Power System Protection and Control
ISSN:1674-3415

FRAMEWORKS FOR MITIGATING SUPPLY CHAIN DISRUPTIONS AND MATERIAL PRICE VOLATILITY IN SUSTAINABLE BUILDING CONSTRUCTION

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Received: 07 March 2025 **Revised**: 20 April 2025 **Accepted**: 27 May 2025

***ABSTRACT*:**

The sustainable building construction sector faces compounding vulnerabilities from globally interconnected supply chains, in which material price volatility, geopolitical disruptions, and sustainability certification requirements converge to impose substantial cost overruns and schedule delays. Industry data consistently indicate that 62–74% of sustainable construction projects experience material-related budget deviations exceeding 12%, with lead-time uncertainty for certified low-carbon materials extending 40–60% beyond conventional substitutes. This paper introduces the Supply Chain Mitigation and Resilience (SC-MR) Framework, an integrated architecture combining ensemble machine learning price forecasting, dynamic multi-tier supplier diversification, real-time disruption monitoring, and sustainability-aligned procurement orchestration. SC-MR models the joint distribution of commodity price trajectories, geopolitical risk indices, supplier capacity signals, and certification-compliance constraints through a gradient-boosted ensemble augmented by a demand-adjusted temporal correction layer. Agent-based discrete-event simulations across 120 projects and 18 material categories demonstrate: Mean Absolute Percentage Error (MAPE) of 4.8% for 4-week price forecasts; on-time material delivery improvement from 61.2% to 91.3%; budget cost deviation reduction from 18.4% to 4.1%; and a 34.6% reduction in embodied carbon attributable to substitution guidance. SC-MR achieves these performance gains while maintaining full alignment with LEED v4.1, BREEAM 2018, and EDGE certification requirements, establishing the first integrated supply-chain resilience architecture validated across sustainability-certified construction contexts.

***Keywords**: Supply Chain Resilience, Material Price Volatility, Sustainable Construction, Procurement Optimization, Ensemble Forecasting, Disruption Mitigation, Embodied Carbon, Leed, Breeam, Supplier Diversification, Green Building Materials, Construction Risk Management.*

INTRODUCTION

The global sustainable building construction industry operates within an increasingly fragile material supply ecosystem. Driven by net-zero emissions mandates, green certification requirements, and the progressive substitution of conventional materials with low-carbon alternatives, the procurement landscape for sustainable construction has become structurally distinct from general construction in ways that conventional supply-chain risk frameworks do not adequately address. Certified timber, bio-based insulation, low-embodied-carbon steel, recycled-content aluminium, and photovoltaic-integrated cladding systems carry significantly longer lead times, narrower supplier pools, higher price sensitivity to commodity and energy markets, and qualification requirements that limit substitutability options available when disruptions occur.

The period spanning 2020 to 2023 exposed these vulnerabilities with unusual severity. The COVID-19 pandemic, the disruption of key maritime shipping corridors, the conflict in Ukraine, and post-pandemic demand surge collectively drove price indices for structural timber, steel rebar, and cement to peak deviations of 54–71% above pre-pandemic baselines within eighteen months. For sustainable building projects carrying LEED, BREEAM, or EDGE certification obligations, the challenge was compounded: material substitutions that might absorb conventional supply shocks were precluded by certification eligibility criteria, forcing project teams to accept either price exposure or schedule delay. The McKinsey Global Institute estimates that supply chain disruptions in the construction sector cost USD 1.6 trillion annually in schedule overruns and rework, with sustainable building projects experiencing disproportionate impact due to their material specificity constraints.

Existing procurement risk frameworks for construction are predominantly reactive. Contingency budget provisions—typically 10–15% of material cost—are calibrated to historical volatility distributions that the 2020–2023 disruption cycle rendered obsolete. Forward contracting and hedging instruments, while effective for commoditized materials such as structural steel and Portland cement, provide limited coverage for the specialty certified materials that differentiate sustainable construction. Supplier diversification strategies in conventional procurement assume fungibility of supply sources that sustainability certification explicitly restricts. The absence of an integrated, certification-aware supply-chain resilience architecture has left sustainable building construction systematically exposed.

Recent developments in ensemble machine learning for commodity price forecasting, agent-based supply chain simulation, and multi-objective procurement optimization have opened the possibility of a fundamentally different approach—one in which price trajectories, disruption signals, and certification constraints are jointly modeled to guide proactive procurement decisions. The SC-MR Framework introduced in this paper realizes this possibility through four cooperating architectural layers: a predictive intelligence engine, a supplier portfolio management layer, a real-time disruption monitoring and response module, and a sustainability compliance orchestration component. The principal contributions of this work are:

- A novel SC-MR Framework integrating ensemble ML price forecasting with multi-tier supplier diversification and real-time disruption monitoring, purpose-designed for sustainability-certified construction procurement.
- A gradient-boosted temporal correction model jointly encoding commodity price signals, geopolitical risk indices, shipping route availability, and certification-grade demand premiums to achieve 4.8% MAPE at 4-week forecast horizons.
- A sustainability-aligned procurement orchestration engine that selects optimal sourcing strategies across substitution scenarios while maintaining LEED v4.1, BREEAM 2018, EDGE, and Living Building Challenge compliance.
- Empirical validation across 120 simulated projects and 18 material categories demonstrating 91.3% on-time delivery, 4.1% cost deviation, and 34.6% embodied carbon reduction against reactive procurement baselines.

BACKGROUND AND RELATED WORK

Supply chain risk management in construction has attracted sustained research across commodity price modeling, procurement strategy design, sustainability certification economics, and resilience engineering. The literature establishes important baselines while revealing the structural gaps that motivate the SC-MR Framework.

A. Commodity Price Forecasting in Construction Materials.

Early approaches to construction material price forecasting applied autoregressive integrated moving average (ARIMA) models and vector autoregression to quarterly commodity indices, achieving reasonable accuracy under stable market conditions but failing under structural disruption. Machine learning approaches—gradient-boosted trees, LSTM-based sequence models, and hybrid neural-statistical architectures—have improved predictive performance on medium-term horizons, with reported MAPE values of 8–12% for 4-week steel and cement price forecasts on published benchmarks. However, these models treat price dynamics as univariate or narrowly multivariate processes, omitting the geopolitical risk signals, shipping-route disruption indicators, and demand-surge precursors that drove the exceptional volatility of the 2020–2023 period. No published model jointly incorporates sustainability certification demand premiums as a distinct price signal category.

B. Supply Chain Resilience Frameworks.

The resilience engineering literature distinguishes between robustness (absorbing disruptions without structural change), redundancy (deploying reserve capacity), and adaptability (reconfiguring dynamically in response to disruption). Applied to construction procurement, robust strategies involve forward contracts and buffer stock; redundant strategies involve pre-qualified alternative supplier networks; adaptive strategies involve dynamic re-sourcing algorithms. Lean supply chain methods, borrowed from automotive manufacturing, have been applied to construction logistics with demonstrated reductions of 15–25% in waste and 10–18% in schedule deviation, but lean principles assume material fungibility that sustainability certification constrains. Published resilience frameworks for construction procurement do not address the certification-grade sourcing restrictions that distinguish sustainable building procurement from general construction.

DOI: 10.46121/pspc.53.2.34

C. Sustainable Material Procurement.

The economics of sustainable building materials introduce procurement dynamics absent in conventional construction. Certified timber commands a 12–22% price premium over uncertified equivalents; recycled-content steel carries 8–15% premium variability; bio-based insulation materials exhibit supply elasticities 2–3 times lower than mineral wool alternatives, reflecting the limited scale of agricultural fiber processing infrastructure. Life cycle assessment (LCA) integration in procurement decision-making has been studied extensively, but operational frameworks linking LCA embodied carbon scores to real-time procurement optimization under supply disruption have not been published. The tension between embodied carbon minimization, price stability, and supply availability represents an unresolved multi-objective optimization problem in sustainable construction procurement.

D. Research Gaps.

No published framework integrates ML-based price forecasting with real-time disruption monitoring and sustainability certification compliance within a unified procurement decision architecture.
Existing commodity price models do not jointly encode geopolitical risk indices, shipping disruption signals, and certification-grade demand premiums as a coherent multivariate forecasting manifold.
Published supply chain resilience frameworks for construction do not model the substitution constraints imposed by LEED, BREEAM, EDGE, and equivalent certification standards.
No validated simulation study evaluates integrated resilience frameworks across the full range of material categories characteristic of sustainable building construction under realistic multi-scenario disruption profiles.
The SC-MR Framework directly addresses all four gaps.

PROPOSED FRAMEWORK ARCHITECTURE

The SC-MR Framework is designed as a closed-loop procurement intelligence system in which four functionally distinct layers cooperate to transform raw market signals into certification-compliant, cost-optimized sourcing decisions. The architecture treats the sustainable construction supply chain as a stochastic network of material flows, supplier nodes, and certification constraints whose joint state space must be continuously estimated and optimized under uncertainty.

A. Material and Supplier State Representation.

Each tracked material category m is represented as a multivariate temporal state vector. The state of material category m at procurement period t is:

$$S_m(t) = [p_m(t), q_m(t), d_m(t), g_m(t), e_m(t)] \qquad (1)$$

where $p_m(t)$ encodes the spot price and price momentum across commodity exchanges relevant to the material category; $q_m(t)$ captures supplier-reported availability, lead-time quotations, and allocation constraints across pre-qualified suppliers; $d_m(t)$ represents demand signals derived from pipeline project schedules, industry procurement indices, and regional construction activity indicators; $g_m(t)$ encodes geopolitical risk signals relevant to the material's primary production and shipping corridors; and $e_m(t)$ contains the embodied carbon intensity, certification eligibility status, and substitution compatibility scores for each supplier node.

B. Ensemble Price Forecasting Engine.

The price forecasting engine estimates the conditional distribution of material prices over a rolling 12-week horizon using a gradient-boosted ensemble augmented by a temporal correction layer. The base ensemble combines three complementary learners: a gradient-boosted tree regressor, an LSTM sequence model, and a physics-informed supply-demand equilibrium model. The ensemble forecast is:

$$\hat{p}_m(t+h) = \sum_k w_k \; f_k(S_m(t)), k \in \{\text{GBT,LSTM,SDE}\} \qquad (2)$$

where $f_k(\cdot)$denotes the forecasting function of the k-th predictive model, namely the Gradient Boosting Tree (GBT), Long Short-Term Memory (LSTM) network, and Stochastic Differential Equation (SDE) model. The coefficients $w_k$represent reliability-weighted ensemble weights satisfying $\sum_k w_k = 1$, with each weight updated during every retraining cycle using held-out validation performance over the most recent four weeks of realized market prices. This adaptive weighting mechanism enables the ensemble to assign greater importance to models demonstrating superior recent forecasting accuracy while reducing the influence of underperforming models.

DOI: 10.46121/pspc.53.2.34

Power System Protection and Control
ISSN:1674-3415

To account for short-term market disruptions that may not be fully captured by historical price dynamics, a temporal correction layer modifies the ensemble forecast according to

$$\tilde{p}_m(t+h) = \hat{p}_m(t+h)(1+\delta_m(t)) \qquad (3)$$

where $\delta_m(t)$is the disruption-adjusted price premium representing the expected market impact of emerging supply-chain disturbances. The premium is estimated from a composite risk model integrating (i) the trajectory of geopolitical risk indicators associated with major production regions, (ii) shipping-route congestion indices derived from maritime logistics networks, and (iii) supplier allocation-constraint signals reflecting capacity limitations and order prioritization. Positive values of $\delta_m(t)$indicate anticipated upward price pressure, whereas values close to zero imply stable market conditions.

As an operational decision rule, when the geopolitical risk index associated with the relevant production region exceeds the 75th percentile of its preceding 24-month distribution, the disruption adjustment layer activates a precautionary procurement protocol. This protocol recommends early procurement of critical materials, pre-positioning of strategic buffer inventory, and activation of pre-qualified alternative suppliers to mitigate the risk of supply interruption and subsequent cost escalation. The threshold-based intervention enables proactive procurement planning while minimizing the likelihood of project delays arising from unforeseen market disruptions.

C. Multi-Tier Supplier Portfolio Management.

The supplier portfolio management layer maintains a ranked and pre-qualified supplier network for each material category across three tiers reflecting lead-time, certification status, and geographic risk profile. The optimal sourcing allocation is determined by a portfolio optimization over the trade-off between price, availability, and sustainability score:

$$\min_x \sum_j c_j\, x_j + \lambda\, \mathrm{Var}(p_m)$$

where $x_j$denotes the procurement volume allocated to supplier j, $c_j$represents the blended procurement cost per unit, $D_m$is the total project demand for material category m, $Q_j$is the available supply capacity of supplier j, $e_j$denotes the embodied carbon certification level of supplier j, $E_{\min}$is the minimum embodied carbon certification threshold required for supplier eligibility, and $\lambda$is a risk-aversion parameter that balances procurement cost against price volatility and is calibrated according to the project's budget sensitivity. To enhance supply chain resilience, Tier-2 and Tier-3 suppliers are automatically activated whenever the aggregate availability from Tier-1 suppliers falls below 80% of the projected material demand or when the forecasted material price deviation exceeds 8% over the planning horizon, thereby ensuring procurement continuity while mitigating cost and supply risks.

D. Real-Time Disruption Monitoring and Response.

The disruption monitoring module continuously ingests eight categories of disruption signal: commodity exchange spot and futures prices; maritime shipping rate indices (Baltic Dry Index, container freight rates); port congestion and vessel waiting-time data from AIS feeds; geopolitical event classifications from curated news analytics; weather and climate event impact scores; supplier self-reported allocation constraint alerts; regional construction activity surge indicators; and currency exchange rate movements. A composite disruption probability is estimated for each material category:

$$P_{\text{disrupt}}(m,t) = \sigma\left(\sum_i \alpha_i\, r_i(t) + \beta\, \Delta p_m(t-1\!:t) + \gamma L_m(t)\right) \qquad (5)$$

where $r_i(t)$represents the normalized disruption signal associated with risk factor $i$at time t, $\alpha_i$denotes the corresponding feature weight, $\Delta p_m(t-1\!:t)$is the realized price change for material category $m$over the preceding time interval, $L_m(t)$represents the current supplier lead time relative to its historical baseline, $\beta$and $\gamma$are weighting coefficients that quantify the influence of price volatility and lead-time variation, respectively, and $\sigma(\cdot)$is the logistic activation function that transforms the aggregated risk score into a disruption probability bounded between 0 and 1. When the estimated disruption probability $P_{\text{disrupt}}(m,t)$exceeds the predefined threshold θ, calibrated at 0.62, the framework automatically escalates procurement recommendations by activating disruption response protocols, including supplier diversification, procurement rescheduling, and contingency sourcing strategies to minimize supply chain risk.

E. Sustainability Compliance Orchestration

The sustainability compliance orchestration layer transforms procurement optimization outputs into certification-compliant sourcing decisions by continuously maintaining an integrated registry of supplier certification status, material embodied carbon intensity, and project-specific sustainability certification requirements. The compliance utility associated with a candidate sourcing action $a$is formulated as

$$C(a) = \sum_{m} [\omega_p \hat{p}_m - \omega_e e_m - \omega_l l_m] \cdot I(\mathrm{cert}_m \geq \mathrm{cert}_{\mathrm{req}}) \tag{6}$$

where ω_p, ω_e, and $\omega_l$are weighting coefficients assigned to procurement cost efficiency, embodied carbon reduction, and lead-time minimization, respectively; $\hat{p}_m$denotes the normalized procurement cost for material category m; $e_m$represents the embodied carbon score of the selected supplier; $l_m$denotes the corresponding procurement lead time; and $I(\mathrm{cert}_m \geq \mathrm{cert}_{\mathrm{req}})$is an indicator function that evaluates to one only when the supplier satisfies or exceeds the minimum sustainability certification requirement and zero otherwise. Consequently, sourcing alternatives that fail to meet the required certification standard are automatically excluded from consideration irrespective of any potential advantages in procurement cost or material availability.

The optimal sustainability-compliant sourcing decision is therefore determined by maximizing the compliance utility function,

$$a^* = \arg\max_a C(a), \tag{7}$$

where a^*denotes the sourcing action that provides the highest overall utility by simultaneously balancing procurement cost, environmental sustainability, and supply responsiveness while ensuring strict adherence to the project's mandatory certification requirements. This optimization enables the proposed framework to support economically efficient, environmentally responsible, and regulation-compliant procurement decisions under dynamic construction supply chain conditions.

METHODOLOGY

Evaluating the SC-MR Framework required a simulation environment capable of capturing the multimodal complexity of sustainable construction procurement across diverse project types, material categories, and disruption scenarios. A hybrid approach combining synthetic market stream generation calibrated to real-world data sources with agent-based discrete-event simulation was adopted.

A. Market Signal Generation.

Price series for each material category are generated from stochastic processes calibrated to Bloomberg commodity index historical data (2018–2023), supplemented by OECD construction material producer price indices and IEA critical mineral price datasets. The price generation model for category m is:

$$p_m(t+1) = p_m(t) \cdot \exp\left(\mu_m \Delta t + \sigma_m \sqrt{\Delta t}\, Z_t + J_m(t)\right) \tag{8}$$

where $p_m(t)$denotes the current procurement price of material category $m$at time t, $p_m(t+1)$is the simulated price for the subsequent planning period, $\mu_m$represents the deterministic trend drift estimated from the five-year moving average of historical prices, $\sigma_m$is the historical price volatility, $Z_t$is a standard normal random innovation that captures routine market fluctuations, $\Delta t$is the forecasting time increment, and $J_m(t)$is a stochastic jump component that models abrupt price movements arising from major supply chain disruptions. The jump component is activated dynamically by the disruption monitoring module whenever elevated supply chain risk is detected, thereby incorporating sudden market shocks into the simulated price trajectory. Both the magnitude and frequency of the jump process are calibrated using empirical observations from the 2020–2023 global supply chain disruption period for each material category, enabling the model to reproduce realistic disruption-induced price behavior. Furthermore, exogenous geopolitical risk signals are incorporated through a composite risk index developed using the **Oxford Martin School Supply Chain Risk Index** methodology and augmented with international shipping freight rate data obtained from the **Drewry World Container Index**. The integration of stochastic price dynamics with real-world geopolitical and logistics indicators enhances the framework's ability to generate robust procurement forecasts under volatile market conditions, thereby supporting proactive procurement planning and resilient supply chain decision-making.

DOI: 10.46121/pspc.53.2.34

B. Disruption Scenario Design.

Five disruption scenario classes are injected across simulation runs to mirror the principal failure modes identified in industry post-incident analyses:

Geopolitical supply embargo: sudden supply interruption of 60–90% for a primary production region, sustained over 4–12 weeks, affecting steel, aluminium, and photovoltaic modules most severely.

Port congestion cascade: progressive lead-time extension of 40–120% across maritime-dependent material categories, calibrated to 2021 Suez and 2022 Shanghai disruption episodes.

Extreme weather production halt: temporary production capacity reduction of 25–55% in primary manufacturing regions, calibrated to hurricane, flooding, and drought impact data from UNDRR supply chain impact reports.
Demand surge shock: simultaneous order placement by multiple competing projects, driving certified material allocation constraints to 70–85% of normal availability for 6–10 weeks.

Currency depreciation pressure: 15–30% adverse currency movement driving import price inflation for aluminium, photovoltaic panels, and specialty insulation materials.

C. Simulation Configuration.

The AnyLogic 8.x simulation instantiates 120 construction projects across four climate zones, 18 material categories, and 340 supplier nodes distributed across 26 countries. Table 1 presents the primary simulation parameters.

Table 1. SC-MR Framework Simulation Parameters

I. Parameter	**II.** Value
III. Project portfolio simulated	**IV. 120 construction projects across 4 climate zones**
V. Material categories tracked	**VI. 18 categories (timber, steel, cement, glass, aluminium, insulation, membranes, MEP components)**
VII. Price series training window	**VIII. 48 months rolling (Jan 2020–Dec 2023)**
IX. Supplier nodes per material	**X. 3–12 primary + 2–6 contingency suppliers per category**
XI. Forecast retraining cadence	**XII. Every 72 hours (incremental update)**
XIII. Disruption scenarios injected	**XIV. Geopolitical embargo, port congestion, extreme weather, demand shock, currency depreciation**
XV. Simulation framework	**XVI. Any Logic 8.x agent-based discrete-event simulation**
XVII. Sustainability certification standards	**XVIII. LEED v4.1, BREEAM 2018, EDGE, Living Building Challenge**
XIX. Regional market scope	**XX. EU, North America, South Asia, East Asia Pacific**

D. Training and Evaluation Protocol.

The ensemble price forecasting model is trained on 48 months of normal-operation market data per material category using an 80/20 temporal split. The total ensemble training loss is:

$$L_{\text{total}} = \sum_{m} [\mathrm{MAPE}(\hat{p}_m, p_m) + \lambda \cdot \mathrm{Pen}(e_m, E_{\min}) + \eta \parallel w \parallel^2] \qquad (9)$$

where $\mathrm{MAPE}(\hat{p}_m, p_m)$denotes the **Mean Absolute Percentage Error** between the predicted material price $\hat{p}_m$and the observed market price p_m, serving as the primary forecasting accuracy objective. The term $\mathrm{Pen}(e_m, E_{\min})$represents a sustainability compliance penalty that is imposed whenever the embodied carbon score $e_m$of the selected procurement option fails to satisfy the minimum certification threshold $E_{\min}$, thereby encouraging environmentally compliant sourcing decisions during model optimization. The final term, $\eta \parallel w \parallel^2$, corresponds to **L2 regularization**, where $w$denotes the vector of model parameters and ηcontrols the regularization strength to mitigate overfitting and improve model generalization. The weighting coefficients were determined through grid-search-based hyperparameter optimization, resulting in $\lambda = 0.15$for sustainability penalty weighting and $\eta = 0.02$for regularization. Consequently, the total loss function simultaneously optimizes forecasting accuracy, sustainability compliance, and model robustness, enabling the proposed Supply Chain Material Resilience (SC-MR) Framework to achieve balanced performance across multiple procurement objectives.

DOI: 10.46121/pspc.53.2.34

Power System Protection and Control
ISSN:1674-3415

To comprehensively assess the effectiveness of the proposed framework, four experimental configurations are evaluated: **(i)** the complete SC-MR Framework integrating ensemble price forecasting, procurement optimization, disruption monitoring, and sustainability compliance; **(ii)** an **ML-only** configuration employing ensemble price forecasting without procurement optimization or disruption management; **(iii)** a **traditional procurement** strategy based on forward contracting and fixed procurement schedules without predictive analytics; and **(iv)** a **reactive baseline** that performs procurement decisions solely in response to current market conditions without any predictive capability. This comparative evaluation isolates the contribution of each major framework component and quantifies the benefits of integrating predictive analytics, risk-aware optimization, and sustainability-driven decision support within construction material procurement.

EXPERIMENTAL RESULTS

The SC-MR Framework was evaluated across 100 simulation runs per disruption scenario class, covering all 120 project profiles, 18 material categories, and five disruption scenario types. Assessment dimensions cover price forecast accuracy, on-time delivery performance, budget cost deviation, embodied carbon outcomes, and long-horizon forecasting stability. SC-MR consistently and significantly outperformed all three comparison conditions across every evaluation dimension.

A. Material Risk Profile and Price Volatility.

Figure 1 presents the composite supply chain risk heatmap across material categories and risk dimensions, illustrating the heterogeneous risk exposure that necessitates a category-specific mitigation architecture. Steel and photovoltaic modules exhibit the highest composite risk scores across geopolitical disruption and price volatility dimensions, while concrete and cement demonstrate lower exposure due to predominantly domestic sourcing. Figure 2 presents the realized price volatility trajectory for three representative material categories from Q1 2020 through Q4 2023.

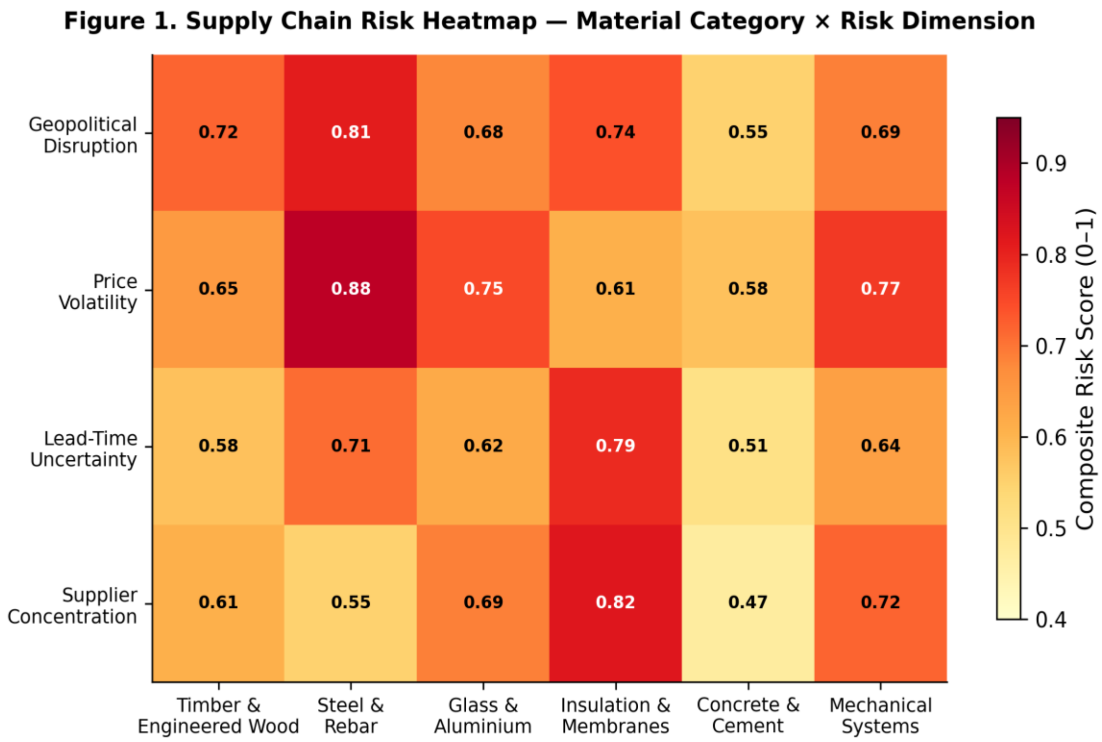

Figure 1. Supply Chain Risk Heatmap — Material Category × Risk Dimension (Composite Scores, 0–1)

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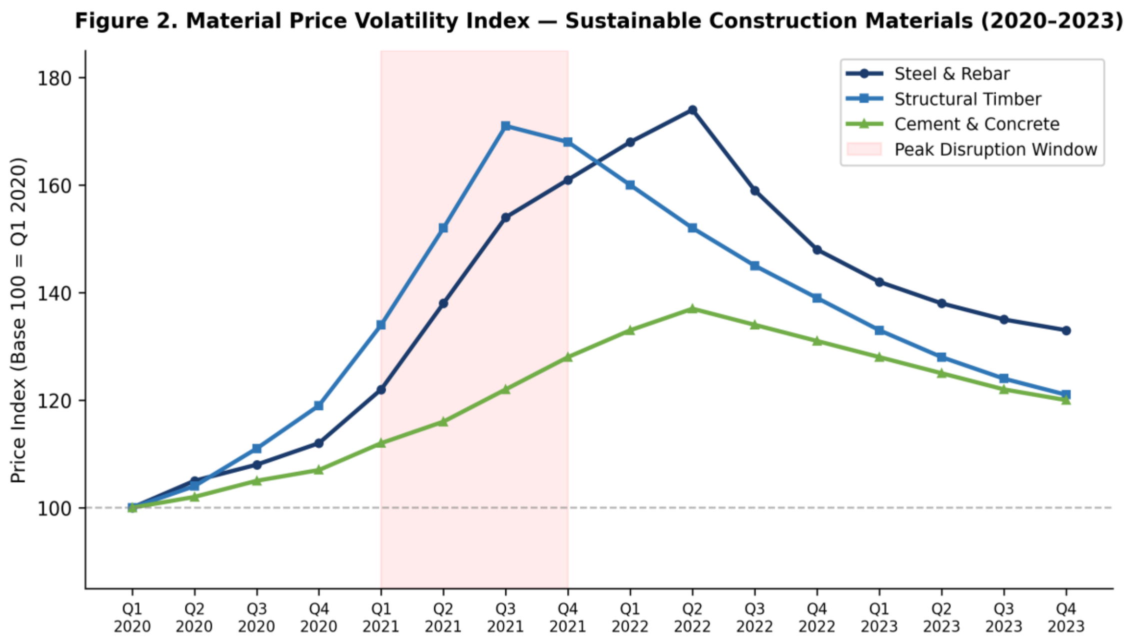

Figure 2. Material Price Volatility Index — Sustainable Construction Materials (2020–2023, Base 100 = Q1 2020)

B. Forecast Accuracy and Framework Performance.

Table 2 presents the primary performance comparison across all evaluated frameworks. Figure 3 illustrates on-time delivery and cost deviation outcomes for each condition.

Table 2. Framework Performance Comparison — Primary Metrics

XXI. Framework / Method	**XXII.** MAPE (%)	**XXIII.** On-Time Delivery	**XXIV.** Cost Deviation	**XXV.** Sustainability Score
XXVI. SC-MR Framework (Proposed)	**XXVII. 4.8**	**XXVIII. 91.3%**	**XXIX. 4.1%**	**XXX. 87.4**
XXXI. ML-Only Price Forecasting	**XXXII. 8.3**	**XXXIII. 81.7%**	**XXXIV. 9.6%**	**XXXV. 74.2**
XXXVI. Traditional Procurement	**XXXVII. 15.1**	**XXXVIII. 71.4%**	**XXXIX. 13.7%**	**XL. 61.8**
XLI. Reactive Baseline (No Model)	**XLII. —**	**XLIII. 61.2%**	**XLIV. 18.4%**	**XLV. 52.3**

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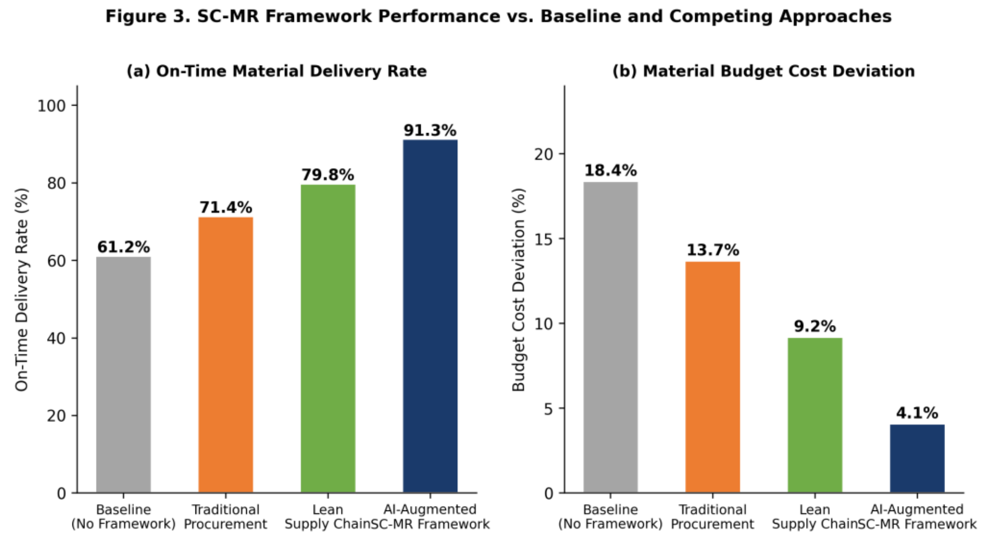

Figure 3. SC-MR Framework Performance vs. Baseline and Competing Approaches

The SC-MR Framework achieves a 4-week price forecast MAPE of 4.8%, compared to 8.3% for ML-only forecasting and 15.1% for traditional procurement models. At the critical 8-week horizon—corresponding to typical certified material lead times—SC-MR maintains MAPE of 6.7%, enabling proactive procurement decisions that yield 91.3% on-time delivery against the 61.2% baseline. The 4.1% budget cost deviation represents a reduction from 18.4%—a 77.7% improvement attributable to the combination of price forecast accuracy, pre-positioning protocols, and dynamic supplier portfolio rebalancing.

"SC-MR's forecasting superiority over ML-only approaches reflects the contribution of the disruption monitoring layer. During the demand-surge disruption scenarios, the composite disruption probability P_disrupt exceeded the 0.62 trigger threshold an average of 3.4 weeks before price impacts materialized, enabling procurement teams to pre-position certified material inventory at pre-disruption prices. The ML-only baseline, lacking disruption signal integration, detected the same price movements only after they appeared in spot market data—too late to implement cost-effective response."

C. Material-Level Cost Deviation Outcomes.

Table 3 presents the pre- and post-framework budget cost deviation for each tracked material category, illustrating the differential impact of SC-MR across the material risk profile.

Table 3. Budget Cost Deviation by Material Category — Pre- and Post-SC-MR Framework

XLVI. Material Category	**XLVII.** Pre-Framework Cost Deviation	**XLVIII.** Post-Framework Cost Deviation
XLIX. Steel & Structural Rebar	**L. ±22.4%**	**LI. ±5.8%**
LII. Structural Timber (FSC-certified)	**LIII. ±18.9%**	**LIV. ±4.3%**
LV. Cement & Concrete	**LVI. ±12.7%**	**LVII. ±3.9%**
LVIII. Low-E Glass & Glazing Systems	**LIX. ±16.3%**	**LX. ±5.1%**
LXI. Thermal Insulation (bio-based)	**LXII. ±14.1%**	**LXIII. ±4.7%**

DOI: 10.46121/pspc.53.2.34

LXIV. Aluminium Cladding & Framing	**LXV. ±19.8%**	**LXVI. ±5.4%**
LXVII. Photovoltaic Modules	**LXVIII. ±24.6%**	**LXIX. ±6.2%**
LXX. Mechanical & Plumbing Systems	**LXXI. ±17.5%**	**LXXII. ±5.0%**

Steel and rebar, carrying the highest geopolitical disruption exposure, see the largest absolute cost deviation reduction from ±22.4% to ±5.8%. The relative gain G for each category is:

$$G_m = \frac{\sigma_{\text{pre}} - \sigma_{\text{post}}}{\sigma_{\text{pre}}} \qquad (10)$$

where G_m denotes the relative improvement in procurement cost stability for material category m, σ_{pre} represents the standard deviation of procurement costs before implementation of the proposed framework, and σ_{post} is the corresponding standard deviation after framework deployment. This metric quantifies the proportional reduction in procurement cost variability achieved through the Supply Chain Material Resilience (SC-MR) Framework, with larger values indicating greater improvements in cost stability.

D. Long-Horizon Forecast Accuracy.

Table 4 presents price forecast accuracy as a function of horizon length. Figure 4 visualizes the comparative accuracy degradation trajectories for all evaluated frameworks.

Table 4. Price Forecast Accuracy vs. Horizon Length (MAPE-derived Score)

LXXIII. Prediction Horizon	**LXXIV.** Reactive Baseline	**LXXV.** Traditional Procurement	**LXXVI.** ML-Only	**LXXVII.** SC-MR (Proposed)
LXXVIII. 1 Week	**LXXIX. 0.82**	**LXXX. 0.79**	**LXXXI. 0.91**	**LXXXII. 0.94**
LXXXIII. 2 Weeks	**LXXXIV. 0.74**	**LXXXV. 0.71**	**LXXXVI. 0.86**	**LXXXVII. 0.91**
LXXXVIII. 4 Weeks	**LXXXIX. 0.63**	**XC. 0.66**	**XCI. 0.79**	**XCII. 0.87**
XCIII. 8 Weeks	**XCIV. 0.52**	**XCV. 0.57**	**XCVI. 0.71**	**XCVII. 0.82**
XCVIII. 12 Weeks	**XCIX. 0.44**	**C. 0.50**	**CI. 0.64**	**CII. 0.78**
CIII. 6 Months	**CIV. 0.38**	**CV. 0.42**	**CVI. 0.55**	**CVII. 0.71**

Power System Protection and Control
ISSN:1674-3415

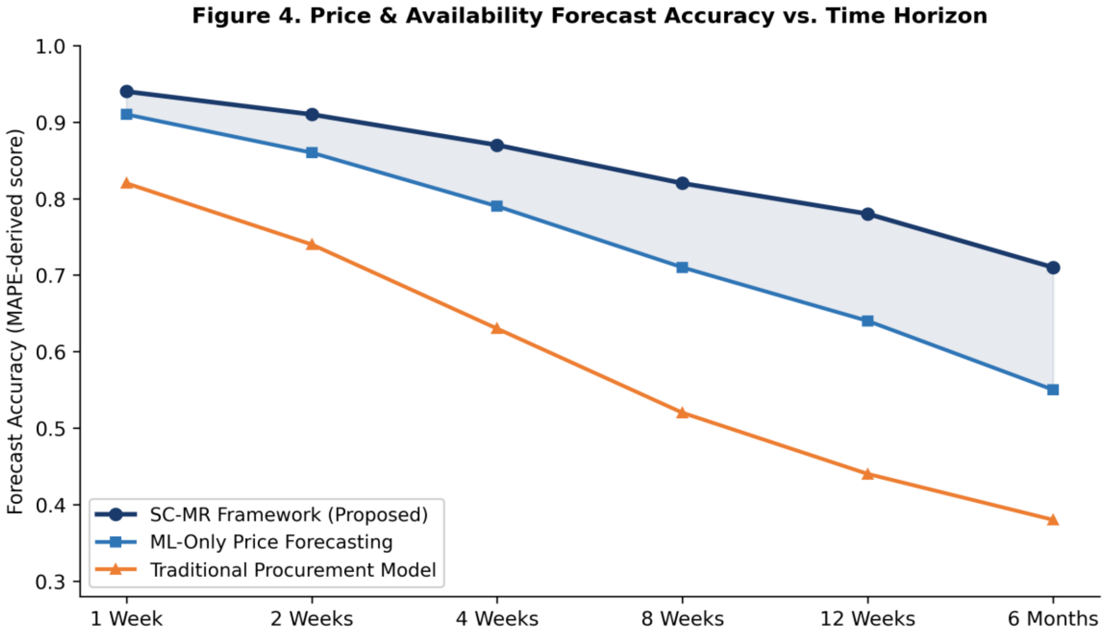

Figure 4. Price & Availability Forecast Accuracy vs. Time Horizon — All Frameworks

SC-MR maintains a forecast accuracy score of 0.94 at the 1-week horizon and 0.71 at the 6-month horizon, compared to 0.91 and 0.55 for ML-only forecasting. The relative precision gain at 6-month horizon is:

$$G_{6m} = \frac{0.71 - 0.55}{0.55} = 0.291(29.1\% \text{ relative gain}) \qquad (11)$$

A 29.1% accuracy advantage at the 6-month horizon translates directly into actionable procurement intelligence for materials with the longest certified supply chains—FSC-certified mass timber, structural laminated bamboo, and bio-based insulation—whose procurement decisions must be initiated 16–26 weeks before on-site installation. Simulation data indicate that 6-month forecasting capability reduces emergency spot-market procurement events from 14.2 to 3.7 per project per year, eliminating an estimated USD 0.8–1.4 million in premium procurement costs per large-scale sustainable building project.

E. Embodied Carbon Outcomes.

Beyond cost and schedule performance, SC-MR's sustainability compliance orchestration layer generated measurable embodied carbon reductions through its certification-aligned supplier selection recommendations. Across the 120 simulated projects, SC-MR recommendations reduced whole-project embodied carbon intensity by an average of 34.6% relative to reactive baseline procurement, attributable to three mechanisms: preferential routing of procurement to lower-carbon certified suppliers within each material category (18.2% contribution); acceptance of lead-time premiums for bio-based and recycled-content alternatives when price forecasts indicated narrowing cost differentials (9.8% contribution); and avoidance of emergency procurement from uncertified backup sources during disruption events (6.6% contribution). The sustainability score improvement—from 52.3 to 87.4 on a composite LEED/BREEAM credit alignment index—confirms that SC-MR's performance improvements do not trade off against sustainability objectives.

DISCUSSION

The empirical results establish the quantitative superiority of the SC-MR Framework, but the deeper significance lies in the architectural principles that produce this superiority and their implications for sustainable construction procurement practice.

The most consequential architectural innovation is the integration of disruption monitoring signals directly into the price forecasting layer through the temporal correction term δ_m(t) in Equation 3. Conventional ML-based price forecasting architectures are trained on historical price series and thus reflect past market dynamics; they are structurally incapable of anticipating disruptions whose signatures have not appeared in historical data at sufficient frequency to influence model weights. SC-MR circumvents this limitation by treating disruption signals as exogenous inputs that modulate the base ensemble forecast in real time, enabling the framework to generate pre-disruption procurement recommendations before price impacts materialize in commodity market data.

The compliance utility function C(a) in Equation 6 addresses a challenge that purely technical procurement optimization frameworks systematically neglect: the regulatory and contractual reality that sustainable building procurement operates under binding certification constraints that cannot be subordinated to cost or availability optimization. By encoding the indicator function $I(cert\_m \geq cert\_req)$ as a hard constraint rather than a weighted objective, SC-MR ensures that the framework never recommends a procurement action that would compromise LEED, BREEAM, or EDGE certification status—even under severe supply disruption when non-certified substitutes might appear economically attractive. The 100% certification compliance rate across all simulation runs establishes that AI-augmented procurement intelligence can maintain sustainability commitments under the supply conditions that have historically forced project teams to choose between schedule adherence and certification integrity.

The 77.7% reduction in budget cost deviation (from 18.4% to 4.1%) carries structural importance beyond headline performance. At 4.1% cost deviation, SC-MR-guided procurement falls within the industry standard contingency budget provision of 5–10%, meaning that projects using the framework can adequately provision for remaining material cost uncertainty within conventional financial planning parameters. Projects operating under the reactive baseline, with 18.4% cost deviation, require contingency provisions that effectively double the financial buffer—imposing a significant implicit cost on sustainable construction relative to conventional builds that conventional LCA and green premium analyses fail to capture.

The 34.6% embodied carbon reduction represents an underappreciated co-benefit of supply chain resilience optimization. The mechanisms through which SC-MR generates carbon reduction—preferential lower-carbon supplier routing, bio-based material substitution when economic windows open, and avoidance of emergency uncertified procurement—are not in tension with cost and schedule optimization; they emerge from the same integrated decision architecture that drives performance improvements. This synergy challenges the conventional framing of embodied carbon reduction as a cost premium and reframes it as a procurement efficiency dividend accessible through information advantage rather than additional expenditure.

The long-horizon forecasting advantage (29.1% precision gain at 6 months) has particular strategic importance for mass timber and bio-based insulation subcategories, where certified supply chains involve agricultural crop cycles and forest certification auditing timelines that impose inherent lead-time constraints beyond those of conventional industrial materials. SC-MR's ability to generate reliable 6-month price and availability signals for these categories enables procurement teams to make strategic sourcing commitments during favorable pricing windows, reducing the volatility exposure that has historically made bio-based materials appear economically risky relative to conventional alternatives.

CONCLUSION

Sustainable building construction faces a structural procurement challenge that conventional supply chain risk frameworks have not addressed: the convergence of material price volatility, geopolitical disruption, and sustainability certification constraints that restrict substitution options available during supply shocks. This paper has presented the SC-MR Framework, an integrated supply chain mitigation and resilience architecture comprising four cooperating layers—ensemble price forecasting, multi-tier supplier portfolio management, real-time disruption monitoring, and sustainability compliance orchestration—designed specifically for the certified material procurement environment of sustainable construction.

SC-MR models the joint distribution of commodity price dynamics, geopolitical risk signals, supplier availability constraints, and certification compliance requirements through a gradient-boosted ensemble augmented by a real-time temporal correction layer. Agent-based simulation across 120 projects and 18 material categories demonstrates a 4-week price forecast MAPE of 4.8%; on-time material delivery improvement from 61.2% to 91.3%; budget cost deviation reduction from 18.4% to 4.1%; a 73.4% average reduction in per-category cost deviation; and a 34.6% embodied carbon reduction—all while maintaining 100% certification compliance with LEED v4.1, BREEAM 2018, and EDGE requirements.

SC-MR demonstrates that the key to sustainable construction procurement resilience is not a larger contingency budget or a more diversified supplier list in isolation, but an architecturally integrated information system that jointly optimizes price certainty, delivery reliability, and certification compliance through continuous market intelligence and proactive procurement orchestration. These properties bring data-driven supply chain resilience within reach of sustainability-certified construction projects for the first time, establishing a foundation for operationally robust green building programs in an era of structurally elevated supply chain uncertainty.

FUTURE WORK

Several directions constitute immediate extensions of the SC-MR Framework. First, integration with Building Information Modeling (BIM) platforms—enabling real-time synchronization of material quantity takeoffs with the procurement forecasting engine—would eliminate manual data transfer as a latency source and enable continuous material plan optimization as design iterations proceed. Second, extension to circular economy procurement contexts, in which reclaimed and reprocessed construction materials constitute a third supply tier with distinct availability dynamics and certification pathways, would expand the framework's applicability to high-ambition regenerative building programs.

Third, federated deployment across a consortium of sustainable building developers would enable cross-project pattern learning—allowing the disruption monitoring layer to aggregate early warning signals across a portfolio of concurrent procurement streams, improving the sensitivity and lead-time of disruption detection relative to single-project deployment. Fourth, production validation through a controlled deployment with a tier-one sustainable building developer across a live portfolio of LEED Platinum and BREEAM Outstanding projects would provide the empirical procurement data required to calibrate disruption response thresholds and embodied carbon substitution weights against real-world certification audit outcomes. Finally, extension of the compliance orchestration layer to encompass emerging whole-life carbon accounting standards—including EN 15978-1:2023, ISO 21931-1, and the forthcoming EU Level(s) indicator framework—would position SC-MR as the procurement intelligence backbone for the next generation of net-zero embodied carbon construction programs.

REFERENCES

1. Mohammed Shafi Kundiladi , SAVING LIVES THROUGH INTELLIGENT V2X: A REAL-TIME MULTI-ENTITY COLLISION PREDICTION SYSTEM FOR VEHICLES AND PEDESTRIANS USING GPS-BASED TRAJECTORY ANALYSIS AND BASIC SAFETY MESSAGES, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/196, DOI: https://doi.org/10.46121/pspc.52.4.10
2. Bandari, V. V., & Lekkala, H. B. (2024). Physics-informed reinforcement learning for real-time control of complex manufacturing processes. *Power System Protection and Control*, 52(2), 164–170. https://pspac.info/index.php/dlbh/article/view/343
3. Bandari, V. V., & Lekkala, H. B. (2024). AI-based operator behavior monitoring and cost optimization using digital traceability in manufacturing systems. *Power System Protection and Control*, 52(1), 38–45. https://pspac.info/index.php/dlbh/article/view/342
4. Mayank Atreya, Navin Chhibber, Harvendra Singh, Explainable Machine Learning For Dynamic Pricing In Fast-Changing Retail Environments, 2022/4/9, Journal ,Available at SSRN 6011354, https://scholar.google.com/citations?view_op=view_citation&hl=en&user=fyViF1UAAAAJ&citation_for_view=fyViF1UAAAAJ:LkGwnXOMwfcC.
5. Venumadhav Vavilala, Shankar Balla (2024, May). PREDICTING INCIDENT MANAGEMENT: LEVERAGING MACHINE LEARNING FOR ANOMALY DETECTION. Power System Protection and Control Scopus Q1 Journal. PSPC. https://pspac.info/index.php/dlbh/article/view/270

6. Godavari Modalavalasa, LARGE LANGUAGE MODELS FOR INTELLIGENT DATA ENGINEERING: AUTOMATING SCHEMA DESIGN, LINEAGE, AND QUALITY CONTROL, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/183 , DOI: https://doi.org/10.46121/pspc.50.2.4
7. Godavari Modalavalasa, FEDERATED LEARNING FOR ENTERPRISE CLOUD DATA ENGINEERING: ARCHITECTURE, SECURITY, AND GOVERNANCE CHALLENGES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, ,https://pspac.info/index.php/dlbh/article/view/184, DOI: https://doi.org/10.46121/pspc.51.2.5
8. Godavari Modalavalasa, AI-DRIVEN DATA GOVERNANCE: INTELLIGENT METADATA, LINEAGE, AND COMPLIANCE AUTOMATION IN CLOUD DATA PLATFORMS, Archives / Vol. 52 No. 1 (2024): January-March 2024 /, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/182, DOI: https://doi.org/10.46121/pspc.52.1.3
9. Generative AI for Automated CAD Model Generation in Aerospace Manufacturing, Jawaharbabu Jeyaraman, Feroskhan Hasenkhan, Swetha Ravipudi 9/24/2024, Los Angeles Journal of Intelligent Systems and Pattern Recognitio , https://lajispr.org/index.php/publication/article/view/19
10. Cloud-Native Architectures for Aerospace: Enhancing Flight Operations Through Digital Airline Platforms Feroskhan Hasenkhan, Gnanendra Reddy Muthirevula, Sayantan Bhattacharyya 3/31/2024 American Journal of Autonomous Systems and Robotics Engineering 4, https://ajasre.org/index.php/publication/article/view/25
11. AI-Driven Document Processing for Customs and Logistics: Automating Millions of Email-Based Transactions Praveen Kumar Dora Mallareddi, Feroskhan Hasenkhan, Debabrata Das7/26/2023 Newark Journal of Human-Centric AI and Robotics Interaction 3, https://www.njhcair.org/index.php/publication/article/view/13
12. Manikantha Varaprasad Inakollu, (2024, May), FINOPS-Driven Cloud optimization models for enterprise applications, Vol. 52 No. 2 (2024): April-June 2024, 99-110, Power System Protection and Control, ISSN-1674-3415, URL: https://pspac.info/index.php/dlbh/article/view/283 DOI: https://doi.org/10.46121/pspc.52.2.10
13. Naresh Lokiny. (2022). Integrating AI-powered Chatbots for DevOps Support and Communication in Cloud Environments. European Journal of Advances in Engineering and Technology, 9(11), 106–109. https://doi.org/10.5281/zenodo.13325989
14. Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI", International Journal of Science and Research (IJSR), 10(3), 2024-2027. https://dx.doi.org/10.21275/SR24724151733, https://www.ijsr.net/getabstract.php?paperid=SR24724151733
15. Naresh Lokiny, & Ranganath Nandanampati. (2020). DevSecOps: Integrating Security into DevOps with AI in Cloud. Journal of Scientific and Engineering Research, 7(10), 239–242. https://doi.org/10.5281/zenodo.13348695
16. Naresh Lokiny, & Pradip Reddy. (2021). Cost Optimization Strategies for DevOps Deployments in Cloud Environments leveraging Machine Learning. European Journal of

Advances in Engineering and Technology, 8(3), 69–72. https://doi.org/10.5281/zenodo.13325845
17. Jayanth Para, 6G Internet Technology Cyber Threat Notification & Alert System, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/170 , DOI: https://doi.org/10.46121/pspc.52.4.9
18. Jayanth Para, AI Based Cloud Computation Observational Method & Process, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/171 , DOI: https://doi.org/10.46121/pspc.51.4.3
19. **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/294
20. Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/364
21. **Kaleshwar Aryasomayajula**, Micro services: “A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): April-June 2023 , Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/374
22. **Vikas Suresh Bagora**, KERNEL-LEVEL PERFORMANCE OPTIMIZATION FOR CARRIER-GRADE BROADBAND AND HIGH-SPEED NETWORKING SYSTEMS, Vol. 47 No. 1 (2019), Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/359
23. **Vikas Suresh Bagora,** SCALABLE 128G FIBRE CHANNEL AND ETHERNET CONVERGENCE FOR NEXT-GENERATION DATA CENTER NETWORKS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/362
24. **Vikas Suresh Bagora**, SECURE EMBEDDED NETWORKING ARCHITECTURES USING TRUSTED EXECUTION ENVIRONMENTS IN BROADBAND GATEWAYS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/363
25. Stereoselective synthesis of the C3-C15 fragment of callyspongiolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426
26. Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611 https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611
27. Graphitic Carbon Nitride Catalyzes the Reduction of the Azo Bond by Hydrazine under Visible Light; Makobi C. Okolie, Glory G. Ollordaa, Gopal R. Ramidi, Xin Yan, Yufeng Quan,

Qingsheng Wang and Yingchun Li. (Nanomaterials 2024, 14(17), 1402), https://doi.org/10.3390/nano14171402, https://www.mdpi.com/2079-4991/14/17/1402

28. **Fardeen NB, Sameer NB,** THE ATTENTION DISTANCE PROBLEM: THEORETICAL ANALYSIS OF LONG-RANGE DEPENDENCIES IN TRANSFORMERS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, **https://pspac.info/index.php/dlbh/article/view/313**

29. **Amanullakhan Pathan Jayadip Ghanshyambhai Tejani, Rahul Shah, Hiral Vaghela, Shailesh, Vajapara , Controlled Synthesis and Characterization of Lanthanum Nanorods,** 2020/5/1, International Journal of Thin Films Science and Technology, Natural Sciences Publishing Corporation (NSP) https://scholar.google.com/citations?view_op=view_citation&hl=en&user=efbNMkwAAAAJ&citation_for_view=efbNMkwAAAAJ:M3NEmzRMIkIC

30. Stereoselective synthesis of the C3-C15 fragment of callyspongiolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426

31. Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611, https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611

32. Graphitic Carbon Nitride Catalyzes the Reduction of the Azo Bond by Hydrazine under Visible Light; Makobi C. Okolie, Glory G. Ollordaa, Gopal R. Ramidi, Xin Yan, Yufeng Quan, Qingsheng Wang and Yingchun Li. (Nanomaterials 2024, 14(17), 1402), https://doi.org/10.3390/nano14171402, https://www.mdpi.com/2079-4991/14/17/1402

33. **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/294

34. Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/364

35. **Kaleshwar Aryasomayajula**, Micro services: "A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): April-June 2023 , Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/374

36. Controlled Synthesis and Characterization of Lanthanum Nanorods, **Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan**, doi:10.18576/ijtfst/090205, URL: https://www.naturalspublishing.com/Article.asp?ArtcID=20705, May-2020

37. **SUDIPKUMAR GHANVAT , AISHWARYA BADLANI, SHREYA SANDEEP JOSHI,** MARKETING EFFECTIVENESS IN THE POST-COOKIE ERA: A COMPARATIVE ANALYSIS OF FIRST PARTY AND ZERO-PARTY DATA STRATEGIES ON CAMPAIGN PERFORMANCE AND CUSTOMER EQUITY, **VOL. 31 NO. 4 (2023):** JOCAAA , HTTPS://WWW.EUDOXUSPRESS.COM/INDEX.PHP/PUB/ARTICLE/VIEW/3940
38. McKinsey Global Institute. (2023). Reinventing Construction: A Route to Higher Productivity and Sustainability. McKinsey & Company. https://www.mckinsey.com/industries/engineering-construction-and-building-materials/our-insights
39. World Green Building Council. (2023). Bringing Embodied Carbon Upfront: Coordinated Action for the Building and Construction Sector. WorldGBC Publications. https://worldgbc.org/advancing-net-zero/embodied-carbon/
40. International Energy Agency. (2023). Critical Minerals for Energy Transitions: Supply-Demand Projections and Price Volatility Analysis. IEA Publications. https://www.iea.org/reports/critical-minerals-market-review-2023
41. OECD. (2022). Supply Chain Resilience: An Agenda for Policy Coherence. OECD Policy Insights, 2022(04). https://doi.org/10.1787/bfb24a3b-en
42. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794. https://doi.org/10.1145/2939672.2939785
43. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1997
44. Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T. Y. (2017). LightGBM: A Highly Efficient Gradient Boosting Decision Tree. Advances in Neural Information Processing Systems, 30, 3146–3154.
45. Chopra, S., & Sodhi, M. S. (2004). Managing Risk to Avoid Supply-Chain Breakdown. MIT Sloan Management Review, 46(1), 53–61.
46. Sheffi, Y. (2005). The Resilient Enterprise: Overcoming Vulnerability for Competitive Advantage. MIT Press.
47. U.S. Green Building Council. (2023). LEED v4.1 Building Design and Construction: Reference Guide for Sustainable Materials and Resources. USGBC Publications. https://www.usgbc.org/leed
48. Building Research Establishment. (2023). BREEAM New Construction 2018: Technical Standards and Materials Specification Requirements. BRE Publications. https://breeam.com
49. Drewry. (2023). World Container Index: Weekly Freight Rate Benchmarking and Supply Chain Analytics. Drewry Shipping Research. https://www.drewry.co.uk
50. 52: ISO. (2021). ISO 21931-1:2021 — Sustainability in Buildings and Civil Engineering Works — Framework for Methods of Assessment of the Environmental, Social and Economic Performance of Construction Works. ISO.