

Article

Modelling and Forecasting Concrete Demand for Sustainable Infrastructure Development in Developing Economies: Evidence from Ghana

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Abstract

Rapid urbanization and infrastructure expansion in Ghana have intensified demand for concrete, yet reliable, context-specific forecasting tools to support long-term infrastructure planning and resource management remain limited. Existing demand models are largely developed for advanced economies or focused on cement production rather than final concrete consumption, limiting the applicability to rapid urbanizing developing countries. This study addresses this gap by developing an integrated forecasting framework to quantify and project concrete demand in Ghana. Using time-series data spanning 2000–2025, the study employs a modelling approach that combines the Autoregressive Distributed Lag (ARDL) model and Error Correction Model (ECM) to examine both short- and long-run relationships between concrete consumption and key macroeconomic indicators, including GDP, population, GDP growth, concrete prices, housing loan interest rates, lending rates, and exchange rates. Forecast results for 2025–2030 indicated a sustained upward trend in concrete consumption, increasing from 39,278.52 m³ in 2026 to 99,430.53 m³ in 2030, with an average annual growth rate of 26.3% and a mean projected demand of 67,730.83 m³. Model evaluation metrics demonstrated high predictive accuracy, confirming the robustness of the proposed framework. The study contributes to the literature on construction demand forecasting by providing a context-specific, empirically validated model of concrete consumption in a developing economy. The findings offer actionable insights for policymakers, urban planners, and construction managers, underscoring the need to proactively scale local production capacity, strengthen supply-chain logistics, and promote sustainable material sourcing to support infrastructure development.

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1. Introduction

Concrete remains the most extensively utilised construction material globally, celebrated for its versatility, strength, and adaptability across diverse structural applications [1,2]. As a composite material comprising cement, fine and coarse aggregates, water, and occasionally admixtures, concrete forms the foundation of both sub-structure and super-structure works in modern construction. Its widespread application, ranging from slabs, stairs, and pavements to bridges and high-rise buildings, highlights its integral role in shaping the built environment [2]. Concrete's popularity is attributed to its high compressive strength, durability, fire resistance, and low maintenance requirements, making it indispensable in the development of resilient infrastructure [3,4].

Historically, concrete has underpinned civilisation's most enduring structures, surviving wars and natural disasters due to its robustness and longevity [5]. Today, its relevance has intensified, with global production estimated at approximately 25 billion tonnes annually, equivalent to 3.8 tonnes per person, representing a threefold increase in per capita consumption compared to four decades ago [6]. This escalating demand highlights the pivotal role of concrete in global infrastructure development and its increasing environmental and economic implications.

Recent market analyses forecast continued expansion of the global concrete and cement industry, projected to grow by USD 157.6 billion between 2023 and 2027, at a compound annual growth rate (CAGR) of 5.6% [7]. Regional projections indicate similar upward trends, with Europe, Asia-Pacific, North America, and West Africa all experiencing growth rates between 4% and 6% [8,9]. These trends are driven primarily by rapid urbanisation and infrastructure expansion, particularly in developing economies.

In Ghana, urbanisation and economic growth have spurred extensive construction activities, resulting in a surging demand for concrete for residential, commercial, and infrastructural projects [10,11]. Ghana's concrete market has experienced notable fluctuations but an overall growth trajectory in recent years. In 2021, the industry recorded an annual demand growth rate of 6%, with total concrete production reaching approximately 7.2 million tonnes [12]. Demand moderated in subsequent years, rising by 3.2% in 2023 to about 6.5 million tonnes, following a 2022 consumption level of 6.3 million tonnes [13]. A strong rebound was observed in 2024, with concrete demand rising 13.6%, reflecting renewed momentum in construction and infrastructure activities [14]. This upward trend continued with the concrete market growth by approximately 10.88% in 2025, underscoring sustained expansion in Ghana's construction sector [14].

Despite significant advances in global modelling of construction material demand, relatively few studies have developed context-specific, empirically grounded forecasting frameworks for developing economies. Existing studies are largely concentrated in advanced economies or rely on aggregated regional datasets that obscure country-level dynamics. For example, Yazdanbakhsh examined trend shifts in cement demand in the United States [15], while Prastuti et al. applied spatial time-series techniques to forecast cement demand across regional markets [16]. Similarly, Kiriakidis developed a comprehensive conceptual framework for cement demand forecasting within the EU-27 [17]. Although methodologically robust, these studies predominantly focus on developed economies and employ broad macro-regional aggregates, limiting their applicability to rapidly urbanising and structurally distinct developing contexts. Moreover, many existing forecasting models emphasise cement production capacity, trade flows, or price dynamics, rather than explicitly modelling final concrete consumption. In the Ghanaian context, empirical research has largely centred on concrete performance characteristics and cement brand preferences, with limited attention to the quantitative forecasting of concrete consumption. Studies by Bonney et al. and Thomas and Kankam focused on cement brand suitability for concrete production [18,19], while Tutu et al. and Mussey et al. examined

the mechanical and durability performance of concrete. While these contributions are valuable from a materials engineering perspective [20,21], they do not address the macroeconomic and sectoral determinants of concrete demand or provide forward-looking consumption forecasts. This study addresses this critical gap by developing a model and forecasting concrete consumption in Ghana using key macroeconomic and sector-specific indicators.

2. Literature Review

2.1. Overview of Concrete and Its Role in Construction

Concrete is globally recognized as the most extensively utilized construction material due to its compressive strength, durability, and versatility and adaptability across structural applications [1]. Its role as the backbone of modern infrastructure, such as bridges, roads, pavements, buildings, and dams, has made it central to economic development worldwide [4]. Globally, concrete consumption has reached approximately 25 billion tonnes annually, equivalent to nearly 3.8 tonnes per capita [6]. While this statistic underscores the concrete significance of infrastructure, it also exposes a critical challenge: at such large volumes, inaccurate demand forecasts can lead to serious economic, logistical, and environmental consequences, especially in resource-constrained economies [22].

Much of the existing literature approaches concrete primarily as a material, focusing on mechanical performance [23–26], durability [27–30] or environmental impacts [31,32]. Although these studies are valuable, they often treat demand as an exogenous or static factor, rather than a dynamic outcome shaped by macroeconomic conditions, institutional capacity, and sectoral structure. This limitation becomes especially pronounced in developing economies, where construction activity is less formalised, and demand signals are more fragmented.

2.2. Global Trends in Concrete Demand and Production

The global concrete and cement market is experiencing substantial growth, projected to increase by USD 157.6 billion between 2023 and 2027, with a compound annual growth rate (CAGR) of over 5.6% [7]. The Asia-Pacific region dominates global consumption, with projected growth from 3.18 billion tonnes in 2024 to 4.32 billion tonnes by 2030 [33]. Europe, North America, and Africa also demonstrate steady growth rates of 4% to 6% annually [8]. These increases are largely attributed to rapid urbanisation, industrialisation, and large-scale infrastructure programs. These studies typically rely on formal-sector indicators such as cement production capacity, registered construction output, trade flows, and price indices.

However, a critical weakness of these global and regional forecasting frameworks is their implicit assumption of a formalised construction sector, in which material flows are well documented and production closely aligns with official statistics. Such assumptions limit their applicability to contexts like Ghana, where a significant proportion of concrete is produced through informal, in-situ mixing on construction sites, often using unrecorded labour and locally sourced aggregates [20]. As a result, demand models calibrated to formal-sector economies systematically underrepresent actual material consumption patterns in countries where informal construction dominates.

Moreover, many global forecasting models focus on cement demand as a proxy for construction activity [15,16,34,35], overlooking that cement use does not translate linearly into concrete consumption in informal markets. Variations in mix proportions, waste levels, and on-site practices introduce substantial uncertainty, which conventional models fail to capture. Consequently, applying these models directly to Ghana risks generating forecasts that are theoretically sound but empirically misleading.

2.3. The Construction Industry in Ghana

The construction industry in Ghana plays a pivotal role in the nation's socio-economic development. It encompasses a broad range of professionals, including architects, engineers, quantity surveyors, contractors, and artisans [10]. Primarily, two key ministries supervise the sector: the Ministry of Works and Housing, responsible for building and civil works, and the Ministry of Roads and Highways, which oversees transport infrastructure projects [36]. These ministries also coordinate the registration and classification of contractors based on financial capacity, technical expertise, and resource capability [36].

Contractors in the housing subsector are categorised from D4K4 (small-scale projects up to USD 75,000) to D1K1 (large-scale projects exceeding USD 500,000) [37]. Most firms fall within the D3K4 and D4K4 categories, indicating a predominance of small to medium-scale operators. Despite its importance, the industry faces structural challenges, including inadequate planning, inefficient resource utilisation, and limited professional regulation [38–40]. Economically, the sector contributes significantly to Ghana's GDP, generating over GHS 12.8 billion (USD 2.1 billion) in 2020 [41]. The construction industry accounts for nearly half of the country's gross fixed capital formation, underscoring its role in capital accumulation and job [38]. However, inefficiencies and corruption in procurement and contracting persist as significant issues that hinder optimal performance and sustainable infrastructure delivery.

2.4. Ghana's Cement and Concrete Demand

Rapid urbanisation, infrastructure development, and an expanding real estate market have driven a substantial increase in demand for cement and concrete in Ghana. Globally, resource consumption is expected to quadruple by 2050 [42], and cement, a key ingredient in concrete, already accounts for approximately 8% of global greenhouse gas emissions [43]. Ghana currently has an installed cement production capacity of approximately 12.1 million tonnes per year, far exceeding its annual consumption of around 7 million tonnes, resulting in an excess capacity of about 5 million tonnes [44]. The country hosts multiple producers, including Dangote Cement, Ghacem Limited, CIMAF, Supacem, Dzata Cement, and Western Diamond Cement [18]. Despite this capacity, informal and small-scale construction activities dominate the sector, often relying on in-situ concrete mixed manually on-site.

Crucially, a large share of concrete production in Ghana occurs outside formal batching plants, with site-mixed concrete prepared by artisans using manual methods [45]. This informal production structure introduces inefficiencies, quality variability, and, most importantly, significant data gaps for forecasting. Existing national statistics capture cement sales and registered projects but fail to account for informal housing construction, incremental building practices, and self-financed developments that dominate urban and peri-urban areas [45].

While previous Ghanaian studies have made important contributions by examining cement brand performance [18,19] and concrete strength characteristics [20,21]. They remain largely material-focused and retrospective. These studies do not model aggregate concrete demand, nor do they integrate macroeconomic drivers such as GDP growth, population expansion, interest rates, or exchange rate volatility. As a result, they offer limited guidance for infrastructure planning, resource allocation, or sustainability-oriented policy formulation.

2.5. Determinants of Cement/Concrete Demand for Construction Projects

The concrete sector has a high potential for job creation due to its connections with other industries, particularly those involved in the manufacturing and distribution of

building supplies and equipment, as well as those providing financial services to the industry [18]. To study and estimate individual and market demand for concrete. Understanding these determinants is crucial for stakeholders in the construction industry to anticipate and respond effectively to market dynamics, ensuring sustainable growth and development in the sector. The demand for cement and concrete in construction projects is influenced by factors such as economic growth, urbanisation, government policies, technological advancements, and environmental considerations.

2.5.1. Economic Factors

The demand for concrete in construction projects is driven by economic factors, including population growth, income growth, inflation, interest rates, and technological advancements.

Gross Domestic Product (GDP)

An increase in GDP enhances overall economic activity and income levels, thereby expanding the financial capacity of individuals and firms to invest in construction and related sectors [46,47]. Consequently, demand for building construction, maintenance, and associated services is expected to rise in line with economic growth [46]. Zhao et al. opined that GDP influences the demand for concrete for building development in New Zealand [48]. The study by Alaloul et al. also recognized GDP as the primary driver in the construction sector. GDP was also mentioned by Saka as an influencing element in the demand for concrete for building projects [49]. Nursjanti identified GDP as the major economic indicator of concrete demand for building work in the development of urban transport in Indonesia [50].

GDP growth in West Africa is highly cyclical, driven by commodity price swings, fiscal constraints, and external financing conditions [51]. In Ghana, periods of strong GDP growth typically coincide with public infrastructure expansion, private real estate development, and large-scale urban projects, all of which rely heavily on reinforced concrete. As a result, concrete demand responds strongly and immediately to GDP upswings [52].

However, when GDP growth slows or contracts, concrete demand declines more sharply than demand for alternative materials such as timber, earth-based blocks, or steel sheets [53,54]. This asymmetry arises because concrete-intensive projects—bridges, highways, multi-storey buildings, and formal housing estates—are often capital-intensive and the first to be postponed or scaled down during economic downturns [53]. In contrast, informal and incremental construction activities, which rely more on non-concrete materials, tend to persist even under weak economic conditions. Thus, GDP volatility in Ghana amplifies fluctuations in concrete consumption more than it does for other construction materials.

Population

Population growth is a significant driver of concrete demand, as expanding populations require increased investments in housing, infrastructure, and public facilities [55]. Consequently, concrete markets are widely regarded as being functionally linked to population dynamics [32,56]. Empirical evidence consistently shows a positive relationship between population growth and aggregate demand for concrete. For instance, Tohlob examined the impact of population growth on construction material prices and concluded that increasing population levels are strongly associated with higher demand for concrete in Egypt [57]. Similarly, Imran et al. observed that rapid population growth leads to a substantial increase in construction activities, resulting in increased consumption of concrete and upward pressure on demand for construction materials [58].

Population growth in Ghana and across West Africa is rapid and relatively predictable; however, its interaction with economic volatility creates uneven demand outcomes [59]. While a rising population increases long-term demand for housing and infrastructure, short-term macroeconomic instability constrains the translation of demographic pressure into concrete consumption [59].

In Ghana, population-driven construction demand often materialises through self-built housing and informal developments, which frequently rely on in-situ mixing, low cement ratios, or alternative materials to reduce costs [60]. Consequently, population growth does not translate linearly into concrete demand unless accompanied by income growth, access to finance, and public infrastructure investment. This explains why concrete demand is more volatile than population growth itself, and more sensitive to macroeconomic conditions than materials used in informal construction [60].

Inflation

Inflation is a significant concern for the construction business, as it increases the prices of building materials, machinery rental rates, consultancy fees, and other inputs required for construction projects [61,62]. As a result, project completion may be delayed, construction costs may rise, and profit margins may be reduced [63]. According to Shiha, inflation was the primary factor influencing the determination and prediction of the association of macroeconomic indicators with concrete demand [64].

Inflation in Ghana and West Africa is persistently high and volatile, affecting construction materials unevenly [65]. Concrete is particularly vulnerable to inflationary pressures because its production involves multiple cost components such as cement, aggregates, fuel, transportation and labour, many of which are directly affected by price instability [66].

High inflation increases cement prices, fuel costs, and logistics expenses, significantly raising the cost per cubic meter of concrete [67]. This often leads to project delays, redesigns, or substitutions away from concrete toward cheaper materials [67]. Unlike materials such as timber or laterite blocks, concrete offers little flexibility for cost reduction once design specifications are fixed [66]. As a result, inflation suppresses concrete demand more than it suppresses demand for alternative materials that enable incremental construction or material substitution.

Interest Rates

Increases in interest rates raise the cost of borrowing, thereby escalating the overall cost of construction projects and construction materials [68]. Higher financing costs reduce investment in construction; this negatively affects demand for concrete. Additionally, higher interest rates reduce the profitability of construction firms, as they are required to service loans at higher costs. From the supply side, rising financing costs for inventory compel material suppliers to transfer these additional costs to consumers through higher prices [68]. Manamgoda et al. found that bank-lending interest rates have a significant impact on road construction costs when developing a construction price prediction model for Sri Lanka [69].

Exchange Rate

Exchange rate fluctuations have a significant impact on the performance of the construction industry [70–72]. Volatility in exchange rates disrupts project execution, often leading to delays that create challenges for subcontractors, including cost overruns, contractual disputes, arbitration, project abandonment, and litigation [71]. In particular, exchange rate depreciation increases the cost of imported raw materials, machinery, and

construction inputs, thereby escalating overall project costs. Zhao et al. noted that fluctuations in exchange rates alter the prices of imported goods, especially in domestic construction sectors that are highly dependent on imported components and raw materials [48]. Consequently, exchange rate movements influence investment performance and can significantly influence demand for concrete within the construction and real estate markets.

Exchange rate depreciation is a persistent feature of West African economies, including Ghana [73]. Concrete production is highly exposed to exchange rate movements because key inputs, such as cement clinker, fuel, spare parts, admixtures, and construction equipment, are either fully imported or priced in foreign currency [74]. Depreciation of the Ghanaian cedi directly raises the domestic price of cement and ready-mix concrete, increasing construction costs and reducing affordability [75]. This effect is more pronounced for concrete than for locally sourced materials such as sandcrete blocks, timber, or earth-based alternatives [75]. Consequently, exchange rate shocks disproportionately suppress concrete demand, particularly in periods of macroeconomic stress.

Government Policy and Stability

Government policies and regulatory frameworks play a crucial role in either fostering or constraining the adoption of innovative techniques and technologies across industries [76,77]. Well-designed and effectively enforced laws and regulations can be leveraged to drive fundamental and structural improvements within the construction sector [78]. In addition, government interventions through fiscal and monetary policies such as taxation, public expenditure, money supply, and interest rate regulations have a significant influence on construction activity and, consequently, concrete demand [79]. Policy stability further enhances investor confidence, encourages long-term infrastructure investment, and supports sustained growth in the construction industry.

2.5.2. Personal Factors

Levels of Income

The level of income within a given country or region is a fundamental determinant of demand [80,81]. Generally, higher aggregate and personal income levels translate into increased purchasing power, which stimulates demand for normal goods such as concrete used in construction projects [81]. Devi and Golden asserted that rising income levels lead to increased demand, particularly within the construction sector [82]. Similarly, fluctuations in national income or gross domestic product (GDP) have a significant impact on construction activity and overall demand for building materials [47]. Any increase or decrease in national income affects concrete demand across both public and private sector projects. As income levels rise, consumers and investors are more likely to demand greater quantities of goods and services at prevailing prices, thereby reinforcing growth in construction output [83].

Availability and Price of Substitute Goods

Concrete consumption decisions are also influenced by the alternative possibilities available to customers in the relevant marketplace [84]. The availability and costs of prospective substitute products play a significant role in determining demand elasticity, both in the short run (static) and over time (long run) [84]. Concrete's dominance as a major construction material for building projects reflects the limited options available at 'reasonable' pricing [78]. According to Sobotka, the acceptability of alternative building materials is influenced by knowledge and availability [85].

Cost of Building Materials

Market forces primarily determine the cost of building materials, particularly the interaction between supply and demand for concrete and other construction inputs [86]. Pradoto et al. identify the price and availability of building materials as among the most critical challenges facing the construction sector [87]. Persistent cost overruns in construction projects remain a significant concern for both contractors and clients, frequently undermining project viability and financial performance [88,89]. Plebankiewicz and Wieczorek emphasise that identifying and understanding the key determinants of construction costs enhances cost estimators' expertise, enabling the development of more sustainable and accurate cost estimation and modelling techniques [90]. A comprehensive understanding of these cost drivers is therefore essential to achieving acceptable levels of accuracy in forecasting overall project costs, including labour, material, and related expenses [90].

2.6. Forecasting Concrete Demand as a Tool for Sustainability

The cement and concrete sector play a significant role in global climate change due to its high-energy intensity and carbon footprint [91]. As one of the most energy-consuming industrial activities worldwide, cement and concrete production accounts for an estimated 5–8% of total anthropogenic carbon dioxide (CO₂) emissions annually [91,92]. This substantial contribution places the sector at the centre of global debates on sustainability and climate mitigation [93,94]. Cheng et al. recognised that accurate demand forecasting is a critical indirect pathway for reducing carbon emissions in construction, particularly in developing economies where inefficiencies and waste are prevalent [95]. At the production level, demand forecasting improves capacity planning and energy efficiency by enabling cement and concrete producers to align output with expected market needs, thereby reducing overproduction, idle capacity, and unnecessary kiln operations, which are major sources of CO₂ emissions [96]. Inaccurate demand signals often lead to emergency production cycles or excess inventory, both of which increase fuel consumption and the emissions intensity per unit of output.

From a supply-chain perspective, forecasting supports logistics optimisation and material flow coordination, reducing transport-related emissions [93]. Concrete supply chains in Ghana are highly fragmented, with materials transported over long distances due to poor coordination between producers, distributors, and construction sites [97]. Zhang et al.' study showed that improved demand visibility reduces unnecessary hauling, batching losses, and on-site wastage, leading to measurable reductions in embodied carbon [98].

The sustainability implications are particularly significant in the informal construction sector, which dominates Ghana's building activity [99]. Informal practices, such as in-situ mixing without standardised batching, over-ordering of cement, and poor storage, are major sources of material waste and excess emissions [100]. Forecast-informed planning allows policymakers and suppliers to anticipate spatial and temporal demand patterns, enabling targeted distribution, better inventory management, and reduced material spoilage [101]. As per Yu et al., demand forecasts provide a quantitative basis for low-carbon policy interventions, including the promotion of blended cements, alternative binders, and staged infrastructure investment [102].

3. Materials and Methods

The methodological approach was selected to capture both short-term fluctuations and long-term trends in concrete consumption. By integrating data-driven forecasting with econometric modelling, the methodological framework ensures robustness, reduces

sensitivity to short-term shocks, and enhances policy relevance. Figure 1 illustrates the research process, from the research approach to the model estimation.

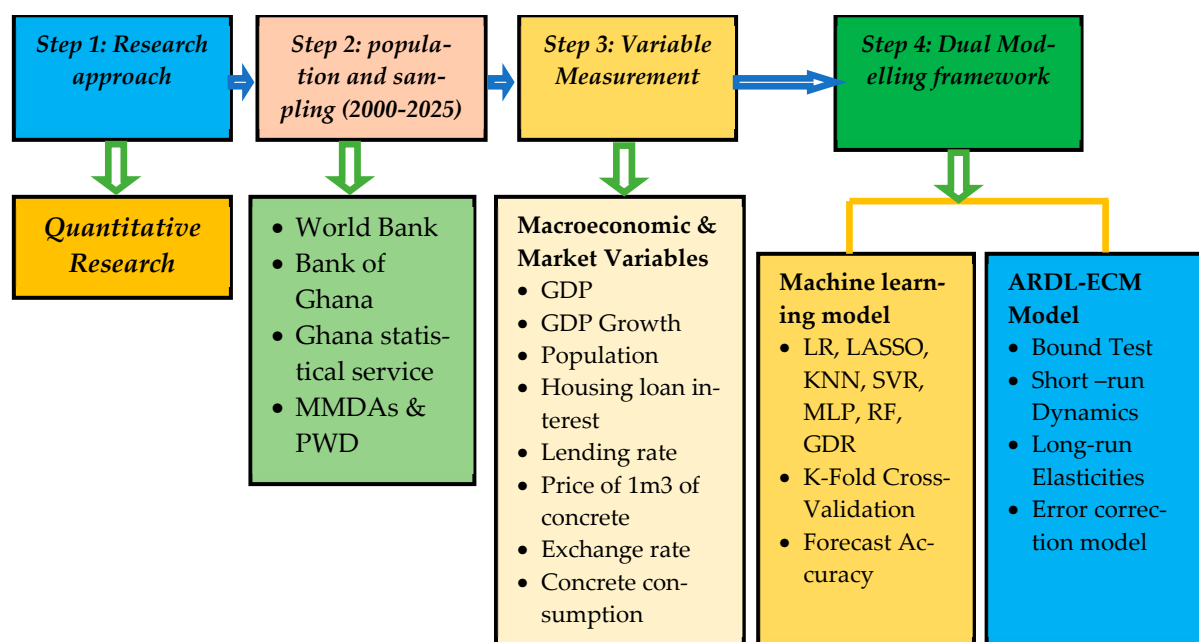


Figure 1. Flowchart of the research process. Source: Author's construct, 2025.

3.1. Research Approach

In this study, a quantitative research methodology was adopted. This approach embraces a deductive and objective perspective, focusing on observable and measurable data such as counts, weights, masses, and other tangible indicators [103]. Ahmed et al. [104] argued that the quantitative method is employed to assess the extent of a problem or to determine the existence of relationships between different aspects of a phenomenon by quantifying their variation [104]. This method typically involves examining frequencies and other measurable variables with the goal of explaining specific patterns or phenomena [104].

3.2. Population and Sampling Procedures

The study population comprised macroeconomic data from 2000 to 2025 on the World Bank Development Indicators (WBDI), the Bank of Ghana (BoG), and the Ghana Statistical Service (GSS), as well as concrete volumes and rates from MMDAs and the Public Works Department (PWD). To improve the study, data from academic papers, existing records, and books were also examined.

3.3. Variable Measurement

Demand for concrete consumption is dependent on Macroeconomic variables, i.e., Gross Domestic Product, Annual Gross Domestic Product Growth, Population growth rate, Housing loan interest rates, lending rates, and exchange rates. The Price of concrete can also influence concrete consumption. The concrete consumption (m³) was proxied using government projects within the years mentioned. Additionally, the informal concrete consumption (m³) was extracted from building designs submitted to the various MMDAs for which permits have been given and/or are yet to be given. Table 1 denotes the summary of the variables' measurements.

Table 1. Summary of the variables' measurements.

	Variable	Notation	Expected Sign
Macroeconomic variable	Gross Domestic Product	GDP	Positive
	Annual Gross Domestic Product Growth	GDPGR	Positive
	Population growth rate	POP _{GR}	Positive
	Housing loan interest	HOULOINT	Negative
	Lending rate	LENRATE	Negative
	Exchange rate	EXRATE	Negative
Concrete demand variables	Price of 1 m ³ of concrete	PRCON	Negative
	Concrete consumption (m ³)	CONSUMP	N/A

Source: Author's construct, 2025.

3.4. Model Formation

To formulate the predictive model for concrete demand, the Machine Learning (ML) technique was employed to capture complex nonlinear relationships in the data. However, if the dataset fails to meet the statistical assumptions or distributional requirements necessary for ML applications, a linear econometric model, such as the Autoregressive Distributed Lag (ARDL) model, is applied to ensure methodological robustness and reliable forecasting performance. This approach combines the data-driven flexibility of ML with the statistical rigour and interpretability of time-series econometric modelling.

3.4.1. Machine Learning Framework

For this study, several supervised learning algorithms were implemented and evaluated to identify the best-performing model for forecasting five-year concrete demand. The following algorithms were considered:

Artificial Neural Networks

This is computed by using the propagation function, $p_j(t)$, where i iterates over the set of nodes connected to node j , o_i is the output from node i , w_{ij} is the weight of the connection between node i and node j , and t is the current time step:

$$p_j(t) = \sum_i o_i(t) w_{ij}$$

The output from node i is computed using some output function, f_{out} , and the activation of the node, $\alpha_i(t)$, as

$$o_i = f_{out}(\alpha_i(t))$$

The activation of node i at $t + 1$ is computed using an activation function, f , which takes in the node's current activation, α_i , a constant activation threshold, θ_i , and the propagation, $p_i(t)$, as

$$\alpha_i(t + 1) = f(\alpha_i(t)p_i(t), \theta_i)$$

Backward propagation is achieved by performing Stochastic Gradient Descent on the model's loss function. In particular, where α is the learning rate, C is the loss function, and $\xi(t)$ is a stochastic term, the new weights can be computed as

$$w_{ij}(t + 1) = w_{ij}(t) + \alpha \frac{\partial C}{\partial w_{ij}} + \xi(t)$$

The result of $\frac{\partial C}{\partial w_{ij}}$ depends on the activation function at that particular node.

A K-Fold cross-validation procedure and Neural Network (MLP) boxplot analysis were used to evaluate model performance across different algorithms. The model with the

lowest test error and highest predictive stability was selected as the optimal forecasting model for concrete demand.

3.4.2. Autoregressive Character of Time Series

If the current value is based solely on the immediately preceding value, it is termed as first-order autoregressive, AR (1), and if it is based on two preceding values, second-order autoregressive, AR (2), and so on. A univariate linear regression model can be estimated as

$$Y_t = \mu + \rho Y_{t-1} + \varepsilon_t$$

Where Y_t is a dependent variable, Y , at period t . μ is a constant parameter. ε_t is the unexplained part (gap) of the actual data and the fitted line by the regression equation, termed as error. Y_{t-1} is the first lagged value of Y , ρ is the coefficient of Y_{t-1} . The equation shows that the value Y_t equals the constant μ plus ρ times its previous value and an unknown component ε_t . The model to be estimated in the Equation above is an AR (1) process. Similarly,

$$Y_t = \mu + \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + \varepsilon_t$$

Stationary and Non-Stationary Time Series

Most macroeconomic variables, such as gross domestic product (GDP), Exchange rate, interest rate, consumption, and consumer price index, exhibit a strong upward or downward movement over time, with no tendency to revert to a fixed mean. Hence, they are non-stationary series. If the time series is non-stationary, it is said to have a unit root. Therefore, in econometrics, the stationarity of a time series is assessed using a unit root test. Mathematically, the series Y_t is stationary if

$$E(Y_t) = E(Y_{t-s}) = \mu \text{ for some } s > 0$$

$$Var(Y_t) = Var(Y_{t-s}) = \sigma_y^2 \text{ and}$$

$$Cov(Y_t, Y_{t-s}) = \gamma_s$$

where

$E(Y_t)$ = Expected value of Y at period t

Var = Variance, the variance or spread of Y_t from $E(Y_t)$

Cov = Covariance, the joint variation of Y_t and Y_{t-s}

Y_{t-s} = Lag of Y up to period $t - s$

Unit Root Test Methods

The Augmented Dickey–Fuller (ADF) test was used in testing unit root. Suppose we have a series y_t for testing unit root. Then, ADF model tests unit root as follows.

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^k \beta_i \Delta y_{t-1} + e_t$$

where

$\delta = \alpha - 1$

α = coefficient of y_{t-1}

Δy_t = first difference of y_t i.e. $y_t - y_{t-1}$

The null hypothesis of ADF is $\delta = 0$ against the alternative hypothesis of $\delta < 0$. If the null is not rejected, the series is non-stationary, whereas rejection means the series is stationary.

Cointegration Test

Using ordinary least square or other similar methods for non-stationary time series may produce spurious results. In other words, regression results may indicate a significant relationship between two variables that are in fact uncorrelated. This test method is based on the relationship between a matrix's rank and its characteristic roots. The model is generalized with 'n' variable vectors:

$$x_t = A_1 x_{t-1} + \varepsilon_t$$

So that

$$\Delta x_t = A_1 x_{t-1} - x_{t-1} + \varepsilon_t$$

$$= (A_1 - I) x_{t-1} + \varepsilon_t \text{ can be written as}$$

$$= \pi x_{t-1} + \varepsilon_t$$

x_t and ε_t are (n.1) vectors

A_1 = an (n.n) matrix of parameters

I = an (n.n) identity matrix

$\Pi = A_1 - I$

Error Correction Models

If the variables are $I(1)$ and there exists a cointegration relationship, then the Error Correction Model (ECM) can be derived. Consider the following bivariate relationship.

$$Y_t = \mu + \beta_1 X_t + \varepsilon_t$$

Based on the representation theorem of Engle and Granger [105], a link between the cointegration and Error Correction Model (ECM) is established by transforming ECM Equation. Cointegration equation between Y_t and X_t are as follows:

$$\varepsilon_t = Y_t - \mu - \beta_1 X_t$$

The Error Correction Model (ECM) for Y_t and X_t

$$\Delta Y_t = \mu Y + \alpha Y \varepsilon_{t-1} + \sum_{h=1}^i \alpha_{1h} \Delta Y_{t-h} + \sum_{h=1}^i b_{1h} \Delta X_{t-h} + \mu Y_t$$

$$\Delta X_t = \mu X + \alpha X \varepsilon_{t-1} + \sum_{h=1}^i \alpha_{2h} \Delta Y_{t-h} + \sum_{h=1}^i b_{2h} \Delta X_{t-h} + \mu X_t$$

where μY_t and μX_t are stationary white noise processes for some number of lags I . The model can be further advanced in multivariate case in a similar way.

3.4.3. Autoregressive Distributed Lag (ARDL) Model

The ARDL approach was employed to estimate both the short-run and long-run relationships between concrete consumption and its key macroeconomic determinants, based on the outcome of the Bounds Test for Cointegration. The ARDL technique is advantageous because it accommodates variables that are integrated of order $I(0)$ or $I(1)$, but not $I(2)$, and it efficiently models the relationship among variables with mixed orders of integration. Moreover, the ARDL model framework inherently integrates the ECM, which captures short-run dynamics while maintaining long-run equilibrium relationships. To illustrate the ARDL modelling framework, a simple autoregressive distributed lag model can be written as:

$$Y_t = \alpha + \beta x_t + \delta z_{t-1} + e_t$$

The error correction version of the ARDL model is given by

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^p \beta_i \Delta Y_{t-i} + \sum_{i=1}^p \delta_i \Delta X_{t-i} + \sum_{i=1}^p \varepsilon_i \Delta Z_{t-i} + \lambda_1 Y_{t-1}$$

The first part of the equation with β , δ , and ε represents the short-run dynamics of the model. The second part with λ s represents the long-run relationship. The null hypothesis in the equation is $\lambda_1 + \lambda_2 + \lambda_3 = 0$, which means the non-existence of a long-run relationship.

The considered regression models include the Ordinary Least Squares (OLS) method, and the Autoregressive Distributed Lag (ARDL) model. These are expressed by Equations 1 and 2, respectively, where CONSUMP_t is the concrete consumption, GDP is Gross Domestic Product (Billion GHC), POP is Gt. Accra Population (Millions), GDPGR is Annual Gross Domestic Product Growth (%), PRCON is Price of 1 m³ of concrete (GHC), HOULLOINT is Housing loans interest (%), LENRATE stand for Lending rate (%), and EXRATE is Exchange rate (%). Equation (1) is shown as follows:

$$\text{CONSUMP}_t = \beta_1 \text{GDP}_t + \beta_2 \text{POP}_t + \beta_3 \text{GDPGR}_t + \beta_4 \text{PRCON}_t + \beta_5 \text{HOULLOINT}_t + \beta_6 \text{LENRATE}_t + \beta_7 \text{EXRATE}_t \quad (1)$$

If cointegration among the variables is established, their estimates will yield long-run coefficients and show only the long-run impact of the independent variables on the dependent variable. In addition to the long-run effects, short-run effects can be investigated using an error correction model (Equation (2)).

$$\begin{aligned} \Delta \text{Consump}_t = & a_0 + \sum_{i=1}^q \beta_i \Delta \text{GDP}_{t-i} + \sum_{i=1}^q \gamma_i \Delta \text{POP}_{t-i} + \sum_{i=1}^q \delta_i \Delta \text{GDPGR}_{t-i} \\ & + \sum_{i=1}^q \phi_i \Delta \text{PRCON}_{t-i} + \sum_{i=1}^q \eta_i \Delta \text{HOULLOINT}_{t-i} + \sum_{i=1}^q \kappa_i \Delta \text{LENRATE}_{t-i} \\ & + \sum_{i=1}^q \lambda_i \Delta \text{EXRATE}_{t-i} + \psi \text{ECM}_{t-1} + e_t \end{aligned} \quad (2)$$

where

- i. $\beta_i, \gamma_i, \delta_i, \phi_i, \eta_i, \kappa_i, \lambda_i$: represent short-run dynamic coefficients, capturing the immediate effect of changes in each explanatory variable on concrete consumption.
- ii. ψ : is the speed of adjustment coefficient (expected to be negative and significant), which measures the rate at which short-run deviations from long-run equilibrium are corrected. Formally, $\psi < 0 \Rightarrow$ stable convergence to equilibrium.
- iii. ECM_{t-1} : quantifies the disequilibrium error from the long-run relationship between concrete consumption and its determinants. When $\text{ECM}_{t-1} \approx 0$, the system is in equilibrium.

4. Results

Model Evaluation

Machine Learning (ML) was used to compare the algorithm's prediction of concrete demand in Ghana. ML models were tested using eight statistical indicators (Concrete consumption (m³), GDP, Gt. Accra Population, GDP Growth, Price of 1 m³ of concrete, Housing loans interest, Lending rate, and Exchange rate). KFold diagram was applied to evaluate the LR, LASSO, EN, KNN, CART, SVR, MLP, ABR, GBR, RFR and ETR models, and the results are graphically shown in Figures 2 and 3.

In selecting the best model, the KFold diagram, the neural network (MLP) boxplot has an error below 0.01 as many other models. However, the Test Error in the Algorithm Comparison diagram is the least with the linear (LR) model among all the other models. Hence, the linear model is selected based on its simplicity, fast training time, linearity of variables, small dataset, small variable features, and easily. The linear regression model (model_LR) was selected as the most statistically appropriate algorithm for forecasting

future concrete consumption. Nevertheless, due to the limited dataset used in model training, the predictions remain subject to sampling and structural error. To enhance robustness and validate the long-run dynamic behaviour, the Autoregressive Distributed Lag (ARDL) model was subsequently estimated as a complementary econometric approach (Table 2).

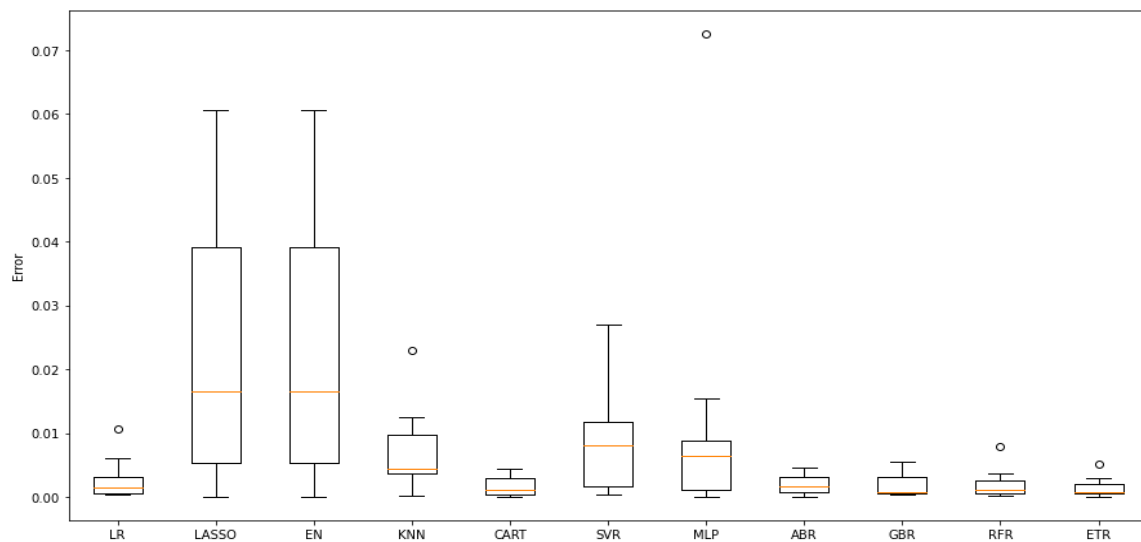


Figure 2. Algorithm comparison: KFold diagram.

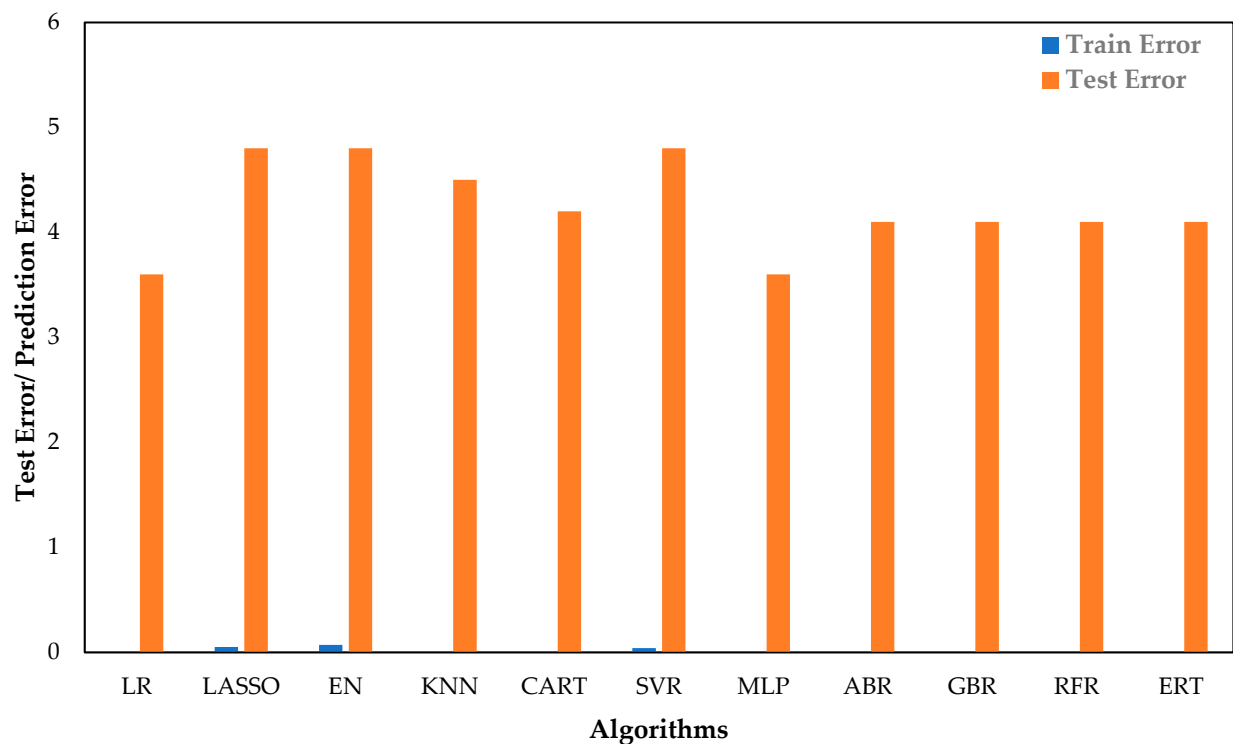


Figure 3. Algorithm performance comparison for forecasting model selection.

Table 2. Estimation of ARDL.

Variable	Coefficient	Std. Error	t-Statistic	Prob
CONSUMP(−1)	−0.056189	0.341207	−0.164677	0.8722
GDP	−2.823086	19.04150	−0.148260	0.8848
GDP(−1)	94.37665	28.70577	3.287724	0.0072
POP	−1954.156	2128.704	−0.918003	0.3783
POP(−1)	3268.635	1210.187	2.700933	0.0206
GDPGR	−139.0328	104.2961	−1.333058	0.2095
GDPGR(−1)	146.7457	131.4019	1.116770	0.2879
PRCON	8.178254	11.89072	0.687784	0.5058
PRCON(−1)	−25.42457	17.70885	−1.435699	0.1789
HOULOINT	1568.648	840.8065	1.865647	0.0890
HOULOINT(−1)	−2564.931	688.2192	−3.726910	0.0033
LENRATE	−105.8600	80.84510	−1.309418	0.2171
EXRATE	−2648.750	1601.622	−1.653793	0.1264
C	22531.04	9241.118	2.438129	0.0329
R-squared	0.992090	Mean dependent var	7936.800	
Adjusted R-squared	0.982742	S.D. dependent var	8189.850	
S.E. of regression	1075.912	Akaike info criterion	17.09874	
Sum squared resid	12733444	Schwarz criterion	17.78131	
Log likelihood	−199.7343	Hannan–Quinn criter.	17.28806	
F-statistic	106.1250	Durbin–Watson stat	2.353760	
Prob(F-statistic)	0.000000			

The lagged Gross Domestic Product (GDP) term $\beta_1 = 94.38$ is positive and significant ($p = 0.007$), confirming that growth in national output in the previous year substantially increases current concrete demand. The lagged population (POP) variable ($\gamma_1 = 3268.64, p = 0.021$) is positive and statistically significant, indicating that population growth exerts upward pressure on housing and infrastructure demand, thus driving concrete consumption. Similarly, the lagged GDP growth rate (GDPGR) ($\delta = 146.7457$) is positive, suggesting that sustained economic expansion fosters increased investment in construction-related activities, though the magnitude of its effect is relatively moderate. Conversely, the lagged price of concrete (PRCON), ($\theta = -25.42457$) exhibits a negative relationship with concrete consumption, implying that higher concrete prices discourage usage, reflecting price elasticity in construction material demand.

The lagged housing loan interest rate (HOULOINT) ($\eta_1 = -2564.93, p = 0.003$) is negative and highly significant, signifying that increases in housing loan rates restrict access to credit, thereby suppressing residential construction activity and lowering concrete demand. The magnitude of the coefficient suggests that increases in borrowing costs materially suppress concrete demand, reinforcing the sensitivity of construction activity to financial accessibility. This finding aligns with Ghana's high lending rate environment and limited mortgage penetration. It further implies that sustaining the projected growth trajectory will require improved construction finance mechanisms, reduced lending spreads, and policy support for housing credit markets.

The lending rate ($\kappa_1 = -105.86, p = 0.217$) and exchange rate ($\lambda_1 = -2648.75, p = 0.126$) have negative but statistically insignificant coefficients, suggesting that financial tightening and currency depreciation moderately constrain construction demand but not at a significant level in the short run. In the short run, concrete demand appears more responsive to income and credit variables than to exchange rate fluctuations. The R^2 and

significant F-statistic indicate a strong explanatory power. The model's dynamic specification ensures that both contemporaneous and lagged effects are captured, and the DW statistic close to 2 confirms model stability. An ARDL bound Test for cointegration was performed to verify the existence of a long-run equilibrium relationship among the variables (Table 3).

Table 3. Critical bounds for the Bound Test.

Significance Level (α)	$I(0)_{10\%}$	$I(0)_{10\%}$	$I(0)_{5\%}$	$I(0)_{5\%}$	$I(0)_{1\%}$	$I(0)_{1\%}$
F-statistic (n/approx30)	2.384	3.728	2.875	3.445	4.104	6.151
Asymptotic F	2.030	3.130	2.320	2.500	2.960	4.260
Asymptotic t	−2.570	−4.230	−2.860	−3.070	−3.430	−5.190

Where $I(0)$ and $I(1)$ represent the lower and upper critical bounds corresponding to the stationary and non-stationary series, respectively.

$$\begin{cases} F_{obs} < I(0)_{\alpha} \Rightarrow \text{Fail to reject } H_0 \text{ (no cointegration)} \\ F_{obs} > I(0)_{\alpha} \Rightarrow \text{Reject } H_0 \text{ (cointegration)} \\ I(0)_{\alpha} \leq F_{obs} \leq I(0)_{\alpha} \Rightarrow \text{Inconclusive result} \end{cases}$$

$$I(0)_{5\%} = 2.875, I(1)_{5\%} = 3.445, \quad F_{obs} = 3.813891$$

$$F_{obs} = 3.813891 > I(1)_{5\%} = 3.445$$

$$I(0)_{5\%} = 2.860, I(1)_{5\%} = 3.070, \quad t_{obs} = -3.095454$$

$$t_{obs} = -3.095454 < I(1)_{5\%} = -3.070$$

$\Rightarrow$ Reject H_0 and conclude that a long-run (levels) relationship exist at the 5% significance level.

ECM estimation confirmed the presence of a long-run equilibrium relationship, while also quantifying the short-run deviations and their speed of adjustment back to equilibrium.

$$\begin{aligned} \Delta \text{Consump}_t = & a_0 + \sum_{i=1}^q \beta_i \Delta \text{GDP}_{t-i} + \sum_{i=1}^q \gamma_i \Delta \text{POP}_{t-i} + \sum_{i=1}^q \delta_i \Delta \text{GDPGR}_{t-i} \\ & + \sum_{i=1}^q \phi_i \Delta \text{PRCON}_{t-i} + \sum_{i=1}^q \eta_i \Delta \text{HOULINT}_{t-i} + \sum_{i=1}^q \kappa_i \Delta \text{LENRATE}_{t-i} \\ & + \sum_{i=1}^q \lambda_i \Delta \text{EXRATE}_{t-i} + \text{ECM}_{t-1} + e_t \end{aligned}$$

The lagged equilibrium error (ECM term) is defined as

$$\text{ECM}_{t-1} = \text{Consump}_{t-1} - (\hat{\alpha} + \hat{\beta}_1 X_{1,t-1} + \hat{\beta}_2 X_{2,t-1} + \dots + \hat{\beta}_n X_{n,t-1})$$

ECM_{t-1} measures the deviation from the long-run equilibrium at time $t - 1$.

$$\begin{cases} > 0, \text{ if actual CONSUMP}_{t-1} \text{ exceeds its long-run equilibrium value;} \\ < 0, \text{ if actual CONSUMP}_{t-1} \text{ falls below its long-run equilibrium value;} \\ 0, \text{ if the system is in long-run equilibrium.} \end{cases}$$

Given the presence of cointegration, $\text{ECM}_{t-1} \approx 0$. was conducted to capture short-run dynamics and the speed of adjustment towards the long-run equilibrium (Table 4).

Table 4. Estimation of ECM (Long run).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−555.2709	706.4184	−0.786037	0.4459
D(GDP(−3))	25.73299	31.29618	0.822240	0.4258

D(POP(−3))	1793.135	1441.051	1.244325	0.2353
D(GDPGR(−3))	161.6467	121.2206	1.333492	0.2053
D(PRCON(−3))	17.45605	16.36127	1.066913	0.3054
D(HOULOINT(−3))	−1089.029	735.1436	−1.481383	0.1623
D(LENRATE(−3))	−3.499564	118.1998	−0.029607	0.9768
D(EXRATE(−3))	1740.445	1969.593	0.883657	0.3929
ECM(−3)	−0.844171	0.464091	−1.818977	0.0920
R-squared	0.653988	Mean dependent var	1256.045	
Adjusted R-squared	0.441057	S.D. dependent var	2058.975	
S.E. of regression	1539.341	Akaike info criterion	17.80818	
Sum squared resid	30804411	Schwarz criterion	18.25452	
Log likelihood	−186.8900	Hannan–Quinn criter.	17.91333	
F-statistic	3.071363	Durbin–Watson stat	2.695889	
Prob(F-statistic)	0.035325			

The coefficient of the error correction term ($\theta = -0.844171$) is negative and statistically significant at the 10% level ($p = 0.092$), confirming the presence of long-run equilibrium adjustment. This indicates approximately 84.4% of the disequilibrium from the previous period is corrected each year. With $R^2 = 0.654$ and $\Delta R^2 = 0.441$, the ECM explains 65.4% of the short-run variation in concrete consumption and the model is statistically significant ($p(F) = 0.035 < 0.05$). The estimated ECM with a 3-lag ECM term is expressed as:

$$\Delta \text{Consump}_t = -555.27 + 25.73 \Delta \text{GDP}_{t-3} + 1793.14 \Delta \text{POP}_{t-3} + 161.65 \Delta \text{GDPGR}_{t-3} \\ + 17.46 \Delta \text{PRCON}_{t-3} - 1089.03 \Delta \text{HOULOINT}_{t-3} - 3.50 \Delta \text{LENRATE}_{t-3} \\ + 1740.45 \Delta \text{EXRATE}_{t-3} - 0.844 \text{ECM}_{t-1} + e_t$$

For the single t -test, the coefficient $\hat{\beta}$ with estimated standard error $SE(\hat{\beta})$, the t -statistic, and two-sided p -value are computed as

$$t = \frac{\hat{\beta}}{SE(\hat{\beta})}, df = n - K$$

$$\text{and } p = 2 \Pr(T_{(df)} > |t|)$$

$$t_{\hat{\theta}} = \frac{-0.844171}{0.464091} = -1.818977, \quad p \approx 0.0920$$

The reported F -statistic tests H_0 all slope coefficients = 0 versus the alternative that at least one slope is nonzero:

$$F = \frac{(SSR_{\text{restricted}} - SSR_{\text{unrestricted}})/q}{SSR_{\text{unrestricted}} / (n - K)} \sim F_{q, n-K},$$

With the reported $F = 3.071363$, and $p = 0.035325$, H_0 is rejected at 5% level but accepted at the 10% level.

$$\text{Forthemodeldiagnostic}, R^2 = 0.654 \text{ means } \frac{\sum(\hat{y}_t - \bar{y})^2}{\sum(y_t - \bar{y})^2} = 0.654$$

- $DW \approx 2.696 \rightarrow$ no evidence of first-order autocorrelation (since $DW \approx 2$ and > 2).
- The model jointly significant: $F_{q, n-K}$, with reported $p < 0.05$.
for the speed of adjustment (ECM coefficient)

The ECM coefficient $\hat{\theta} = -0.844171$ satisfied $\hat{\theta} < 0$.

$$\Delta \text{Consump}_t = \dots + \hat{\theta} \text{ECM}_{t-3} + \varepsilon_t, \quad \hat{\theta} = -0.844171$$

A one – unit positive disequilibrium $\text{ECM}_{t-3} > 0$ reduces

$\Delta \text{Consump}_t$ by 0.844171 units on average. In percent terms, it corrects approximately

$$/ \hat{\theta} / \times 100\% \approx 84.42\%$$

*of the previous period's disequilibrium per period (period = 1).
 for each $\hat{\beta}_i$:*

$$H_0 : \beta_i = 0 \quad \text{vs} H_0 : \beta_i \neq 0,$$

*reject H_0 if $|t|$
 $> t_{\alpha/2, df}$. Using the reported values, none of the differenced*

regressors are significant at the 5% level (all $P > 0.05$); $\hat{\theta}$ is significant

at the 10% level ($p \approx 0.0920$)

To ensure the robustness and reliability of the findings, the estimated ECM was subjected to the Breusch–Godfrey Serial Correlation LM Test and the CUSUM stability test. The LM Test provides two equivalent statistics:

- F-statistic:

$$F = 1.63544 \text{ with } \text{Prob}(F_{(3,10)}) = 0.2430$$

- LM (Lagrange Multiplier) version ($\text{Obs} \times R^2$):

$$LM = nR^2 = 7.241173 \text{ with } \text{Prob}(\chi^2_{(3)}) = 0.0646$$

$$\begin{cases} \text{Reject } H_0, & \text{if } p > \alpha \\ \text{Fail to reject } H_0, & \text{if } p \geq \alpha \end{cases}$$

At the 5% significance level ($\alpha = 0.05$)

$$PF = 0.2430 > 0.05, P\chi^2 = 0.0646 > 0.05$$

$$\Rightarrow \text{Fail to reject } H_0$$

H_0 : No serial correlation up to lag 3 cannot be rejected

$$\therefore \text{Cov}(\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \varepsilon_{t-3}) = 0, \quad \forall k \leq 3$$

The CUSUM stability test conducted denotes $\pm C_t^{(0.05)}$.

$$\begin{cases} |W_t| \leq C_t^{(0.05)} \Rightarrow \text{Fail to reject } H_0 \text{ (parameters are stable)} \\ |W_t| > C_t^{(0.05)} \Rightarrow \text{Reject } H_0 \text{ (parameters are unstable)} \end{cases}$$

H_0 : Model parameters are stable overtime

Given that the computed CUSUM path lies within the 5% confidence boundaries (Figure 4)

$$\max_t |W_t| < C_t^{(0.05)} \Rightarrow \text{Fail to reject } H_0.$$

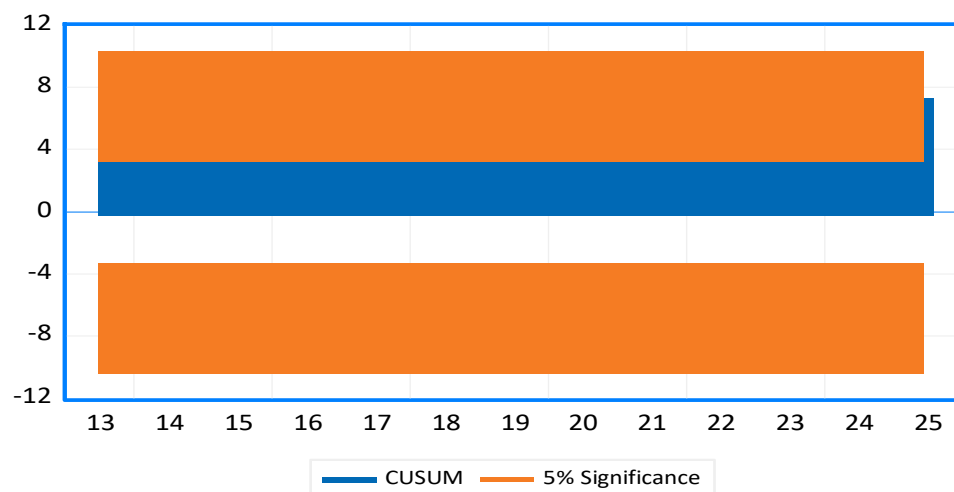


Figure 4. CUSUM Test of ARDL model.

The CUSUM path lies within the 5% critical bounds; hence, the model parameters are stable over the sample period:

$$\therefore W_t \in [-C_t^{(0.05)}, C_t^{(0.05)}] \forall t,$$

Therefore, the previous residuals do not affect current errors, confirming that the ARDL–ECM meets the stability and diagnostic standards required for accurate inference and dependable forecasting of concrete consumption, as shown in Figure 5.

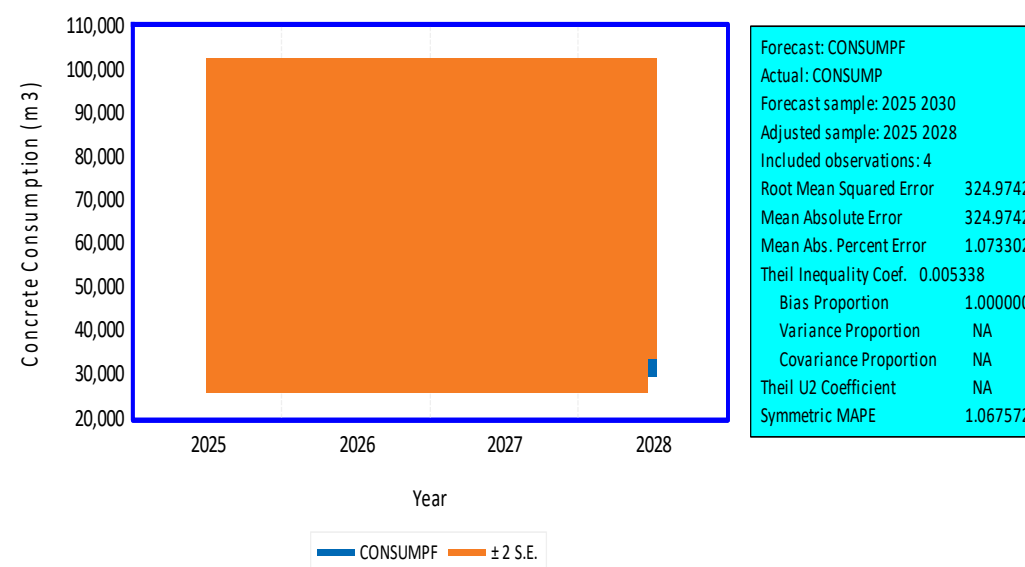


Figure 5. Forecast concrete consumption, 2025–2030.

Concrete consumption in Ghana is projected to continue expanding over the projection horizon, according to the ARDL–ECM forecast, which covers the period from 2025 to 2030. With an RMSE of 324.9742, the model is flawed. If the root-mean-squared error (RMSE) is low, the forecast is very accurate because the actual and predicted values are not too far apart. This finding lends credence to the idea that the model can accurately forecast concrete demand. U, the Theil's Inequality Coefficient, is almost nil at 0.005338. When the system is in long-run equilibrium, $(fOM - t - 1)$ is nearly equivalent to zero, because $U \rightarrow 0$ signifies flawless predicting performance. Cointegration necessitated an ECM to gauge the short-term dynamics and the rate of adjustment to the long-term equilibrium (Table 3). According to this outcome, the predicted and measured concrete consumption

amounts are very close. With a bias proportion (UB) of 1.000, we see very few systematic errors in our forecasts, and the majority of variations are either completely random or poorly planned. This result provides more evidence that the model is stable and well-specified. The following is a statistical summary of the predicted performance metrics:

$$\text{RMSE} = 324.9742$$

$$U = 0.0053438$$

$$U_B = 1.00$$

Since $U \approx 0$ and $U_B \approx 1$, it follows that the model possesses strong predictive capability and efficiently forecasts concrete consumption based on the given economic and structural input variables. Therefore, the ARDL–ECM meets the statistical criteria for a robust and stable forecasting model, making it suitable for policy formulation, demand planning, and infrastructure development projections related to concrete consumption in Ghana. Figure 6 shows the actual and predicted concrete consumption from 2025 to 2030.

The forecast indicates a consistent upward trend in concrete consumption in Ghana, a developing country, over the next five years. The year-to-year increase is represented by the first difference:

$$\Delta \hat{Y}_{2027} = 51640.79 - 39278.52 = 12,362.27,$$

$$\Delta \hat{Y}_{2028} = 66,803.75 - 51,640.79 = 15,162.96,$$

$$\Delta \hat{Y}_{2029} = 81,500.58 - 66,803.75 = 14,696.83,$$

$$\Delta \hat{Y}_{2030} = 99,430.53 - 81,500.58 = 17,929.95.$$

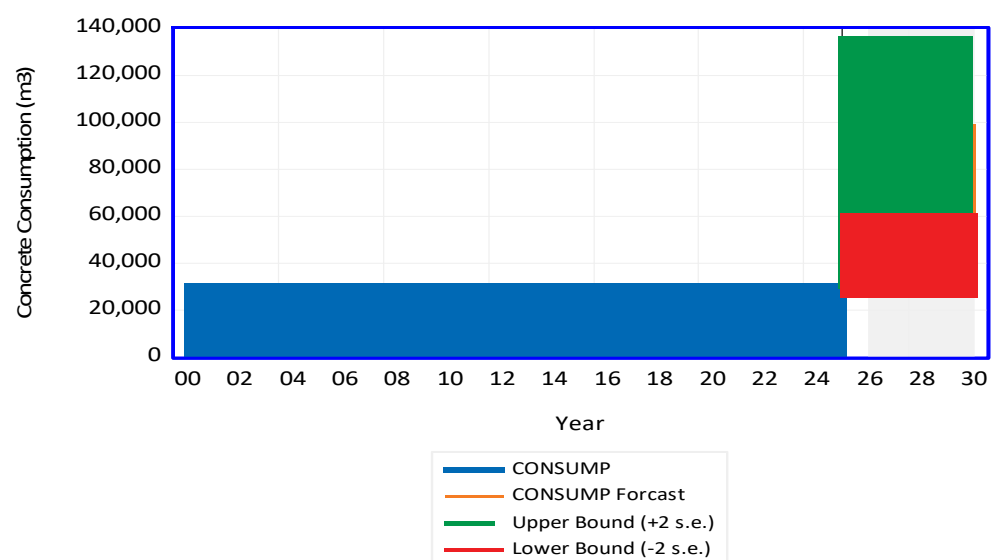


Figure 6. Actual and predicted concrete consumption, 2025–2030.

The model, therefore, suggested annual increments in concrete demand ranging from approximately 12,362 m³ to 17,930 m³, reflecting sustained sectoral growth.

The average forecasted consumption (ACC) over the five-year horizon is

$$\text{ACC} = \frac{1}{5} \sum_{t=20026}^{2030} \hat{Y}_t = \frac{39278.52 + 51640.79 + 66803.75 + 81500.58 + 99430.53}{5}$$

$$ACC = 67,730.8 \text{ m}^3$$

The mean projected consumption is 67,730.83 m³, implying strong demand for concrete in the forecast period. The average annual growth rate (AAGR) is given by

$$AAGR = \left[\left(\frac{\hat{Y}_{2030}}{\hat{Y}_{2026}} \right)^{\frac{1}{4}} - 1 \right] \times 100 = \left[\left(\frac{99,430.53}{39,278.52} \right)^{0.25} - 1 \right] \times 100 = 26.3\%$$

The forecast suggested an average annual growth rate of approximately 26.3% in concrete consumption from 2026 to 2030.

5. Discussion

The forecast indicated an average annual growth rate (AAGR) of approximately 26.3% in concrete consumption between 2026 and 2030. This growth trajectory appears markedly higher than the global concrete market CAGR of about 5.6%, necessitating careful contextual interpretation. Importantly, this disparity reflects Ghana's position as a rapidly urbanising, infrastructure-deficient economy undergoing a structural catch-up phase. Unlike mature markets, where growth largely follows replacement and incremental expansion, concrete demand in Ghana is driven by first-time infrastructure provision, accelerated housing needs, and delayed capital investment accumulated during previous periods of economic instability. Ghana's concrete market demonstrates notable resilience despite macroeconomic volatility, high interest rates, and exchange rate depreciation. The key stabilising factor is the country's substantial installed cement production capacity, estimated at approximately 12.1 million tonnes annually, relative to current consumption of about 7 million tonnes. This excess capacity of roughly 5 million tonnes functions as a structural buffer, allowing the sector to absorb short-term demand shocks, supply chain disruptions, and price volatility without immediate production constraints.

In a sensitivity assessment, a sustained extreme depreciation of the Ghanaian Cedi would materially dampen growth through increased clinker and fuel import costs, higher construction input prices, and tightened credit conditions due to inflationary pressures. Under a high-depreciation scenario, growth would likely moderate toward a mid-range trajectory rather than the upper-bound 26.3% projection. This suggests that the reported AAGR represents a conditional growth path assuming relative macroeconomic stabilisation. In the absence of currency stability, effective growth could retract substantially, potentially converging closer to emerging-market benchmarks than to the forecast upper band.

The high forecasted growth rate is not incidental; rather, it directly reflects Ghana's accelerating urbanisation trajectory and the intensification of housing and infrastructure delivery, particularly within the capital city (Greater Accra Region), where construction activity remains most concentrated [106]. This structural expansion in the built environment creates a sustained and unavoidable demand for concrete and cement, thereby reinforcing the credibility of the projected upward trend. Importantly, the study's results are not isolated estimates but are independently supported by industry evidence. Reports by GlobalData show that Ghana's construction sector maintained an average annual growth rate of 3.4–5.2% between 2024 and 2025 [107], a pace of expansion that logically necessitates increased material inputs. Such persistent sectoral growth provides a compelling and rational explanation for the progressive rise in cement consumption observed nationally [108]. This relationship is further substantiated by empirical market data. Aidoo reported a substantial 10.6% year-on-year increase in cement sales for concrete production in May 2024, climbing from 212,584.38 tonnes to 235,050.55 tonnes, largely driven by renewed investments in building and infrastructure projects [42]. Taken together, these converging

lines of macroeconomic, industry, and sales evidence strongly validate the study's forecasts and demonstrate that continued growth in concrete demand is not speculative but structurally grounded in ongoing development dynamics.

Additionally, the dominance of informal and small-scale construction in Ghana amplifies demand volatility but also accelerates aggregate consumption during growth phases. Unlike formal, centrally planned construction markets, informal in-situ concrete production responds quickly to population growth, remittance inflows, and incremental housing expansion. This structural feature helps explain why concrete demand in Ghana can grow at rates substantially above global averages, even in the presence of governance challenges, planning inefficiencies, and procurement constraints highlighted earlier in the study. These findings collectively mirror global consumption patterns identified by Geng, who projected that global concrete demand will quadruple by 2050 due to the acceleration of urbanisation and development needs in emerging economies [42].

5.1. Policy Implications

The projected steady rise in concrete consumption between 2025 and 2030 highlighted the urgent need for strategic policy planning to manage resource demand, promote sustainability, and support industrial growth. Policymakers should integrate these forecast results into national infrastructure and urban development strategies, particularly within Ghana's long-term development agenda. The government should strengthen policies that promote the use of eco-friendly and alternative materials to reduce the environmental footprint of increased concrete consumption. Since GDP growth, population expansion, and construction activity jointly drive material consumption, fiscal and monetary policies should be aligned, in order to maintain economic stability, ensuring that material price fluctuations and financing constraints do not disrupt construction progress.

5.2. Practical Implications

The ARDL–ECM provides a reliable forecasting tool that can be directly applied by policymakers, planners, and firms to anticipate future material requirements and enhance infrastructure planning. The model supports project timeline forecasting, ensuring material availability aligns with construction milestones, thereby preventing delays and cost overruns. The projections provide a basis for collaboration between government agencies and private-sector actors to plan production capacity and transportation infrastructure for material delivery. The findings contribute to academic and professional understanding of construction demand forecasting, offering a reference framework for engineering economics, sustainable construction, and policy studies.

5.3. Limitations and Future Research Directions

The study is constrained by the limited sample size, which is inherent in the availability of annual macroeconomic data for Ghana. The forecast assumes macroeconomic recovery will continue and does not fully account for extreme shocks, such as prolonged currency crises, energy supply disruptions, or abrupt policy reversals. In addition, limitations in informal-sector data may understate or overstate actual consumption levels. These unresolved issues suggest that while the projected growth is economically plausible, it should be interpreted as a high-growth scenario contingent on moderate macroeconomic stabilisation and continued infrastructure investment.

The ARDL approach is well suited for small samples. The inclusion of higher-frequency data (e.g., quarterly or monthly observations) in future studies could improve estimation efficiency, enhance dynamic responsiveness, and provide deeper insights into short-run fluctuations in concrete consumption. Additionally, the study focuses on aggre-

gate national-level data, which may obscure regional heterogeneity in construction activity. Concrete demand is often spatially uneven, particularly in rapidly urbanising regions such as Greater Accra. Future research could extend this analysis by employing regional or city-level datasets to capture spatial variations in infrastructure development and material consumption.

Furthermore, although key macroeconomic determinants were included, other potentially influential factors, such as government capital expenditure, urban housing deficit, adoption of construction technology, climate policy interventions, and energy costs, were not explicitly incorporated due to data limitations. Incorporating these variables into future studies may enhance the model's explanatory power and facilitate a more comprehensive understanding of concrete demand dynamics. Moreover, although machine-learning models were applied for comparative evaluation, the final forecasting relied primarily on the linear ARDL–ECM framework due to the small dataset. Future research could explore advanced deep learning architectures, such as Long Short-Term Memory (LSTM) networks or hybrid ARDL–ML ensembles, especially when larger datasets become available, to further enhance predictive performance. The forecast horizon was limited to five years (2025–2030). While appropriate for medium-term planning, extending the forecast period under alternative economic and policy scenarios, such as green construction policies or carbon pricing mechanisms, would provide valuable insights into the long-term sustainability implications of rising concrete consumption.

6. Conclusions

This study confirmed the existence of a stable long-run relationship between concrete consumption and macroeconomic fundamentals. GDP and population exerted positive, statistically significant effects, highlighting the central role of economic growth and population growth in driving construction demand. In contrast, the housing loan interest rate exerted a negative, significant influence, indicating that higher borrowing costs suppress construction activity. The statistically significant negative error-correction term indicated rapid adjustment, with approximately 84% of short-run disequilibrium corrected annually, confirming long-run stability in the system. Forecast evaluation further demonstrated the strong predictive performance of the ARDL–ECM. The low Root Mean Square Error and near-zero Theil's Inequality Coefficient indicated minimal deviation between observed and predicted values. The forecasts revealed a consistent upward trend in concrete consumption between 2025 and 2030, with annual increases ranging from approximately 12,000 m³ to 18,000 m³ and an average annual growth rate of 26.3%. These projections reflect Ghana's accelerating urbanisation, infrastructure expansion, and growth in the construction sector.

Therefore, although the forecasted growth is statistically sound and economically plausible given Ghana's infrastructure deficit and catch-up dynamics, its real-world feasibility hinges on improvements in institutional coordination, construction finance accessibility, logistics efficiency, and regulatory enforcement. Ghana's construction industry can absorb substantial growth, but sustaining such rapid expansion will require deliberate capacity upgrading and governance reforms to convert rising demand into durable, efficient, and sustainable infrastructure outcomes.

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