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Dynamic Cement Supply Chain Planning Using Integrated Logarithmic Regression and Fuzzy Inference in Indonesia

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Abstract

This study introduces a dynamic simulation framework to address the limitations of static planning in Indonesia's cement industry, where demand volatility and logistics disruptions undermine efficiency. By integrating System Dynamics, Game Theory, and Fuzzy Inference Systems, the model captures both quantitative trends and qualitative uncertainties, offering a more resilient decision-making tool. The model incorporates critical variables such as demand fluctuations, production capacity constraints, inventory policies, and logistics disruptions, providing a robust tool for predicting system behaviour under diverse conditions. Applied to a real-world case in the Indonesian cement industry, the framework evaluates three scenarios: Optimistic, Moderate, and Pessimistic. In the Optimistic scenario, characterized by a 12% annual demand increase and an 8% capacity expansion, logistics costs decreased by 20%, and order fulfilment improved by 15%. The Moderate scenario, with a 5% demand rise and 3% capacity growth, yielded stable costs and marginal efficiency gains. Conversely, the Pessimistic scenario, marked by stagnant demand (2%) and unchanged capacity, resulted in an 18% increase in logistics costs and a 12% decline in order fulfilment. These findings underscore the effectiveness of dynamic simulation in enhancing logistics strategies, mitigating risks, and strengthening competitiveness within the cement supply chain.

1. Introduction

In recent decades, the cement industry has encountered growing complexity in both operational and strategic decision-making. Factors such as fluctuating demand, volatile raw material prices, evolving environmental regulations, and intensifying market competition have amplified the need for adaptive and forward-looking planning methodologies. Traditional static strategic planning approaches often fail to capture the intricate interdependencies and feedback loops inherent in real-world industrial systems. Consequently, there is increasing interest in dynamic modelling frameworks that can accommodate these complexities and provide robust decision support. Dynamic Strategic Planning (DSP) integrates time-based analysis with system behaviour, enabling firms to navigate uncertainty and respond proactively to future scenarios. This dynamic approach is particularly critical in the cement sector, where capital investments are substantial and market cycles are prolonged. Moreover, the interplay among key variables such as demand, supply, and pricing necessitates analytical tools capable of simulating future conditions and deriving strategic insights [1].

To address these challenges, this study proposes a hybrid framework that combines System Dynamics, Game Theory, and Fuzzy Inference Systems (FIS) to model and optimize strategic planning in the cement industry. The approach begins by identifying the primary subsystems demand, supply, and price and analysing their interrelationships using multiple linear regression on historical data. This empirical foundation supports the construction of static and dynamic scenarios, which are simulated through System Dynamics modelling. Leader-follower and coalition game theory paradigms capture strategic interactions among market players in a dynamic setting [2]. Simulation results are then utilized to extract fuzzy rules through an FIS, enabling the prediction of future system states and the evaluation of probable market outcomes [3]. Based on this analysis, the most reliable long-term strategy for the average-case scenario is identified and recommended for implementation [4]. The proposed model incorporates short-term disturbances through its inherent dynamic feedback structure, ensuring long-term strategic robustness [5]. The methodology is validated through a real-world case study in the cement industry, demonstrating its practical viability and effectiveness in supporting long-term strategic decisions [6]. This research contributes a novel, adaptable tool for decision-makers seeking sustainable competitive advantage in complex industrial environments by integrating quantitative modelling, strategic game theory, and soft computing techniques [7].

Strategic industries such as cement increasingly operate in environments marked by complexity and volatility, driven by shifting market demands, competitive pressures, unpredictable costs, and the need for adaptable long-term strategies. Conventional strategic planning methods, which are typically static, often fail to address the complex feedback loops, non-linear dynamics, qualitative factors, and inherent uncertainties associated with strategic choices. While individual techniques such as logarithmic regression, System Dynamics, Game Theory-based strategic interaction modelling, and Fuzzy Inference Systems have demonstrated effectiveness in addressing specific aspects of complex systems, a significant gap remains in synthesizing these tools into a unified framework that supports dynamic strategy development. This research aims to construct an integrated hybrid model that combines these methodologies to facilitate more effective strategic planning within the cement industry's supply chain. It also seeks to identify key elements and interactions within the supply chain that significantly influence strategic outcomes, including operational efficiency, profitability, market competitiveness, and environmental sustainability. Furthermore, the study examines how this model can be applied to evaluate and compare various strategic alternatives such as pricing adjustments, capacity expansions, competitive tactics, and responses to demand variability thereby providing more robust and adaptable strategic guidance for the industry.

Despite the cement industry's pivot toward sophisticated operational models, a critical disconnect persists between the inherent volatility of the global market and the static nature of conventional strategic planning. Current methodologies often fail to account for the non-linear feedback loops and multi-stakeholder strategic interactions such as price wars and capacity competitions that define the sector. While individual tools like System Dynamics or Game Theory offer localized insights, there is a lack of a unified, hybrid framework capable of synthesizing quantitative historical data with qualitative uncertainty. Consequently, decision-makers are frequently forced to rely on fragmented models that cannot simulate the long-term consequences of short-term disturbances. The objective of this research is to bridge this gap by developing an integrated hybrid model combining System Dynamics, Game Theory, and Fuzzy Inference Systems (FIS) to facilitate dynamic strategic planning. By identifying the key variables within the supply chain and simulating diverse competitive scenarios, this study seeks to provide a robust analytical tool that evaluates strategic alternatives, ensuring that long-term investments in the cement industry are both resilient to market shifts and aligned with sustainable competitive advantages.

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2. Current Trend in Dynamic Strategic Planning Framework

The contemporary industrial landscape is defined by heightened volatility and structural complexity, rendering traditional, static strategic planning models increasingly obsolete. Conventional frameworks frequently lack the analytical depth to account for non-linear feedback loops, environmental uncertainties, and the reflexive nature of competitive behaviour. Consequently, recent scholarship has shifted toward a multi-dimensional paradigm that synthesizes Logarithmic Regression, System Dynamics, Strategic Interaction Modelling (Game Theory), and Fuzzy Inference Systems (FIS). By integrating these disparate computational tools, researchers are moving beyond rigid, deterministic forecasting toward the creation of Dynamic Strategic Planning (DSP) frameworks. This hybrid approach enables organizations to navigate linguistic ambiguity through fuzzy logic, simulate temporal system behaviours via SD, and anticipate competitor manoeuvres through game-theoretic analysis.

Ultimately, this integration facilitates a shift from reactive decision-making to a state of continuous strategic evolution and long-term resilience. The evolution of strategic planning in complex industrial sectors necessitates a transition from linear forecasting to a multi-layered, integrated computational approach. At the foundational level, logarithmic regression serves as a robust quantitative engine for deciphering non-linear market trends, particularly where diminishing returns or market saturation render standard linear models ineffective [8]. These empirical foundations are subsequently embedded within a System Dynamics framework, which maps the structural complexity of the industry through stocks, flows, and recursive feedback loops [9], [10]. While SD provides the "sandbox" for temporal simulation, it often lacks the behavioural nuance of competitive rivalry. To address this, Strategic Interaction Modelling, grounded in Game Theory, is integrated to capture the reflexive nature of market participants, such as leader-follower dynamics or coalition-building [11]–[13].

Despite the precision of these quantitative tools, strategic environments remain permeated by linguistic ambiguity and expert intuition. Fuzzy Inference Systems (FIS) bridge this gap by translating qualitative expert knowledge into actionable "if-then" logic, allowing the model to process imprecise variables like "market sentiment" or "competitive intensity" [14]. The true power of this research lies in the methodological synergy of these four components: regression provides the data-driven baseline, SD structures the systemic behaviour, Game Theory simulates the competitive chess match, and FIS manages the inherent uncertainty [15]–[17]. This integrated paradigm facilitates a move away from rigid, one-off predictions toward a Dynamic Strategic Planning (DSP) framework, ensuring that industrial strategies remain resilient, adaptive, and grounded in both historical reality and future volatility [18].

3. Methodology

This research integrates four key methodological tools to analyse strategic dynamics in a quantitative and adaptive framework: logarithmic regression, system dynamics modelling, dynamic game theory, and fuzzy inference systems (FIS) [19], [20]. Each approach is detailed below, including its mathematical foundations. Logarithmic regression was used to capture non-linear relationships and diminishing marginal returns between strategic predictor variables and outcomes. The mathematical model is as in Equation 1, where Y is the strategic output variable (e.g., organizational performance), X is a predictor variable (e.g., investment, technology adoption), α and β are intercept and logarithmic coefficient respectively, while ϵ represent a residual error. The integration framework ensures continuous feedback: regression establishes empirical baselines, SD simulates temporal dynamics, Game Theory models competitive responses, and FIS translates uncertainty into actionable rules.

$$Y = \alpha + \beta . \ln(X) + \epsilon \tag{1}$$

The parameter was estimated using Ordinary Least Squares (OLS) by minimizing the sum of squared residuals, as shown in Equation 2.

$$OLS = min_{\alpha,\beta} \sum_{i=1}^{n} (Y_i - \alpha - \beta . \ln(X_i))^2 \tag{2}$$

System dynamics (SD) modelling was employed to represent complex behaviour evolving over time, characterized by feedback loops, time delays, and accumulations. Generic stock-flow model,

$$\frac{dK(t)}{dt} = \gamma . I(t) - \delta . K(t) \tag{3}$$

where $K(t)$ represent an accumulated knowledge at time t, $I(t)$ is investment in R&D, γ is a learning rate and δ represent a depreciation rate. For the simulation, Euler integration was used as in Equation 4 below.

$$K(t) + K(t + \Delta t) = K(t) + \Delta t \cdot (\gamma \cdot I(t) - \delta \cdot K(t)) \tag{4}$$

3.1 Fuzzy Inference System (*FIS*)

A fuzzy inference system was employed to handle uncertainty and interpret linguistic variables derived from expert judgment in strategic decision-making. During the fuzzification stage, numerical inputs are converted into fuzzy sets through membership functions, such as the triangular membership function shown in Equation 5. An example rule is: IF investment is *High* AND risk is *Low*, THEN strategy is *Expand*.

$$\mu_A(x) = \begin{cases} 0 & x \leq a \\ \dfrac{x-a}{b-a} & a < x \leq b \\ \dfrac{c-x}{c-b} & b < x \leq c \\ 0 & x > 0 \end{cases} \quad (5)$$

For the Mamdani inference process, fuzzy logic operators specifically the minimum operator for AND and the maximum operator for OR are used to compute the rule outcomes, as described in Equation 6. Finally, defuzzification is performed to obtain a crisp output value, using the Centroid Method illustrated in Equation 7.

$$\mu_{output}(z) = max_i(\min(\mu_{A_i}(x), \mu_{B_i}(y)) \quad (6)$$

$$dzz^* = \frac{\int z \cdot \mu_{output}(z) \cdot dz}{\int \mu_{output}(z) \cdot dz} \quad (7)$$

All methods were integrated into a feedback-driven adaptive framework in which logarithmic regression supplied empirical coefficients that shaped the flow functions within the system dynamics model. The system dynamics simulations then produced time-dependent state variables that served as inputs to the strategic interaction models. These models identified optimal player strategies, which were subsequently enhanced through fuzzy inference systems. The resulting FIS outputs were fed back into the system dynamics model, enabling continuous strategic adaptation under conditions of uncertainty.

The proposed model explains how key parts of the cement supply chain such as demand, material supply, production, pricing, and distribution are connected and influence one another. External market demand is the main driver. When demand changes, it affects how many raw materials are ordered, how much stock is available, and ultimately how much can be produced. Finished products are then distributed to customers at a controlled rate to meet demand effectively. Pricing plays an important role in regulating the system. Prices adjust based on production costs and market conditions. When demand is high, prices rise, encouraging more production. When demand is low, prices fall, signalling companies to reduce output. The model also includes feedback loops that allow the system to adapt to changing conditions. If demand increases or if materials become limited, the system automatically adjusts production and distribution rates. This flexibility helps maintain balance even when disruptions occur.

The model is useful for managers because it helps them test different scenarios and choose the best strategies for production, inventory, and distribution. It supports better decision-making under uncertain market conditions. Three scenarios were tested:

i. Optimistic: Stable demand and strong production capacity led to efficient operations and low costs.
ii. Moderate: Some fluctuations caused delays and moderate inventory costs.
iii. Pessimistic: High demand changes and limited capacity increased costs and reduced order fulfilment.

Overall, the model helps evaluate both short-term performance and long-term sustainability of the cement supply chain.

4. Results and Discussion

The dynamic simulation results reveal distinct supply chain behaviour under the three evaluated scenarios, reflecting the influence of demand growth and production capacity constraints on inventory dynamics, distribution performance, and import dependency. Overall, the simulation demonstrates that cement supply chain performance is highly sensitive to structural feedback mechanisms and time delays embedded in the production–inventory distribution system. Under the optimistic scenario, high demand growth accompanied by sufficient production capacity expansion results in relatively stable inventory levels over the simulation horizon. Production rates are able to adjust gradually to increasing demand, reducing the frequency and magnitude of inventory shortages. Distribution performance remains high, with most market demand satisfied through domestic production. Consequently, reliance on imports is minimal and primarily occurs during short-term demand peaks, indicating a resilient supply chain structure under favourable operating conditions.

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In the moderate scenario, where demand growth is stable and capacity adjustment is more gradual, the system exhibits moderate inventory fluctuations. While production and distribution remain generally balanced, periodic inventory drawdowns occur due to delayed capacity responses to demand changes. These imbalances lead to intermittent import requirements, suggesting that even moderate demand uncertainty can introduce structural inefficiencies when capacity flexibility is limited. Nevertheless, the overall system remains stable, and inventory oscillations do not escalate over time.

In contrast, the pessimistic scenario produces pronounced dynamic instability. Constrained production capacity combined with low or volatile demand growth leads to significant inventory depletion and irregular production–distribution alignment. The simulation shows frequent and sustained reliance on imports to compensate for domestic supply shortages. Inventory levels fluctuate sharply, and distribution performance deteriorates, indicating reduced system robustness. These results highlight the amplifying effect of delayed capacity adjustments and limited production flexibility under unfavourable conditions. Figure 1 shown the framework dynamic simulation and scenario evaluation.

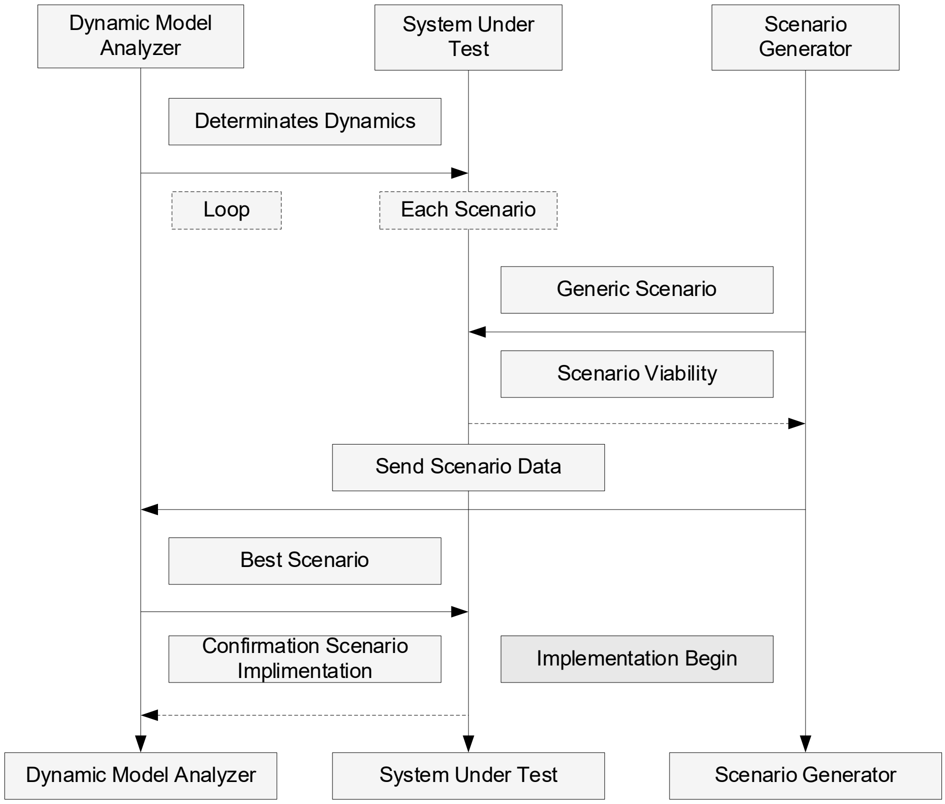

Fig. 1 *Framework dynamic simulation and scenario evaluation*

Comparative analysis across scenarios confirms that inventory stability and import dependency are strongly governed by endogenous feedback mechanisms rather than isolated parameter changes. In particular, delays in production capacity adjustment exacerbate supply–demand mismatches, leading to persistent inventory oscillations and increased import reliance. The results demonstrate that dynamic simulation is essential for capturing these behaviours, which cannot be adequately identified through static or short-term analytical approaches.

4.1 System Dynamics Simulation

The comprehensive system dynamics model in Figure 2 shows how material supply interacts with production rates, pricing mechanisms, distribution flows, and demand in the cement market. These relationships are influenced by the internal structure of the system (such as stocks, tariffs, and feedback cycles) as well as external economic factors represented in the economic scenario in Table 1. The scenario table divides the cement market into three economic States: growth, stability and recession, as well as determines the appropriate level for the initial market parameters and independent variables. These settings provide input for running simulations to assess the response of cement supply chains to different macroeconomic conditions.

Table 1 *Analysis and system dynamics simulation*

Economic Scenario	Initial Cement Market Parameters	Supply	Demand	Independent Variables	Dollar Rate	Inflation
	Price			Clinker Price		
Growth	Medium	High	High	High	Low	Low
Stability	Medium	Medium	Medium	Medium	Medium	Medium
Recession	Low	High	Low	Low	High	Low

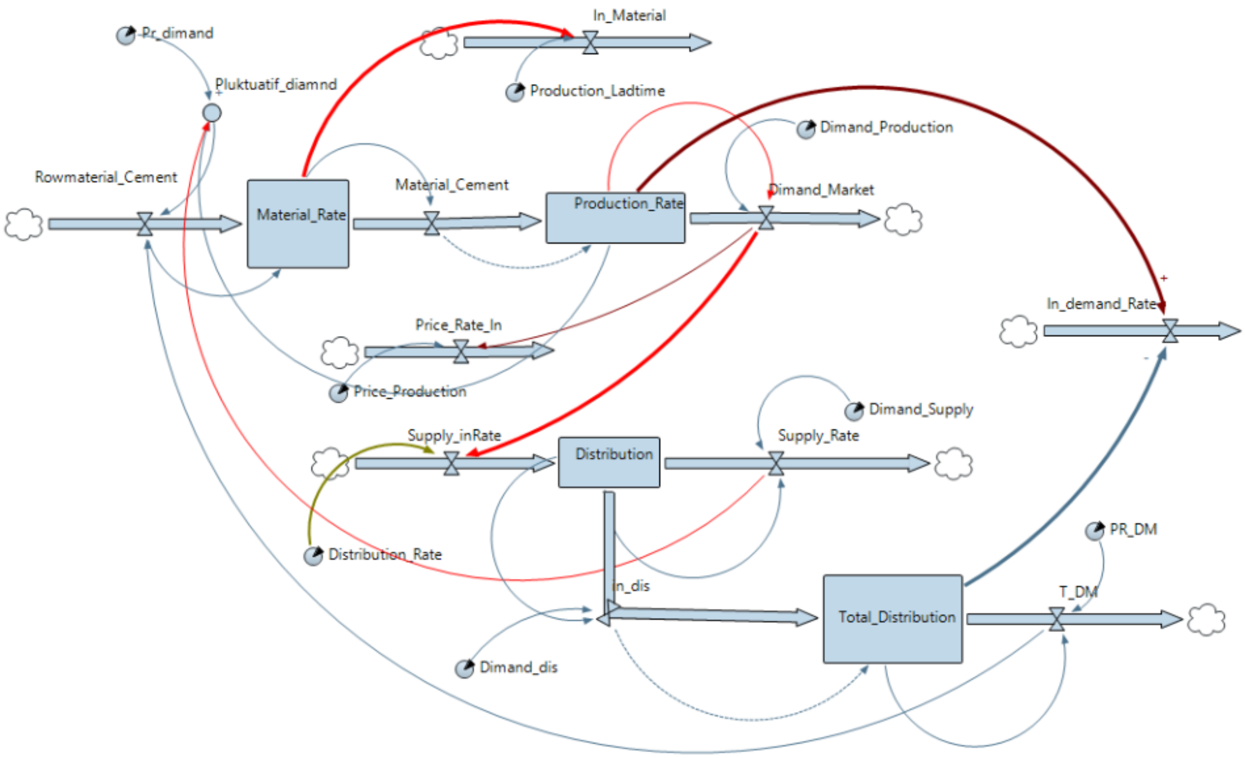

Fig. 2 *Comprehensive system dynamic model*

4.1.1 Growth Scenario Analysis

In the growth scenario, both supply and demand are high, while cement prices stay at a moderate level. This shows that the market is expanding, mainly because construction and infrastructure activities are increasing. The high supply level suggests that factories are producing enough to meet the strong demand. Clinker prices are high, meaning raw materials are under pressure due to competing demand in other industries. However, the dollar value and inflation remain low, helping to keep production costs stable. Overall, this creates a positive cycle where strong demand leads to increased production, which helps keep prices stable even with rising input costs. The model may show higher production levels, increased distribution, and some minor supply challenges.

4.1.2 Stability Scenario Analysis

In the stability scenario, supply, demand, and cement prices are all at moderate and balanced levels. This represents a mature market with steady business operations and minimal fluctuations. Clinker prices, the dollar value, and inflation are also moderate, signalling stable economic conditions. In the simulation, these factors support smooth production cycles, predictable delivery schedules, and steady inventory levels. Because supply and demand are balanced, the system stays in equilibrium, leading to consistent profits and efficient operations.

4.1.3 Recession Scenario Analysis

In the recession scenario, market conditions change significantly. Cement prices fall because demand decreases, while supply stays high, leading to oversupply. Low demand reflects reduced construction activity and slower economic growth. Even when prices drop, manufacturers may still produce at high levels due to fixed costs or existing inventory. Independent variables low clinker prices, a strong dollar, and low inflation reflect typical recession conditions. A strong dollar raises import costs, while low clinker prices show reduced global demand. In the simulation, these factors slow down production. With weak demand, distribution decreases, inventory piles up, prices stay low, and cash flow becomes tight. Overall, the recession scenario negatively affects the whole model, causing inefficiencies, higher inventories, and lower profits.

4.2 Analysis of System Dynamics in Various Scenarios

Across all scenarios, the dynamic model shows several consistent behaviours. Strengthened feedback loops heavily influence system performance. In growth periods, high demand boosts production and distribution, reinforcing market expansion. Rising prices also encourage producers to increase output. In contrast, during recessions, balancing feedback dominates: weak demand and excess supply push production downward to restore market stability. External pressures such as high dollar exchange rates raise production costs, reduce profits, and further limit output. Key stock variables like material stock, distribution levels, and demand rates determine the market's overall balance. In growth scenarios, these stocks change quickly due to fast turnover, while in recessions, they accumulate, revealing the system's sensitivity to slower market conditions.

The three scenarios—Optimistic, Moderate, and Pessimistic—were evaluated to assess supply chain performance under different market conditions using key indicators such as inventory costs, lead times, and order fulfilment rates.

i. Optimistic Scenario - The supply chain functions efficiently with stable demand and sufficient production capacity, resulting in low transportation expenses, minimal inventory costs, and smooth operations.
ii. Moderate Scenario - Fluctuations in demand and production lead to occasional delays, causing moderate inventory holding costs and variability in lead times.
iii. Pessimistic Scenario - Large demand swings and restricted production capacity increase system complexity, raising overall costs and reducing order fulfilment performance.

In this study, System Dynamics modelling was used to examine how material inventory (Material Stock), delivery rate (Material Rate), and production rate (Production Rate) interact within the cement industry supply chain. The simulation over 50-time units (Figure 3) demonstrates the system's response to high initial production and highlights the adjustments needed to maintain balance between raw material supply and production output. The results illustrate production stability, material availability trends, and potential risks arising from supply demand mismatches.

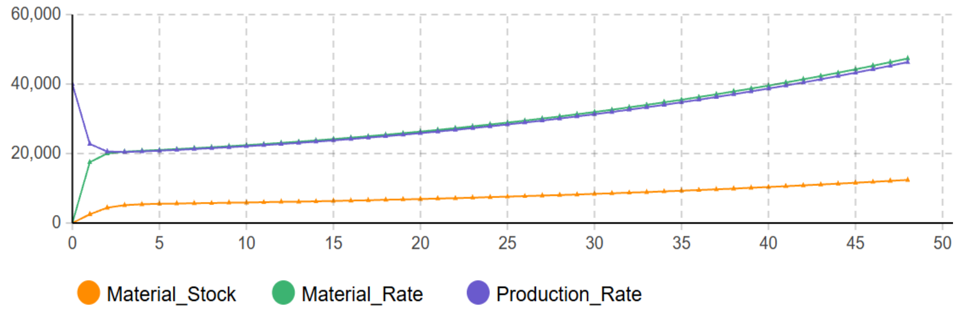

Fig. 3 *Simulation material stock, material rate and production rate*

From the figure, it shows how Material Stock, Material Rate, and Production Rate change over time. At the start, production is very high (about 40,000 tons) but quickly drops to around 20,000 tons because raw materials are not yet sufficient. Meanwhile, the Material Rate rises from 0 to about 18,000 tons, allowing Material Stock to gradually build up to around 6,000 tons. Between time units 5 and 30, the system stabilizes. Production Rate and Material Rate increase steadily (25,000–35,000 tons), and Material Stock grows slowly, reflecting efficient, lean inventory use. In the final phase (time 45–50), Production Rate reaches about 47,000 tons, closely followed by the Material Rate. Material Stock remains stable at 12,000–14,000 tons, ensuring smooth production. Overall, the simulation shows that the system becomes stable after early imbalances. The supply chain adapts well to production needs, though improving safety stock planning would help manage demand fluctuations more effectively.

Figure 4 illustrates the trends of total cement imports, demand rate, and supply rate over 60 months. Cement imports (purple line) rise sharply at the beginning, reaching their peak around months 15–20. After that, imports drop quickly and fall below zero after month 30, suggesting either a severe supply issue or a move toward reduced import dependence. The demand rate (orange line) shows a steady decline throughout the period, possibly due to policy changes, shifting market needs, or slower construction activity. The supply rate (green-brown line) increases slowly and remains relatively stable, but it does not fully compensate for the drop in imports. Overall, the graph indicates a changing supply structure, with a risk of imbalance when imports fall too quickly while local supply remains insufficient. In the early phase, high import levels reflect strong dependence on foreign supply.

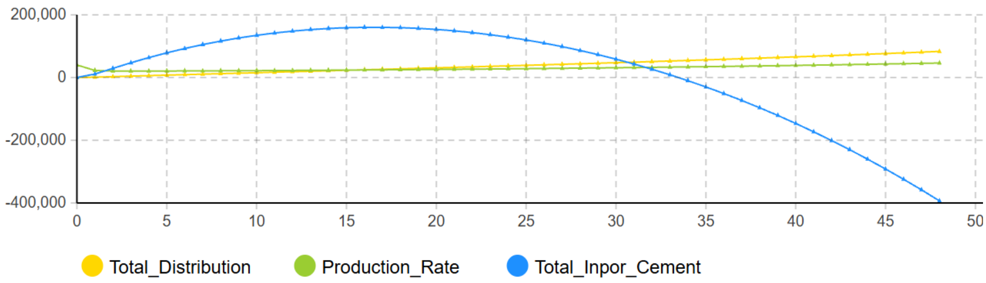

Fig. 4 *Temporal analysis of import vs. domestic production rates*

Between months 20–30, imports decline as domestic supply tries to cover demand, but the supply rate still cannot keep up. After month 35, imports decrease sharply into negative values, highlighting a potential supply crisis. With demand still high and domestic supply not increasing fast enough, the market may face shortages, project delays, and rising prices. The simulation suggests that reducing imports must be done gradually and supported by stronger domestic production, better inventory management, and improved demand forecasting. These actions are necessary to maintain supply–demand balance and ensure long-term stability in the cement supply chain.

Figure 5 shows that national cement demand fluctuates, and in the early months, this demand is mostly met through imports. Although domestic supply increases over time, it does not grow fast enough to match the steady demand trend. When imports drop sharply between months 30 and 50, the system becomes unstable. Imports fall into negative values, indicating a supply shortage. With demand still high and domestic supply unable to keep up, the market faces risks such as stockouts, project delays, and rising prices. The AnyLogic simulation further highlights the dynamic relationship between cement imports, production rates, and distribution volumes. At the beginning (up to months 15–20), imports rise significantly because domestic production cannot yet meet distribution needs. Imports peak in the middle period and then decline sharply approaching month 45. This pattern suggests that domestic production gradually becomes capable of replacing imports, eventually leading to potential oversupply.

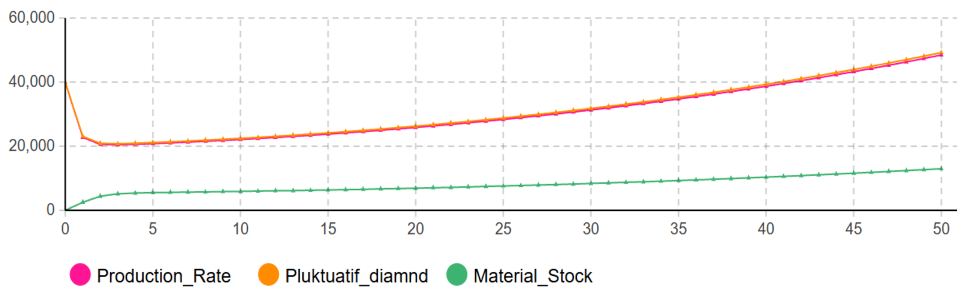

Fig. 5 *Fluctuation demand*

Production rates increase slowly but consistently, reflecting controlled expansion of domestic capacity. Total distribution also rises with market demand and slightly exceeds production towards the end, indicating pressure that must be managed through proper inventory planning. Overall, the simulation shows a transition from heavy import reliance to stronger domestic supply. These insights can guide supply chain strategies such as planning optimal production capacity, strengthening inventory policies, and managing import levels to reduce logistics costs and avoid excess stock or shortages.

The comparative scenario analysis highlights how demand growth and capacity expansion directly shape logistics efficiency and order fulfilment in the cement supply chain. In the Optimistic scenario, a 12% rise in demand coupled with an 8% increase in capacity leads to a 20% reduction in logistics costs and a 15% improvement in order fulfilment, reflecting strong resilience and operational efficiency. The Moderate scenario, with more modest growth (5% demand and 3% capacity), results in stable costs and only marginal gains in fulfilment (+3%), suggesting a balanced but less dynamic system. Conversely, the Pessimistic scenario, marked by stagnant demand growth (2%) and no capacity expansion, produces an 18% increase in logistics costs and a 12% decline in order fulfilment, underscoring the risks of inflexible capacity planning and the vulnerability of the supply chain under adverse conditions. This comparison as summarize in Table 2 demonstrates the critical importance of proactive capacity management in sustaining competitiveness and mitigating risks. In the model, negative import values represent a transition to net exports rather than unmet demand. This indicates that domestic production exceeded local demand, allowing surplus cement to be exported.

Table 2 *Comparative scenario analysis of demand growth and capacity expansion in cement supply chain*

Scenario	Demand Growth	Capacity Growth	Logistics Cost Change	Order Fulfilment Change
Optimistic	+12%	+8%	-20%	+15%
Moderate	+5%	+3%	Stable	+3%
Pessimistic	+2%	0%	+18%	-12%

5. Conclusion

This study developed an integrated dynamic strategic planning framework that combines System Dynamics, Game Theory, and Fuzzy Inference Systems to analyse and optimize the cement supply chain under diverse economic and market conditions. The simulation results reveal that supply chain performance is highly sensitive to feedback structures, demand fluctuations, production capacity constraints, and the timing of import adjustments. By evaluating optimistic, moderate, and pessimistic scenarios, the model effectively captured inventory behaviour, production–distribution alignment, and the system's reliance on imports. The findings emphasize that strong domestic production capacity and timely expansion are critical for maintaining stable inventory levels and reducing import dependency, particularly under favourable demand conditions. In contrast, limited production flexibility and abrupt reductions in imports can trigger significant imbalances, leading to shortages, higher costs, and weaker service performance. The integrated modelling approach underscores the importance of gradual import policy transitions, strengthened inventory management, and accurate demand forecasting to sustain long-term resilience. Overall, the proposed hybrid framework offers a robust decision-support tool for evaluating strategic alternatives in the cement supply chain. It enables policymakers and industry stakeholders to design adaptive, resilient, and cost-effective strategies that ensure sustainable performance amid uncertainty and dynamic market environments. Managers should employ dynamic simulation tools to anticipate demand variability, adjust capacity proactively, and reduce reliance on imports, while policymakers can leverage the framework to stabilize costs, enhance competitiveness, and strengthen supply chain resilience.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Yudi Maulana, Bukhari Manshoor, Syahreen Nurmutia;* ***data collection:*** *Yudi Maulana, Mairizal Zainuddin, Cristine Rothe;* ***analysis and interpretation of results:*** *Reazul Haq Abdul Haq, Mohammad Fahmi Abdul Ghafir, Izzuddin Zaman;* ***draft manuscript preparation:*** *Abdul Rafeq Saleman, Mohd Nizam Ibrahim. All authors reviewed the results and approved the final version of the manuscript.*

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