models, including an econometric baseline model, Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX), and several deep learning architectures, namely Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Attention-based LSTM (ATT-LSTM). These models are trained and evaluated independently, and their forecasting performance is compared using multiple error metrics. By analysing model performance across different sequence lengths and assessing predictive robustness during periods of economic instability, the study aims to develop a forecasting framework suitable for Sri Lanka's volatile economic environment.

The objectives of this study are as follows:

1. To analyse historical cement price fluctuations in Sri Lanka (2006–2025) and assess the relationship between cement prices and selected macroeconomic variables through correlation analysis to identify significant predictive variables.
2. To compare the predictive performance of a baseline ARIMAX model against deep learning architectures (LSTM, GRU, and ATT-LSTM) in forecasting volatile cement prices.
3. To investigate the impact of varying historical sequence lengths (3 to 24 months) on deep learning accuracy to determine the optimal look-back period for time-series forecasting.
4. To evaluate model resilience and error metrics during periods of extreme market volatility and structural economic breaks.

2. LITERATURE REVIEW

Accurate forecasting of cement prices is critically important for the construction industry because cement represents a fundamental input in infrastructure and building projects (Petrova, 2024). Fluctuations in cement prices directly influence project cost estimation, procurement planning, and financial risk management (Ma et al., 2024). Sudden increases in material prices can lead to budget overruns, contract disputes, and project delays, particularly in economies experiencing macroeconomic instability (Abdelalim et al., 2024).

Research on construction material price forecasting has traditionally relied on statistical modelling techniques, particularly in developed economies with relatively stable markets (Xiong et al., 2025). These approaches typically utilize historical price data together with macroeconomic variables such as inflation, exchange rates, fuel costs, and interest rates (Shiha & El-adaway, 2024). Common statistical techniques include regression-based models and time-series methods such as Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Vector Autoregression (VAR) (Alzubi, 2023). These models perform well when market behaviour follows relatively stable linear or seasonal trends. However, their predictive accuracy often declines when markets experience abrupt economic disruptions or non-linear price volatility (Xiong et al., 2025).

To address these limitations, Artificial Intelligence (AI) techniques, particularly Machine Learning (ML) and Deep Learning (DL), have increasingly been applied to price forecasting problems. Deep neural networks such as Feedforward Neural Networks and Multilayer Perceptrons can capture complex relationships within economic data (Zhang et al., 2022). However, these architectures do not inherently capture temporal dependencies. Recurrent Neural Networks (RNNs) address this limitation by incorporating feedback connections that allow the model to retain sequential information (Mienye et al., 2024). Advanced variants including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) further improve performance by enabling models to learn long-term dependencies within time-series data and mitigate vanishing gradient problems (Mienye et al., 2024). Empirical studies indicate that LSTM-based models frequently outperform traditional neural networks when forecasting complex commodity price dynamics (Xiong et al., 2025).

Recent research has therefore explored hybrid modelling approaches that combine the interpretability of econometric models with the predictive power of deep learning techniques (Osman & Otaibi, 2025). Such approaches have shown promising results in forecasting complex commodity markets. However, limited studies have examined the application of these forecasting techniques to cement price prediction within highly volatile emerging economies such as Sri Lanka. This gap highlights the need for a comprehensive forecasting framework capable of evaluating econometric and deep learning models under conditions of significant economic instability.

3. RESEARCH METHODOLOGY

This section describes the macroeconomic dataset, the data pre-processing steps including feature selection via correlation analysis, the architectural details of the econometric and deep learning models, and the proposed forecasting model.

3.1 CEMENT PRICE AND MACROECONOMIC DATASET

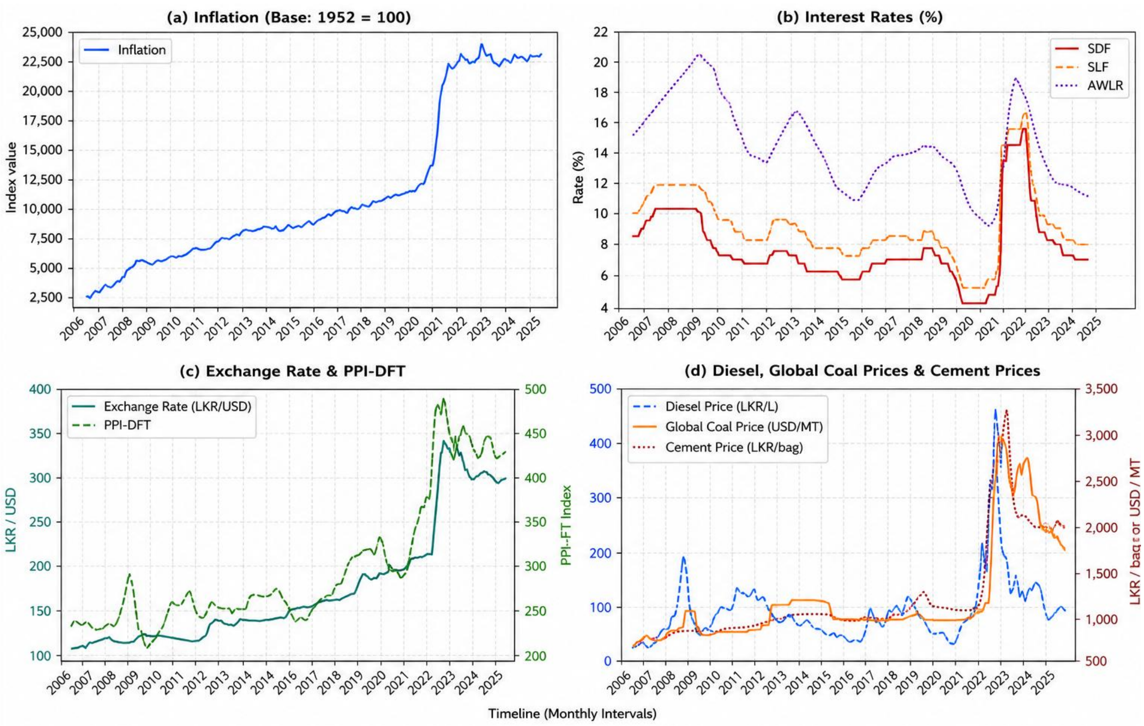

Figure 1: Historical trajectory of cement price and macroeconomic variables and energy indices

The dataset comprises monthly observations from January 2006 to December 2025. The dependent variable is the Monthly Cement Price Index. Exogenous macroeconomic variables were obtained from the Central Bank of Sri Lanka (CBSL), the Department of Census and Statistics, and global energy market sources. These variables include Inflation (Base 1952 = 100), Standing Deposit Facility (SDF), Standing Lending Facility (SLF), Exchange Rate (LKR/USD), Average Weighted Lending Rate (AWLR), Producer Price Index for Deep Sea Freight Transportation (PPI-DFT), Diesel Price, and Global Coal Prices (GCP).

Figure 1 illustrates the historical trajectories of cement prices and macroeconomic variables using a dual-axis format to accommodate scale differences. The dataset captures both long-term macroeconomic trends and periods of heightened volatility.

3.2 DATA PRE-PROCESSING AND FEATURE SELECTION

Missing values were handled using forward filling to maintain continuity in monthly observations. Due to substantial scale variation across variables, Min-Max normalization was applied to rescale all features into the range [−1, 1] as defined in Equation 1, where each feature value x is rescaled linearly based on its minimum (x_{min}) and maximum (x_{max}) values to transform it into the desired range[a ,b], in this case [-1, 1] (Han et al., 2011).

$$x_{Scaled} = a + \frac{(x-x_{min})(b-a)}{x_{max}-x_{min}} \qquad (01)$$

To refine the feature set and reduce redundancy, Pearson correlation analysis was conducted as a preliminary feature-screening technique to assess linear relationships between cement prices and candidate predictors. The analysis was intended to support variable selection rather than establish causal relationships. The correlation coefficient was computed using Equation (2), where X_i and Y_i represent the individual data points of the two variables being compared, $\bar{X}$ and $\bar{Y}$ are their respective means (Cohen et al., 2003).

$$r = \frac{\sum(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum(X_i-\bar{X})^2\sum(Y_i-\bar{Y})^2}} \qquad (02)$$

Variables exhibiting weak explanatory contribution were excluded to enhance model stability.

3.3 MODELS

The methodological framework was selected to capture both linear macroeconomic relationships and complex non-linear price dynamics. Pearson correlation analysis was employed as an initial feature-screening technique to identify variables strongly associated with cement prices and reduce redundant inputs. Min-Max normalization was applied to ensure consistent scaling across variables and improve neural network training stability. ARIMAX was selected as an interpretable econometric benchmark capable of incorporating exogenous macroeconomic variables, while LSTM, GRU, and ATT-LSTM were adopted due to their ability to model temporal dependencies and non-linear relationships commonly observed in volatile economic time series.

3.3.1 Auto Regressive Integrated Moving Average with Exogenous Variables (ARIMAX)

The ARIMAX model extends ARIMA by incorporating external predictors. It captures linear relationships between historical cement prices and macroeconomic variables (Zhang et al., 2025). The general model is shown in Equation 3, where y_t denote the dependent variable at time t; ϕ_i represent the autoregressive coefficient, θ_j denote the moving average coefficients; $y_{k,t}$ represents the k^{th} exogenous variable at time t; β_k are corresponding coefficients of the exogenous variables, and ϵ_t is the error term at time t (Hyndman & Athanasopoulos, 2021).

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{r} \beta_k y_{k,t} + \epsilon_t \qquad (03)$$

3.3.2 Gated Recurrent Unit (GRU)

The Gated Recurrent Unit is a variation of recurrent neural networks designed to utilize reset and update gates to regulate information flow with a simplified structure (Mienye et al., 2024). The update gate determines how much of the previous information needs to be passed along to the future, while the reset gate decides how much of the past information to forget.

3.3.3 Long Short-Term Memory (LSTM)

The LSTM network, which employs input, forget, and output gates to capture long-term temporal dependencies (Osman & Otaibi, 2025). This architecture allows LSTM networks to map complex input sequences of macroeconomic variables $(x_1, x_2, \ldots, x_n)$ an output sequence of predicted cement prices $(y_1, y_2, \ldots, y_n)$ without losing information from early time steps.

3.3.4 Attention-based LSTM(ATT-LSTM)

The ATT-LSTM, which integrates an attention mechanism to weight influential time steps in the input sequence (Liao et al., 2023). The architecture of the ATT-LSTM follows a systematic five-stage experimental process, encompassing data acquisition, comprehensive pre-processing and feature selection, attentional weighting of temporal sequences, LSTM-based predictive modeling, and the final evaluation of denormalized results as illustrated in Figure 2.

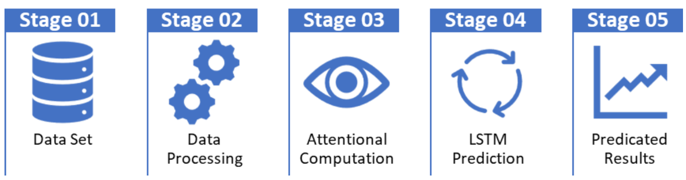

Figure 2: Five-stage experimental process for the ATT-LSTM architecture

3.3.5 Hyperparameters

This study focuses on selecting the optimal model architecture and corresponding hyperparameters for predicting monthly cement prices in Sri Lanka. A suitable model is one that accurately captures complex macroeconomic data patterns, avoids both overfitting and underfitting, and maintains a structure that is both computationally efficient and industrially applicable. The deep learning models were trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. All architectures were trained for 200 epochs with a batch size of 16, and a validation split of 10% was used during training. To reduce overfitting, a dropout rate of 0.2 was applied after each recurrent layer. The input sequence length representing the historical look-back period was varied between 3 and 24 months, while other hyperparameters remained constant across experiments to ensure fair model comparison.

3.4 PROPOSED MODEL

The proposed workflow for cement price forecasting includes five key stages: (1) data preprocessing, which encompasses handling missing values, Pearson correlation-based feature selection, and Min-Max normalization; (2) preparation of input sequences using a sliding window approach; (3) model training across econometric and deep learning architectures; (4) denormalization of the predicted price indices; and (5) performance evaluation.

The dataset was divided into a training period (January 2006 to December 2021) and a testing period (January 2022 to December 2025), corresponding to approximately an 80%–20% chronological split. Input sequences were generated using a sliding-window approach, where the preceding 3 to 24 months of observations were used to predict the subsequent month's cement price. The training dataset represents relatively stable economic conditions, whereas the testing dataset includes the 2022 economic crisis and the subsequent market adjustment period. This design enables an out-of-sample crisis evaluation in which the models are trained only on pre-crisis data and tested on their ability to forecast cement price dynamics during and after a major economic disruption. A rolling window approach was intentionally avoided to prevent information from the crisis period entering the training phase. This ensures that the forecasting models are evaluated under realistic conditions where future economic shocks are not observed during model training. The forecasting experiments include an econometric baseline (ARIMAX) and deep learning models (LSTM, GRU, and ATT-LSTM). The ARIMAX model incorporates the filtered exogenous variables (Diesel Price, GCP, Exchange Rate, PPI-DFT, and Inflation) alongside the historical price lag and seasonal orders. The deep learning models utilize specialized architectures to capture non-linear dependencies.

All deep learning models employed two recurrent layers (100 and 50 units), followed by dropout (0.2) and dense output layers. The models were trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function as shown in Equation 4 (Chai & Draxler, 2014). To evaluate the accuracy and reliability of the forecasting models, four statistical metrics were utilized. These metrics compare the actual cement price (y_i) against the predicted value ($\widehat{y_i}$) over n total observations. Mean Absolute Percentage Error (MAPE), defined in Equation (5), expresses accuracy as a percentage, allowing easier comparison across different datasets and timeframes (Kim & Kim, 2016). Mean Absolute Error (MAE), presented in Equation (6), provides a linear score where all individual differences are weighted equally (Willmott & Matsuura, 2005). Root Mean Square Error (RMSE), calculated using Equation (7), penalizes larger errors more heavily, highlighting significant deviations during price spikes (Chai & Draxler, 2014). Finally, the coefficient of determination (R^2) shown in Equation (8), evaluates the model's ability to explain variance in cement price fluctuations (Chicco et al., 2021).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \qquad (04)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \tag{05}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{06}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{07}$$

$$R^2 = 1 - \frac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y})^2} \tag{08}$$

4. RESULTS AND DISCUSSIONS

This section presents and critically analyses the forecasting performance of the econometric baseline and Deep Learning architectures during the high-volatility period of the Sri Lankan economic crisis. The evaluation proceeds in four stages: feature refinement, sequence length sensitivity, structural break behaviour, and final out-of-sample testing performance.

4.1 FEATURE SELECTION AND CORRELATION ANALYSIS

A Pearson correlation analysis was conducted to examine the relationship between cement prices and selected macroeconomic variables. The initial set of variables was identified based on industry evidence reported in the Tokyo Cement Company (Lanka) PLC Annual Report 2024/25, which indicates that cement prices are influenced by factors such as inflation, policy interest rates, exchange rate movements, global freight costs, and energy prices. These variables affect cement production, import, transportation, and distribution costs, making them potential drivers of cement price fluctuations. Based on these industry insights and data availability, the study selected Inflation, Standing Deposit Facility (SDF), Standing Lending Facility (SLF), Exchange Rate (LKR/USD), Average Weighted Lending Rate (AWLR), Producer Price Index for Deep Sea Freight Transportation (PPI-DFT), Diesel Price, and Global Coal Prices (GCP) as candidate explanatory variables.

Pearson correlation analysis was then performed to quantify the strength of the linear relationships between these macroeconomic indicators and cement prices. In this study, correlation coefficients above 0.70 were interpreted as strong positive relationships, values between 0.30 and 0.70 as moderate relationships, and values below 0.30 as weak relationships. As illustrated in Figure 3, strong positive correlations were observed between cement prices and key cost-related variables, particularly the Exchange Rate (0.97) and Diesel Price (0.98), confirming the import-dependent and energy-intensive structure of Sri Lanka's cement supply chain.

The correlation heatmap further indicates that freight-related and fuel-linked variables exhibit relatively high associations with cement prices, whereas the Average Weighted Lending Rate (AWLR) shows a weak and slightly negative correlation (−0.10). Given its minimal explanatory contribution and potential to introduce noise into the forecasting models, AWLR was excluded from the final feature set. Consequently, the refined input variables used for model development included Inflation, SDF, SLF, Exchange Rate (LKR/USD), PPI-DFT, Diesel Price, and GCP. Furthermore, the selected variables were supported by prior construction economics literature and industry evidence regarding cement price formation. This feature selection process improves model parsimony while retaining the macroeconomic factors most strongly associated with cement price dynamics.

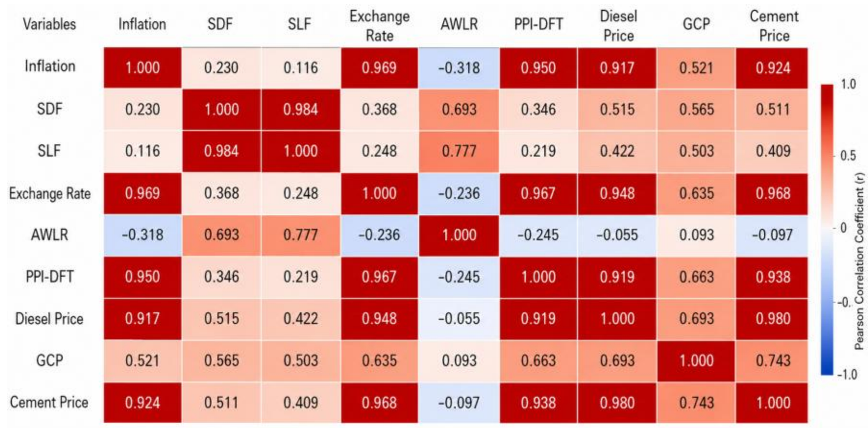

Figure 3: Feature correlation heatmap

4.2 PERFORMANCE ANALYSIS ACROSS SEQUENCE LENGTHS

To determine the optimal historical context for forecasting cement prices under volatile market conditions, forecasting experiments were conducted using multiple sequence lengths (look-back windows) ranging from 3 to 24 months, where sequence length represents the number of previous monthly observations used as model inputs. For each sequence configuration, the models were trained and used to generate out-of-sample forecasts for the testing period (2022–2025). The resulting predictions were then compared with the actual observed cement prices, and the forecasting errors were calculated. The detailed performance results for each sequence length are presented in Tables 1 to 4. Dark yellow shading indicates the best-performing result, while light yellow shading indicates the second-best result.

Four evaluation metrics were used to assess model performance: MAPE, MAE, RMSE, and R^2. Among these metrics, MAPE is emphasized in the analysis because it expresses forecasting error as a percentage, allowing easier comparison across different models and sequence configurations. While MAE and RMSE provide absolute error magnitudes and R^2 measures explanatory power, MAPE offers a more interpretable indicator of relative prediction accuracy in time-series forecasting studies.

Table 1: Mean Absolute Percentage Error (MAPE) analysis across sequence lengths (3 to 24 months)

Months / Model	3	6	9	12	15	18	21	24
ARIMAX	40.52	40.52	40.52	40.52	40.52	40.52	40.52	40.52
LSTM	12.89	15.52	20.49	22.97	24.18	32.41	32.39	22.91
GRU	13.97	13.84	10.71	11.06	13.34	15.00	7.39	15.03
ATT-LSTM	28.46	44.11	44.85	10.22	11.7	25.23	39.07	37.41

Table 2: Mean Absolute Error (MAE) analysis across sequence lengths (3 to 24 months)

Model \ Months	3	6	9	12	15	18	21	24
ARIMAX	965.3	965.3	965.3	965.3	965.3	965.3	965.3	965.3
LSTM	296.73	470.54	674.63	765.91	552.92	498.39	695.81	642.4
GRU	330.92	373.05	317.61	296.46	232.26	487.39	212.51	361.01
ATT-LSTM	794.37	900.59	958.72	833.23	354.27	310.94	639.76	1020.94

Table 3: Root Mean Square Error (RMSE) analysis across sequence lengths (3 to 24 months).

Model \ Months	3	6	9	12	15	18	21	24
ARIMAX	1038.22	1038.22	1038.22	1038.22	1038.22	1038.22	1038.22	1038.22
LSTM	535.33	698.32	714.5	495.49	348.51	663.45	638.06	817.76
GRU	502.15	486.59	552.01	431.84	321.49	138.78	272.57	279.78
ATT-LSTM	1145.07	1171.48	1160.47	588.17	341.87	584.97	791.95	838.09

Table 4: R-squared (R^2) analysis across sequence lengths (3 to 24 months).

Model \ Months	3	6	9	12	15	18	21	24
ARIMAX	-5.55	-5.55	-5.55	-5.55	-5.55	-5.55	-5.55	-5.55
LSTM	-0.92	-3.33	-2.01	-2.12	-0.98	-0.80	-1.51	-4.75
GRU	-0.30	-1.17	-1.32	-0.02	-2.38	0.55	0.19	0.54
ATT-LSTM	-8.56	-10.92	-6.59	-0.35	0.22	-0.05	-3.44	-5.87

As shown in Table 1, the ARIMAX model records a constant MAPE value of 40.52% across the experiment. Table 3 further reports an RMSE of 1038.22 LKR, while Table 4 indicates an R^2 value of −5.55. Unlike the deep learning models, the ARIMAX model does not rely on sliding-window input sequences; instead, it operates using predefined autoregressive and moving average lag structures. Consequently, its performance remains unchanged across the sequence-length experiments, which were specifically designed for the deep learning architectures. The negative R^2 values indicate that ARIMAX struggled to capture the sudden and severe price fluctuations experienced during the economic crisis.

The standard LSTM achieved its optimal performance at a 3-month sequence length, producing a MAPE of 12.89%, MAE of 296.73 LKR, and RMSE of 535.33 LKR, as shown in Tables 1 to 3. However, the R^2 remained negative −0.92, indicating limited variance explanation despite reduced magnitude error. As sequence length increased, performance deteriorated, with MAPE rising to 32.41% at 18 months. This suggests that LSTM benefits from short-term dependency structures rather than extended historical memory in volatile environments.

The GRU architecture demonstrated superior stability at longer windows. While initial performance at 3 months produced a MAPE of 13.97%, accuracy improved significantly as the window extended. At 21 months, GRU achieved its optimal results, with MAPE 7.39%, MAE 212.51 LKR, RMSE 272.57 LKR, and a positive R^2 of 0.19, as shown in Tables 1 to 4. Additionally, GRU achieved higher R^2 values at 18 months 0.55 and 24 months 0.54, indicating improved variance explanation when longer temporal contexts were incorporated. These findings suggest that changes in macroeconomic conditions influence cement prices over several months, and the GRU model was better able to capture these delayed effects.

The ATT- LSTM achieved its best configuration at 12 months, with a MAPE of 10.22%, MAE of 833.23 LKR, RMSE of 588.17 LKR, and R^2 of −0.35. Although attention mechanisms theoretically enhance temporal weighting, the model exhibited instability across windows, with MAPE fluctuating from 28.46% at 3 months to 44.85% at 9 months and increasing again to 39.07% at 21 months. This indicates that the ATT-LSTM model was highly sensitive to prolonged economic shocks, leading to less stable forecasts.

4.3 STRUCTURAL BREAK BEHAVIOUR DURING THE 2022 CRISIS

A critical observation from Table 4 is that several configurations yielded negative R^2 values, particularly for ARIMAX (−5.55) and LSTM (−0.92 at optimal window). These results reflect the unprecedented magnitude of the 2022 hyper-inflationary surge, during which cement prices increased by nearly 3,000 LKR within a short time frame. RMSE values consistently exceed MAE values across all models, confirming that large-magnitude peak errors disproportionately influenced evaluation metrics due to the squared error penalty.

The temporal prediction shift is further illustrated in Figure 4, where model-predicted peaks occur later than the actual mid-2022 market peak. This lag arises because macroeconomic variables such as the Exchange Rate and Diesel Price remained elevated into late 2022. Given the sliding window structure, cumulative macroeconomic shocks continued influencing model outputs into early 2023.

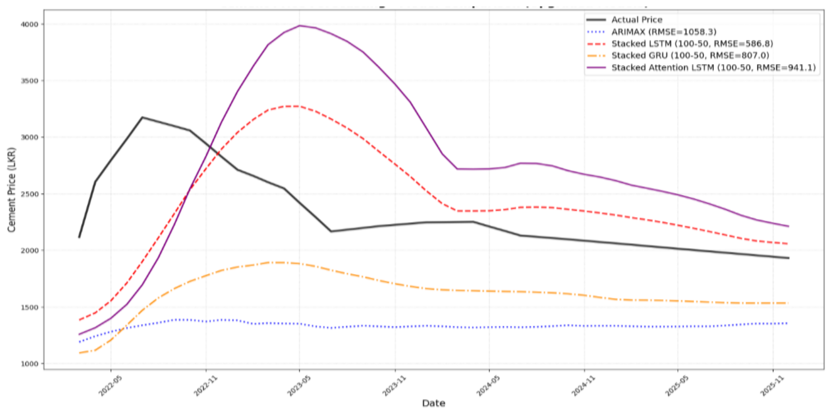

Figure 4 :Visualization of market reality vs. computational forecasting

The ATT-LSTM exhibited pronounced overshooting behaviour, reaching nearly 4,000 LKR, reflecting over-sensitivity to prolonged currency depreciation. In contrast, GRU demonstrated smoother adjustment dynamics, while LSTM provided a more moderated trajectory.

4.4 OUT-OF-SAMPLE TESTING PERFORMANCE (2022–2025)

The forecasting performance during the 2022–2025 testing window was evaluated by comparing the predicted cement prices with the actual observed values. The resulting error metrics are summarized in Table 5. Yellow shading indicates the best-performing result.

Table 5: Summary of final performance metrics for ARIMAX, LSTM, GRU, and ATT-LSTM (2022–2025 Testing Period).

Model	MAE (LKR)	MAPE (%)	RMSE (LKR)	R2
ARIMAX	1005.05	41.93	1070.81	-7.6752
LSTM	462.51	18.99	586.82	-1.6053
GRU	705.72	28.94	806.96	-3.9266
ATT-LSTM	822.56	35.03	941.1	-5.7008

ARIMAX recorded a MAPE of 41.93%, MAE of 1005.05 LKR, RMSE of 1070.81 LKR, and R^2 of −7.6752, confirming limited predictive capability under structural instability. Among deep learning models, LSTM achieved the lowest testing MAPE of 18.99% and RMSE of 586.82 LKR, outperforming GRU, MAPE 28.94%, RMSE 806.96 LKR and ATT-LSTM, MAPE 35.03%, RMSE 941.10 LKR. Although GRU exhibited superior performance under optimal window experimentation, LSTM demonstrated comparatively greater stability during the extended crisis testing period. This distinction indicates that optimal experimental accuracy does not necessarily translate into long-horizon crisis robustness.

4.5 OVERALL MODEL ASSESSMENT

The results reveal two key insights:

- GRU provides the best performance under optimized sequence-length configuration, achieving the lowest overall MAPE 7.39% and positive R^2 0.19.
- LSTM demonstrates more balanced and stable behaviour during prolonged crisis testing, achieving the lowest out-of-sample MAPE 18.99%.

Therefore, model suitability depends on forecasting objective. For optimized short-to-medium term forecasting under controlled conditions, GRU is preferable. For extended crisis-period robustness, LSTM exhibits greater stability. Overall, the findings show that deep learning models can provide more reliable cement price forecasts than traditional econometric methods during periods of economic instability. From a practical perspective, improved forecasting accuracy can support contractors, suppliers, and quantity surveyors in procurement planning, budgeting, and cost-risk management. From a policy perspective, the identified influence of exchange rate and energy-related variables highlights the importance of macroeconomic stability for construction material price management.

5. CONCLUSIONS

This study developed and evaluated a macroeconomically driven forecasting framework for cement prices in Sri Lanka by integrating selected macroeconomic variables with advanced deep learning architectures. Pearson correlation analysis confirmed that cement price movements are strongly associated with cost-driven variables, particularly the Exchange Rate and Diesel Price, while the Average Weighted Lending Rate exhibited weak explanatory power and was therefore excluded from the final feature set. The refined dataset ensured that the forecasting models concentrated on economically meaningful external shocks linked to import dependency, energy intensity, and distribution costs within the construction sector. Comparative analysis between the econometric baseline and deep learning models revealed substantial differences in their ability to handle extreme market volatility. The ARIMAX model produced a MAPE of 41.93%, during the 2022–2025 testing period, indicating limited capacity to capture non-linear price surges associated with the economic crisis. In contrast, deep learning architectures demonstrated superior adaptability. Under optimized sequence-length experimentation, the GRU model achieved the best overall performance, recording a minimum MAPE of 7.39% and a positive R^2 of 0.19 at a 21-month window. However, during extended out-of-sample crisis testing, the standard LSTM exhibited greater stability, achieving the lowest testing MAPE of 18.99%. The ATT-LSTM showed sensitivity to prolonged macroeconomic shocks and occasional overshooting of peak values.

A temporal prediction lag was observed during the 2022 economic crisis, as prolonged increases in macroeconomic variables such as the Exchange Rate and Diesel Price caused forecasted cement price peaks to extend into early 2023. Several model configurations produced negative R^2 values, highlighting the difficulty of predicting unprecedented market disruptions using models trained primarily on stable pre-crisis data. Overall, deep learning models outperformed the ARIMAX baseline, with GRU achieving the highest forecasting accuracy and LSTM demonstrating greater stability during prolonged economic volatility. These findings suggest the potential value of adaptive or hybrid forecasting approaches for improving performance under extreme economic shocks.

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