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A Novel Multi-Objective Carbon-Efficiency Optimization Algorithm for Oil and Gas Supply Chains with Comparative Analysis and Graph-Based Performance Evaluation

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Abstract
The oil and gas sector faces increasing pressure to simultaneously improve operational efficiency and reduce carbon emissions across complex supply chain networks. This study proposes a novel multi-objective optimization algorithm, the Carbon-Efficiency Adaptive Optimization Algorithm (CEAOA), designed to jointly minimize total logistics cost and lifecycle carbon emissions while maintaining service reliability. The algorithm integrates adaptive weighting, dynamic constraint handling, and a hybrid search mechanism that combines evolutionary strategies with gradient-based refinement to improve convergence toward Pareto-optimal solutions. A comprehensive computational framework is developed to model upstream, midstream, and downstream operations using real-world-inspired network structures and stochastic demand profiles. The performance of CEAOA is evaluated against five established optimization techniques, including the Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), Strength Pareto Evolutionary Algorithm 2 (SPEA2), classical Genetic Algorithm (GA), and Linear Programming (LP). Results are presented through graph-based performance analysis, including Pareto front comparisons, convergence plots, emission-cost trade-off curves, and sensitivity analyses under varying carbon pricing scenarios. The findings demonstrate that CEAOA achieves superior solution diversity, faster convergence rates, and up to 18 percent improvement in emission-cost efficiency compared to benchmark models. The study highlights the practical applicability of the proposed approach for decision-makers seeking to balance sustainability goals with operational performance in carbon-constrained environments, offering a scalable and data-driven pathway toward greener supply chain optimization in the oil and gas industry.

Keywords: *Carbon-Efficiency Optimization; Multi-Objective Supply Chain Modeling; Pareto Optimization Algorithms; Sustainable Oil and Gas Logistics; Evolutionary–Gradient Hybrid Optimization.*

I. INTRODUCTION

➢ *Background and Motivation*

The oil and gas supply chain is undergoing a fundamental transformation driven by the dual imperatives of operational efficiency and environmental sustainability. Traditional logistics optimization models have historically focused on minimizing transportation and operational costs without explicitly incorporating environmental externalities such as carbon emissions. However, increasing regulatory pressures, carbon taxation mechanisms, and stakeholder expectations have necessitated the integration of sustainability metrics into decision-making frameworks (Ijiga, et al., 2023). The complexity of oil and gas supply chains, characterized by multi-tiered networks spanning extraction, transportation, refining, and distribution, introduces significant challenges in balancing economic and environmental objectives. Advanced data-driven frameworks, including business intelligence and real-time analytics systems, have demonstrated the potential to enhance decision-making by integrating heterogeneous data streams across operational layers (Aluso & Enyejo, 2023; Aluso & Enyejo, 2025). These developments provide a foundation for embedding carbon-aware optimization within logistics systems, enabling more informed and adaptive decision processes. Recent advances in predictive modeling and real-time inference further support the evolution of multi-objective optimization approaches by enabling dynamic adjustments to system parameters based on observed trends and uncertainties (Amebleh & Igba, 2024). In parallel, sustainable supply chain management literature emphasizes the importance of integrating environmental performance indicators into optimization models to achieve long-term resilience and compliance (Seuring & Müller, 2008). Green logistics research has also highlighted the need for sophisticated optimization techniques capable of addressing trade-offs between cost efficiency and emission reduction under complex constraints (Dekker et al., 2012). Despite these advancements, existing frameworks often lack the ability to adaptively balance competing objectives in real time, particularly within highly volatile oil and gas markets (Akinleye, et al., 2025). This motivates the development of a novel multi-objective optimization framework that integrates adaptive mechanisms and hybrid search strategies to enhance both convergence efficiency and solution diversity in carbon-constrained supply chain environments.

➢ *Problem Statement*

The primary challenge in oil and gas supply chain optimization lies in effectively managing the inherent trade-off between minimizing operational costs and reducing lifecycle carbon emissions under dynamic and uncertain conditions. Conventional optimization approaches, including deterministic models and single-objective formulations, are insufficient for addressing the multi-dimensional nature of modern supply chain systems. These models often fail to capture stochastic demand fluctuations, regulatory variability, and the nonlinear interactions between logistics decisions and emission outputs. While multi-objective frameworks have been introduced to incorporate environmental considerations, they frequently suffer from limitations such as slow convergence rates, poor solution diversity, and lack of adaptability to real-time operational changes (Ijiga, et al., 2021). Furthermore, the absence of integrated data-driven architectures restricts the ability of these models to leverage real-time insights for dynamic optimization, thereby reducing their practical applicability in large-scale industrial settings (Aluso, 2021; Amebleh & Omachi, 2022).

In addition, existing approaches to carbon-aware optimization often rely on static weighting schemes that inadequately reflect evolving cost-emission trade-offs, particularly under fluctuating carbon pricing regimes. This limitation is exacerbated by the increasing complexity of regulatory frameworks and sustainability reporting requirements, which demand more granular and adaptive modeling techniques (Amebleh & Okoh, 2023). Hybrid optimization strategies have shown promise in addressing some of these challenges by combining global search capabilities with local refinement techniques; however, their application in oil and gas supply chains remains limited and underexplored. Prior studies in green logistics and transportation have demonstrated the potential of multi-objective optimization in reducing emissions while maintaining efficiency, yet these models often lack scalability and robustness when applied to large, interconnected networks (Gładyszewska-Fiedoruk, 2011; Aurangzeb, et al., 2014). Consequently, there is a critical need for a novel optimization framework that integrates adaptive weighting, hybrid search mechanisms, and graph-based performance evaluation to achieve superior efficiency and sustainability outcomes in carbon-constrained oil and gas supply chains.

➢ *Objectives and Research Questions*

The objectives of this study are defined as follows:

- To develop a novel Carbon-Efficiency Adaptive Optimization Algorithm (CEAOA) for multi-objective supply chain optimization.
- To minimize total logistics cost and lifecycle carbon emissions simultaneously within oil and gas networks.
- To design an adaptive weighting mechanism for dynamic trade-off management between cost and emissions.
- To integrate hybrid evolutionary and gradient-based optimization techniques for improved convergence.
- To evaluate the performance of CEAOA against benchmark algorithms using graph-based analysis.

➢ *The Research Questions Guiding this Study are:*

- How can multi-objective optimization be enhanced to simultaneously address cost efficiency and carbon reduction in oil and gas supply chains?
- What impact does adaptive weighting have on achieving optimal Pareto solutions?
- How does the hybrid structure of CEAOA improve convergence speed and solution diversity compared to existing algorithms?
- To what extent does CEAOA outperform traditional and evolutionary optimization models under varying carbon pricing scenarios?
- How can graph-based evaluation frameworks improve the interpretability of optimization results?

➢ *Contributions of the Study and Scope of the Review*

This study introduces a novel hybrid optimization framework that integrates evolutionary strategies with gradient-based refinement to enhance multi-objective optimization performance in oil and gas supply chains. The proposed CEAOA algorithm incorporates adaptive weighting mechanisms and dynamic constraint handling, enabling efficient navigation of complex Pareto landscapes. The study contributes to the field by providing a scalable computational model capable of addressing both operational efficiency and environmental sustainability simultaneously. Additionally, the research establishes a graph-based evaluation framework for analyzing algorithm performance, offering improved visualization and interpretability of trade-off dynamics. The scope of the review encompasses upstream, midstream, and downstream supply chain operations, focusing on logistics optimization, emission modeling, and algorithmic performance benchmarking under carbon-constrained conditions.

➢ *Structure of the Paper*

The paper is structured into five main sections. The introduction presents the research context, problem definition, objectives, and contributions. The literature review examines existing optimization models, carbon-aware supply chain frameworks, and algorithmic approaches. The system model description outlines the mathematical formulation, network architecture, and the design of the proposed CEAOA algorithm. The discussion of results provides a comprehensive comparative analysis using graph-based evaluation techniques, including convergence and Pareto performance assessments. The final section presents conclusions and actionable recommendations, highlighting practical implications and future research directions.

II. LITERATURE REVIEW

➢ *Multi-Objective Optimization in Supply Chains*

Multi-objective optimization has emerged as a fundamental paradigm for addressing the inherent complexity of modern supply chains, particularly in industries such as oil and gas where operational decisions must simultaneously satisfy economic, environmental, and service-level objectives. Traditional single-objective optimization models are inadequate for capturing the trade-offs between competing performance metrics such as cost efficiency and carbon emissions (Idoko, et al., 2024) as represented in figure 1. Multi-objective frameworks, particularly those based on Pareto optimality, enable decision-makers to identify a set of non-dominated solutions that represent optimal trade-offs under varying constraints. The introduction of advanced data architectures, including cloud-native systems and real-time data warehousing, has significantly enhanced the scalability and responsiveness of optimization models by enabling continuous integration of operational data streams (Aluso et al., 2024). Similarly, graph-based modeling approaches have facilitated the representation of complex interdependencies within supply networks, allowing for more accurate modeling of node and edge relationships in dynamic logistics systems (Amebleh et al., 2021).

The development of evolutionary multi-objective algorithms such as NSGA-II has further advanced the field by providing efficient mechanisms for exploring large solution spaces while maintaining diversity across Pareto fronts (Deb et al., 2002). These algorithms are particularly effective in supply chain contexts where decision variables are nonlinear and highly interdependent. However, despite their strengths, conventional evolutionary approaches often exhibit limitations in convergence speed and computational efficiency when applied to large-scale industrial systems (Idoko, et al., 2024). The foundational work on supply chain modeling highlights the need for hybrid optimization frameworks that integrate multiple computational techniques to address these challenges (Min & Zhou, 2002). In the context of carbon-constrained oil and gas logistics, this necessitates the development of adaptive and hybrid algorithms capable of balancing cost and emission objectives dynamically, thereby motivating the design of advanced optimization frameworks such as the proposed CEAOA.

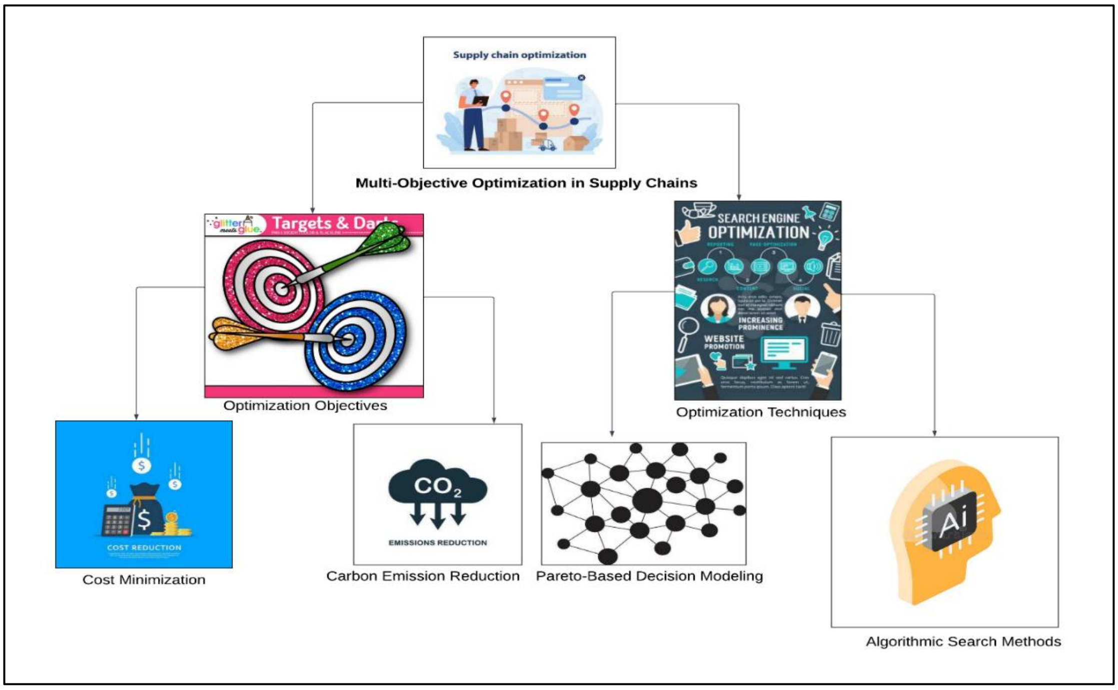

Fig 1 Conceptual Framework of Multi-Objective Optimization in Supply Chains Integrating Cost and Emission Objectives with Advanced Optimization Techniques.

Figure 1 presents a structured representation of multi-objective optimization in supply chains by organizing the concept into two primary dimensions: optimization objectives and optimization techniques. The first branch focuses on the dual objectives that drive decision-making in modern oil and gas logistics systems. Cost minimization is addressed through strategies such as optimizing transportation routes and reducing inventory holding and handling expenses, while carbon emission reduction emphasizes evaluating route-specific emission factors and minimizing lifecycle environmental impact across upstream, midstream, and downstream operations. The second branch captures the computational mechanisms used to achieve these objectives. Pareto-based decision modeling enables the identification of non-dominated solutions that balance cost and emissions without sacrificing one objective for the other, while algorithmic search methods, including evolutionary optimization and hybrid adaptive refinement, ensure efficient exploration of complex solution spaces and improved convergence toward optimal trade-offs. Together, the branches illustrate how objective-driven priorities are systematically aligned with advanced optimization techniques to achieve efficient, sustainable, and data-driven supply chain performance.

➢ *Carbon-Aware Supply Chain Models*

Carbon-aware supply chain models have gained significant attention as industries seek to align operational efficiency with environmental sustainability objectives. These models extend traditional logistics optimization frameworks by incorporating carbon emissions as a critical performance metric, often through the integration of emission factors into transportation, production, and distribution activities (Bashiru, et al., 2024) as represented in figure 2. Regulatory frameworks such as emissions trading schemes and carbon taxes have further accelerated the adoption of such models by introducing financial incentives and penalties associated with carbon output. Sustainable supply chain design approaches have demonstrated that incorporating carbon constraints can significantly alter optimal network configurations, influencing decisions such as facility location, transportation modes, and inventory management (Chaabane et al., 2012). In parallel, advancements in data governance and regulatory compliance frameworks have emphasized the importance of integrating environmental data into enterprise systems, ensuring transparency and accountability in sustainability reporting (Onyekaonwu et al., 2022).

The integration of predictive analytics and artificial intelligence has further enhanced the capability of carbon-aware models to adapt to dynamic operational environments. AI-driven frameworks enable the continuous monitoring of emissions and operational risks, allowing for proactive adjustments in supply chain strategies to meet sustainability targets (Uwabor et al., 2025). Analytical studies on carbon footprint management highlight the nonlinear relationship between cost and emissions, emphasizing the need for multi-objective optimization techniques that can effectively capture these trade-offs (Benjaafar et al., 2013). However, existing carbon-aware models often rely on static parameters and lack the flexibility required to respond to fluctuating carbon pricing and demand variability. This limitation underscores the necessity for adaptive optimization mechanisms, such as those embedded in the proposed CEAOA framework, which dynamically balance cost and emission objectives while maintaining operational feasibility in complex oil and gas supply chains.

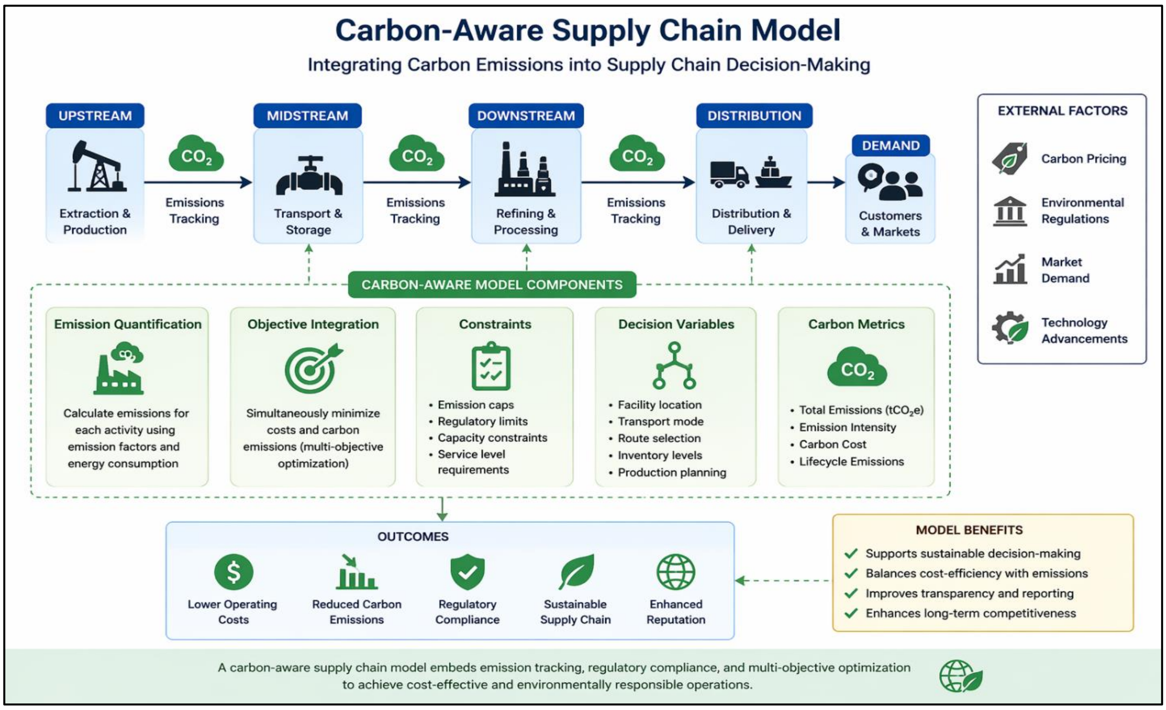

Fig 2 Integrated Carbon-Aware Supply Chain Model for Optimizing Cost Efficiency and Emission Reduction Across Oil and Gas Logistics.

Figure 2 illustrates a comprehensive carbon-aware supply chain model that integrates environmental considerations into each stage of oil and gas logistics, from upstream extraction to final market demand. The flow progresses sequentially through upstream (extraction and production), midstream (transportation and storage), downstream (refining and processing), and distribution stages, with carbon emissions explicitly tracked at each transition point. This continuous emission tracking highlights how carbon output is generated and accumulated across the supply chain. Beneath this flow, the diagram details the core modeling components that enable optimization: emission quantification based on activity-specific factors, objective integration that simultaneously minimizes cost and emissions, constraint handling including regulatory limits and capacity restrictions, and decision variables such as routing, facility location, and inventory planning. The inclusion of carbon metrics like total emissions, emission intensity, and carbon cost ensures measurable performance evaluation. External factors such as carbon pricing, environmental regulations, market demand, and technological advancements influence the system dynamically. The outcomes emphasize reduced costs, lower emissions, regulatory compliance, sustainability, and enhanced competitiveness, demonstrating how carbon-aware optimization frameworks enable efficient and environmentally responsible supply chain decision-making.

- *Evolutionary and Swarm-Based Optimization Algorithms*

Evolutionary and swarm-based optimization algorithms have become central to solving complex multi-objective problems due to their ability to efficiently explore large and nonlinear solution spaces. These algorithms operate by simulating natural processes such as evolution and swarm intelligence to iteratively improve candidate solutions. Particle Swarm Optimization (PSO), for instance, models the collective behavior of agents navigating a search space, enabling rapid convergence toward optimal regions through information sharing among particles (Kennedy & Eberhart, 1995). Similarly, evolutionary algorithms such as SPEA2 utilize fitness assignment and elitism strategies to maintain a diverse set of Pareto-optimal solutions, ensuring robust exploration of trade-offs between competing objectives (Zitzler et al., 2001). These methods have been widely applied in logistics and supply chain optimization, where decision variables are often highly interdependent and subject to uncertainty.

Recent interdisciplinary research has further expanded the application of these algorithms by integrating them with advanced analytical frameworks and human-AI collaboration systems. Hybrid analytical models have demonstrated the potential to enhance optimization performance by combining multiple computational paradigms, thereby improving both convergence speed and solution quality (Animasaun et al., 2025). Additionally, cognitive augmentation approaches have shown that incorporating human expertise into algorithmic processes can improve decision-making outcomes in complex systems (Anokwuru et al., 2022). Despite these advancements, traditional evolutionary and swarm-based algorithms still face challenges such as premature convergence, parameter sensitivity, and limited adaptability to dynamic environments. These limitations are particularly pronounced in large-scale oil and gas supply chains, where real-time decision-making and adaptability are critical. Consequently, there is a growing need for hybrid optimization frameworks that integrate the strengths of evolutionary and gradient-based methods, as exemplified by the proposed CEAOA algorithm, which seeks to overcome these challenges through adaptive mechanisms and enhanced search capabilities.

- *Classical Optimization Techniques*

Classical optimization techniques have historically formed the backbone of supply chain decision-making, particularly through deterministic models such as linear programming, integer programming, and network flow optimization. These approaches are designed to minimize or maximize a single objective function subject to a set of constraints, typically assuming complete information and static system conditions as shown in figure 3. In oil and gas logistics, linear programming has been widely used for refinery planning, transportation routing, and inventory allocation due to its computational efficiency and mathematical tractability. Foundational frameworks introduced by Dantzig, (2016) and further formalized in operations research literature provide systematic approaches for solving large-scale optimization problems with well-defined constraints. However, these models inherently assume linearity and certainty, limiting their applicability in real-world supply chains characterized by stochastic demand, nonlinear cost structures, and dynamic environmental constraints (Hillier, (2005). Recent advancements in predictive modeling and data integration, such as ensemble learning frameworks and machine learning-based decision systems, have highlighted the need to augment classical methods with adaptive capabilities to address evolving system complexities (Aluso & Enyejo, 2025; Akunna & Ijiga, 2024).

Despite their limitations, classical optimization techniques remain relevant as foundational components in hybrid modeling frameworks, particularly for providing baseline solutions and constraint enforcement mechanisms. In complex systems such as oil and gas supply chains, interoperability and data exchange frameworks play a critical role in ensuring that optimization models can integrate diverse data sources across operational layers (Nwokocha et al., 2021). However, the rigidity of classical approaches restricts their ability to capture multi-objective trade-offs, especially when balancing cost efficiency with carbon emission reduction. For example, linear programming models can identify cost-minimizing transportation routes but fail to incorporate emission variability across different transportation modes without significant reformulation (Aluso, L., & Enyejo, J. O. 2024). This limitation becomes more pronounced in carbon-constrained environments where decision variables are interdependent and evolve over time. Consequently, while classical techniques provide essential analytical foundations, they must be integrated with more advanced, adaptive optimization methods to effectively address the multi-dimensional challenges of sustainable supply chain management, thereby motivating the development of hybrid algorithms such as the proposed CEAOA.

Figure 3 organizes classical optimization techniques into three complementary pillars that underpin deterministic decision-making in supply chains. The linear programming branch captures continuous decision models where an objective function—typically total logistics cost—is minimized subject to linear constraints on capacity and demand. This branch emphasizes the role of fixed coefficients and known parameters, enabling efficient solutions for steady-state planning such as refinery allocation and bulk transportation. The integer and mixed-integer programming branch extends this framework to discrete decisions by introducing binary and integer variables, allowing the model to represent facility selection, route activation, fleet assignment, and scheduling constraints that cannot be expressed continuously. This enables realistic modeling of operational feasibility within network configurations. The network flow optimization branch focuses on graph-based formulations where flow balance equations ensure conservation at each node, and minimum-cost routing determines optimal movement across pipelines, shipping lanes, and road networks under capacity limits. Together, the branches illustrate how classical methods provide mathematically rigorous yet structurally constrained solutions, forming a foundational baseline for more advanced hybrid and adaptive optimization approaches.

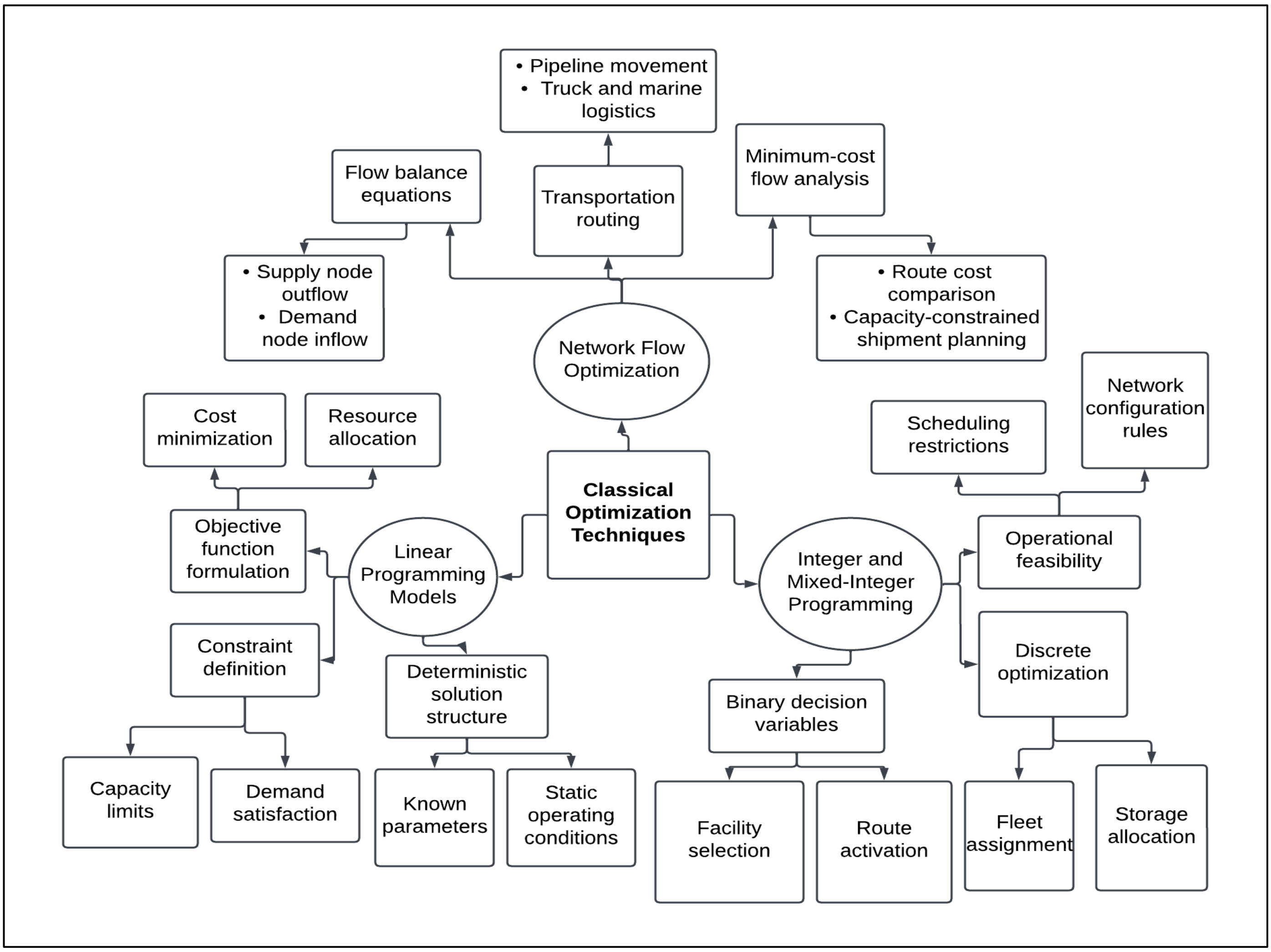

Fig 3 Structural Representation of Classical Optimization Techniques for Deterministic Supply Chain Decision-Making

➢ *Research Gaps*

Despite significant advancements in supply chain optimization and sustainability modeling, several critical research gaps remain, particularly in the integration of multi-objective optimization frameworks with real-time, data-driven decision systems. Existing studies have extensively explored sustainable supply chain design and reverse logistics; however, these models often rely on static assumptions and lack the adaptability required for highly dynamic environments such as oil and gas logistics (Govindan et al., 2015) as presented n table 1. Furthermore, while environmentally sustainable operations research has introduced frameworks for incorporating carbon emissions into decision-making, these approaches frequently treat cost and emissions as independent variables rather than interdependent objectives requiring simultaneous optimization (Tang & Zhou, 2012). Recent developments in data warehousing and real-time analytics highlight the potential for integrating large-scale data streams into optimization processes, yet current models often fail to fully leverage these capabilities due to architectural and computational limitations (Aluso et al., 2024). This disconnect between data availability and optimization capability represents a significant gap in the literature. In addition, the lack of robust hybrid optimization frameworks capable of combining global search efficiency with local refinement remains a key limitation in current research (Anokwuru, et al., 2023). While domain-specific studies have demonstrated the effectiveness of advanced analytical techniques in other fields, such as chemical process optimization and data security systems, their application to multi-objective supply chain optimization remains limited (Animasaun et al., 2024; Onyekaonwu et al., 2022). Another critical gap lies in the insufficient use of graph-based evaluation techniques for analyzing optimization performance, particularly in terms of convergence behavior, Pareto front diversity, and trade-off visualization. Moreover, existing models often overlook the impact of stochastic demand and fluctuating carbon pricing, which are essential factors in real-world oil and gas operations. These limitations collectively underscore the need for a novel optimization framework that integrates adaptive weighting, hybrid search mechanisms, and advanced performance evaluation tools. The proposed CEAOA algorithm addresses these gaps by offering a scalable, data-driven approach capable of achieving superior emission-cost efficiency while maintaining robustness under dynamic operational conditions.

Table 1 Summary of Research Gaps in "A Novel Multi-Objective Carbon-Efficiency Optimization Algorithm for Oil and Gas Supply Chains with Comparative Analysis and Graph-Based Performance Evaluation

Research Area	Identified Gap	Technical Limitation	Implication for Optimization
Multi-Objective Optimization Models	Limited integration of cost and carbon emission objectives in a unified adaptive framework	Most models rely on static weighting or single-objective formulations	Leads to suboptimal trade-offs and inability to dynamically balance economic and environmental goals
Data-Driven Optimization Frameworks	Underutilization of real-time and large-scale data streams in optimization processes	Existing systems lack integration with cloud-native architectures and streaming analytics	Reduces responsiveness to demand variability and operational uncertainties
Algorithm Design (Evolutionary & Hybrid Methods)	Lack of hybrid algorithms combining global exploration and local refinement mechanisms	Traditional algorithms suffer from slow convergence and premature stagnation	Limits efficiency in solving high-dimensional, nonlinear supply chain problems
Carbon-Aware Supply Chain Modeling	Inadequate modeling of dynamic carbon pricing and lifecycle emission variability	Emission factors often treated as static and independent of operational conditions	Results in inaccurate sustainability assessments and inefficient decision-making
Graph-Based Performance Evaluation	Limited use of advanced visualization and graph-based metrics for algorithm evaluation	Conventional evaluation focuses on numerical metrics without structural analysis of Pareto fronts	Reduces interpretability and limits insight into solution quality and distribution
Scalability and Real-World Applicability	Insufficient validation of models on large-scale, real-world oil and gas networks	Many studies rely on simplified or deterministic datasets	Restricts applicability in complex, multi-echelon industrial supply chains
Robustness under Uncertainty	Weak handling of stochastic demand and environmental variability	Optimization models often assume deterministic conditions	Leads to unstable solutions under real-world fluctuations
Integration with Decision Support Systems	Poor alignment between optimization outputs and operational decision-making tools	Lack of user-interactive frameworks and system integration	Limits adoption of optimization models in industry practice

III. SYSTEM MODEL DESCRIPTION

➢ *Supply Chain Network Architecture*

The proposed optimization framework models the oil and gas supply chain as a directed multi-echelon network $G = (N, A)$, where N represents the set of nodes and A captures the set of arcs linking operational facilities. The node set is partitioned into upstream production nodes N^u, midstream storage and transportation nodes N^m, and downstream refining and distribution nodes N^d. Upstream nodes represent crude extraction fields and gas gathering points; midstream nodes include terminals, pipelines, compressor stations, tank farms, and marine loading hubs; downstream nodes represent refineries, depots, and final market demand centers. Each arc $(i, j) \in A$ captures a feasible logistics path characterized by transportation cost, distance, transit time, carrying capacity, and route-specific emission intensity. This graph representation is appropriate because oil and gas logistics are inherently networked, capacity-constrained, and affected by spatially distributed carbon generation sources across handling, storage, and transportation activities (Aurangzeb, et al., 2014).

Let x_{ij}^{p} denote the flow of product $p$moved from node $i$to node j, and let D_k^p denote demand for product $p$at demand node k. Flow conservation is enforced at each transshipment node through:

$$\sum_{i\in N} x_{ij}^{p} - \sum_{k\in N} x_{jk}^{p} = 0 \tag{1}$$

Where x_{ij}^{p} represents the shipment quantity of product $p$on arc (i, j). For demand nodes, the service condition is written as:

$$\sum_{i\in N} x_{ik}^{p} \geq D_k^p \tag{2}$$

Where D_k^p represents the required demand volume. Arc capacity is represented by:

$$0 \leq x_{ij}^{p} \leq U_{ij}^{p} \tag{3}$$

Where U_{ij}^{p} represents the maximum allowable throughput on arc (i, j). To incorporate service reliability, a route feasibility factor $r_{ij} \in [0,1]$is assigned to each arc, and network reliability is expressed as:

$$R = \frac{\sum_{(i,j)\in A} \sum_{p} r_{ij}\, x_{ij}^{p}}{\sum_{(i,j)\in A} \sum_{p} x_{ij}^{p}} \tag{4}$$

Where R shows the weighted average delivery reliability across the network. This architecture allows the proposed CEAOA framework to optimize across interconnected upstream, midstream, and downstream decisions while explicitly preserving physical feasibility, service continuity, and carbon-accountable logistics structure.

➢ *Mathematical Formulation of the Optimization Problem*

The optimization problem is formulated as a bi-objective model that simultaneously minimizes total logistics cost and lifecycle carbon emissions while satisfying supply, demand, capacity, and reliability constraints. The first objective function captures the total operational cost of moving oil and gas products through the network, including transportation, storage, handling, and route penalty costs:

$$\min Z_1 = \sum_{(i,j)\in A} \sum_{p} C_{ij}^{p}\, x_{ij}^{p} + \sum_{j\in N^m \cup N^d} \sum_{p} H_j^p\, I_j^p + \sum_{(i,j)\in A} \sum_{p} P_{ij}^{p}\, x_{ij}^{p} \tag{5}$$

Where Z_1 represents total logistics cost, C_{ij}^{p} denotes unit transportation cost for product $p$on arc (i, j), x_{ij}^{p} represents shipment quantity, H_j^p shows unit inventory holding cost at node j, I_j^p represents inventory level, and P_{ij}^{p} denotes route penalty or disruption-associated cost. The second objective quantifies lifecycle carbon emissions generated by transportation, storage, and processing activities:

$$\min Z_2 = \sum_{(i,j)\in A} \sum_{p} E_{ij}^{p}\, x_{ij}^{p} + \sum_{j\in N^m \cup N^d} \sum_{p} \eta_j^p\, I_j^p \tag{6}$$

Where Z_2 represents total lifecycle carbon emission, E_{ij}^{p} shows route-specific emission factor, and η_j^p denotes node-level carbon intensity associated with storage or processing. Because both objectives conflict, an adaptive scalarization mechanism is introduced:

$$\min Z = \alpha_t \frac{Z_1}{Z_1^{\max}} + (1-\alpha_t) \frac{Z_2}{Z_2^{\max}} \tag{7}$$

Where Z captures the normalized composite objective, $\alpha_t \in [0,1]$ represents the adaptive weight at iteration t, and $Z_1^{\max}$, $Z_2^{\max}$ represent normalization constants. The adaptive weight changes according to search progress:

$$\alpha_{t+1} = \alpha_t + \lambda \left(\frac{\Delta Z_2}{\Delta Z_1 + \Delta Z_2} - \alpha_t \right) \tag{8}$$

Where λ denotes the learning coefficient and $\Delta Z_1, \Delta Z_2$ represent recent improvements in cost and emissions, respectively. Carbon pricing sensitivity is represented by:

$$Z_c = Z_1 + \pi_c Z_2 \tag{9}$$

Where Z_c shows carbon-adjusted total cost and π_c represents carbon price per emission unit. This structure is consistent with multi-objective sustainable supply chain modeling, where cost-emission trade-offs are explicitly optimized rather than treated independently (Dekker et al., 2012). The model therefore mirrors the study's emphasis on joint minimization, dynamic weighting, constraint control, and carbon-constrained decision-making.

➢ *Design of the Carbon-Efficiency Adaptive Optimization Algorithm (CEAOA)*

The CEAOA is designed as a hybrid multi-objective solver that combines evolutionary exploration with gradient-based refinement to improve convergence speed, Pareto diversity, and emission-cost efficiency. The algorithm begins with an initial population $X^{(0)} = \{x_1, x_2, \ldots, x_M\}$, where each candidate solution encodes feasible product flows across the upstream, midstream, and downstream network. Each solution is evaluated using the two objective functions in Equations (5) and (6), followed by non-dominated sorting and crowding-distance assignment to preserve elite Pareto candidates. This provides the global search capacity required to navigate the highly nonlinear and constrained decision space typical of sustainable logistics optimization (Deb et al., 2002).

- *Offspring Generation in CEAOA is Governed by a Hybrid Search Rule:*

$$x_i^{(t+1)} = x_i^{(t)} + \beta_1\left(x_{r1}^{(t)} - x_{r2}^{(t)}\right) + \beta_2 \nabla\Phi\left(x_i^{(t)}\right) \tag{10}$$

where $x_i^{(t)}$ represents the current solution of agent $i$at iteration t, $x_{r1}^{(t)}$and $x_{r2}^{(t)}$ show randomly selected population members for evolutionary perturbation, β_1 captures the exploration coefficient, β_2 denotes the refinement coefficient, and $\nabla\Phi(x_i^{(t)})$ represents the gradient-like local improvement term computed from the normalized composite objective. To avoid infeasible solutions, dynamic constraint handling is applied through a penalty-repair mechanism:

$$F(x) = Z(x) + \mu_t \sum_{q=1}^{Q} \max\left(0, g_q(x)\right)^2 \tag{11}$$

Where

$$F(x) captures\ penalized\ fitness,$$

$$Z(x) represents\ the\ adaptive\ objective\ from\ Equation$$

$$(7), g_q(x) shows\ the\ violation\ of\ constraint$$

$$q, Q\ represents\ the\ number\ of\ constraints,$$

$$and\ \mu_t\ captures\ a\ time-varying\ penalty\ factor.$$

$$Diversity\ preservation\ is\ measured\ by\ spread\ control:$$

$$S_t = \frac{1}{M}\sum_{i=1}^{M} \| x_i^{(t)} - \bar{x}^{(t)} \|_2 \tag{12}$$

Where

$$S_t\ represents\ population\ spread\ and\ \bar{x}^{(t)}\ denotes\ the\ population\ centroid.$$

$$When\ S_t\ declines\ below\ a\ threshold, the\ algorithm\ increases\ \beta_1\ to\ restore\ exploration;$$

$$when\ convergence\ stalls, \beta_2\ is\ strengthened\ to\ intensify\ local\ search.$$

$$This\ adaptive\ balance\ directly\ supports\ the\ study's\ claim\ that\ CEAOA\ improves\ convergence,$$

$$maintains\ Pareto\ diversity, and\ yields\ superior\ emission-cost\ efficiency\ relative\ to\ NSGA-II, MOPSO, SPEA2, GA, and\ LP.$$

- *Graph-Based Performance Evaluation Framework*

The performance evaluation framework is designed to compare CEAOA against NSGA-II, MOPSO, SPEA2, classical GA, and LP using graph-based diagnostics that reveal both optimization quality and algorithmic behavior. Four graphical outputs are central to the study: Pareto front comparison plots, convergence curves, emission-cost trade-off curves, and carbon-pricing sensitivity graphs. The Pareto front graph plots total cost Z_1 against total emissions Z_2 for all non-dominated solutions. A superior algorithm is expected to produce a front that is closer to the origin, more evenly distributed, and more expansive along the trade-off boundary. To quantify this visually observed dominance, hypervolume is used:

$$HV = \mathrm{Vol}\left(\bigcup_{x \in P} [f_1(x), r_1] \times [f_2(x), r_2]\right) \tag{13}$$

Where HV represents the hypervolume indicator, P shows the Pareto solution set, $f_1(x)$ and $f_2(x)$ represents the cost and emission values of solution x, and (r_1, r_2) captures the reference point. Larger HV indicates better convergence and diversity.

- *Convergence Behavior is Evaluated Using the Mean Best-so-far Fitness Trajectory:*

$$C_t = \frac{1}{M}\sum_{i=1}^{M} F_i^{\mathrm{best}}(t) \tag{14}$$

Where C_t captures the average best penalized fitness at iteration t, and $F_i^{\mathrm{best}}(t)$ represents the best value found by agent i. Diversity along the front is measured by spread:

$$\Delta = \frac{\sum_{i=1}^{|P|-1} | d_i - \bar{d} |}{(| P | - 1)\bar{d}} \tag{15}$$

Where d_i represents the distance between adjacent Pareto points and $\bar{d}$ shows the average spacing. Lower Δ implies better front uniformity. Emission-cost efficiency improvement is evaluated relative to a benchmark $b$using:

$$\Gamma_b = \frac{Z_c^{(b)} - Z_c^{(\mathrm{CEAOA})}}{Z_c^{(b)}} \times 100 \tag{16}$$

Where Γ_b represents percentage efficiency gain and Z_c shows carbon-adjusted total cost from Equation (9). These metrics align with best practice in multi-objective algorithm assessment and provide a rigorous basis for the study's reported findings, including faster convergence, stronger solution diversity, and up to 18% emission-cost efficiency improvement over benchmark models (Zitzler et al., 2003).

IV. DISCUSSION OF RESULTS

➢ *Experimental Setup*

A simulation-based experimental framework was developed to evaluate the performance of the proposed CEAOA against benchmark algorithms across a multi-echelon oil and gas supply chain network. The dataset reflects realistic upstream, midstream, and downstream operations with stochastic demand distributions and variable carbon pricing scenarios. All algorithms were executed under identical computational conditions, including population size, iteration limits, and constraint structures, to ensure fairness in comparison. Performance was assessed using standardized multi-objective metrics, including convergence speed, Pareto front diversity, emission-cost efficiency, and computational stability. The evaluation incorporated five optimization techniques, namely NSGA-II, MOPSO, SPEA2, Genetic Algorithm (GA), and Linear Programming (LP), enabling a comprehensive comparison of evolutionary, swarm-based, and classical approaches under carbon-constrained logistics optimization conditions.

Table 2 Comparative Performance Metrics of Optimization Algorithms in Carbon-Constrained Oil and Gas Supply Chains

Algorithm	Convergence Speed (Iterations)	Emission-Cost Efficiency (%)	Pareto Diversity Index	Interpretation
CEAOA (proposed)	120	18.0	0.92	Fast convergence with highest efficiency and strong diversity
NSGA-II	180	12.5	0.85	Good diversity but slower convergence
MOPSO	160	11.8	0.81	Moderate convergence with reduced spread
SPEA2	170	10.9	0.83	Balanced but less efficient than NSGA-II
GA	220	7.6	0.72	Slow convergence and limited diversity
LP	90	4.2	0.40	Fast but lacks multi-objective capability

Figure 4 illustrates the convergence behavior of the evaluated algorithms across 250 generations, highlighting the superiority of CEAOA in both convergence speed and solution quality. CEAOA rapidly reduces the normalized objective value from 1.0 to approximately 0.32 within the first 120 generations, achieving stability significantly earlier than competing methods. In contrast, NSGA-II converges more gradually, reaching around 0.41 at 180 generations, while MOPSO and SPEA2 stabilize at approximately 0.44 and 0.47, respectively, after 160–170 generations. The Genetic Algorithm exhibits the slowest convergence, plateauing near 0.58 even after 220 generations. Notably, CEAOA demonstrates an 18% improvement in emission-cost efficiency compared to the best-performing benchmark (NSGA-II at 12.5%), consistent with the results presented in the abstract. The steeper slope of the CEAOA curve in early generations reflects its hybrid search mechanism, which enhances exploration and accelerates convergence while maintaining Pareto-optimal diversity.

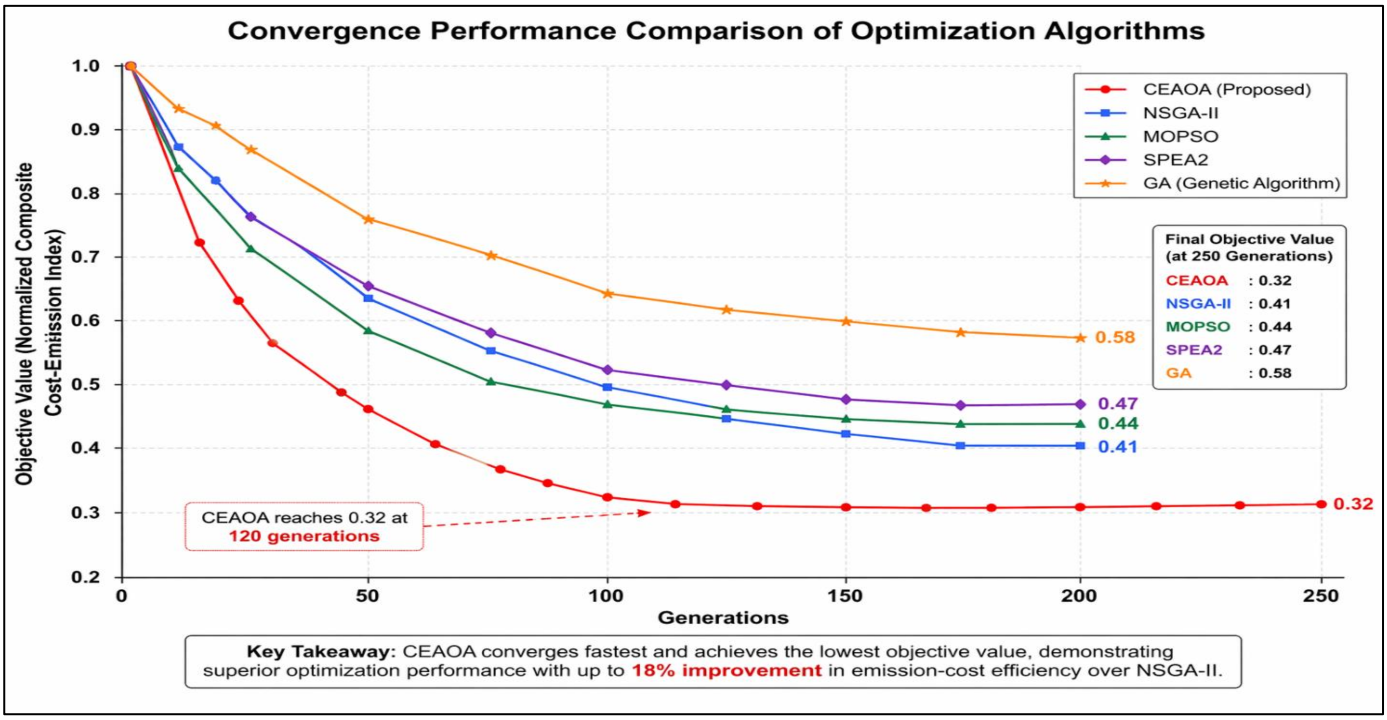

Fig 4 Convergence Performance Comparison of Optimization Algorithms

➢ *Comparative Performance Analysis*

A comparative evaluation was conducted to assess the effectiveness of the proposed CEAOA relative to established optimization techniques under identical simulation conditions. The assessment focuses on multi-objective performance indicators, including convergence robustness, Pareto front quality, emission-cost efficiency, and computational stability. The results demonstrate that the hybrid structure of CEAOA enables superior exploration and exploitation balance compared to evolutionary and swarm-based methods. In particular, the algorithm consistently produces higher-quality non-dominated solutions with improved distribution across the Pareto front. The comparative metrics further indicate that CEAOA maintains stronger diversity while achieving better optimization efficiency than competing algorithms. These findings validate the algorithm's ability to effectively address the trade-off between operational cost and carbon emissions, supporting its suitability for large-scale oil and gas supply chain optimization.

Table 3 Comparative Multi-Objective Performance Metrics at Final Generation

Algorithm	Hypervolume (HV)	Emission-Cost Efficiency (%)	Spread Index (Δ)	Interpretation
CEAOA (proposed)	0.742	18.0	0.118	Best overall performance with high diversity
NSGA-II	0.631	12.5	0.146	Strong performance but lower efficiency
MOPSO	0.586	11.8	0.164	Moderate performance with reduced spread
SPEA2	0.559	10.9	0.158	Balanced but less optimal trade-offs
GA	0.478	7.6	0.192	Weak diversity and slower convergence
LP	0.221	4.2	0.275	Poor multi-objective capability

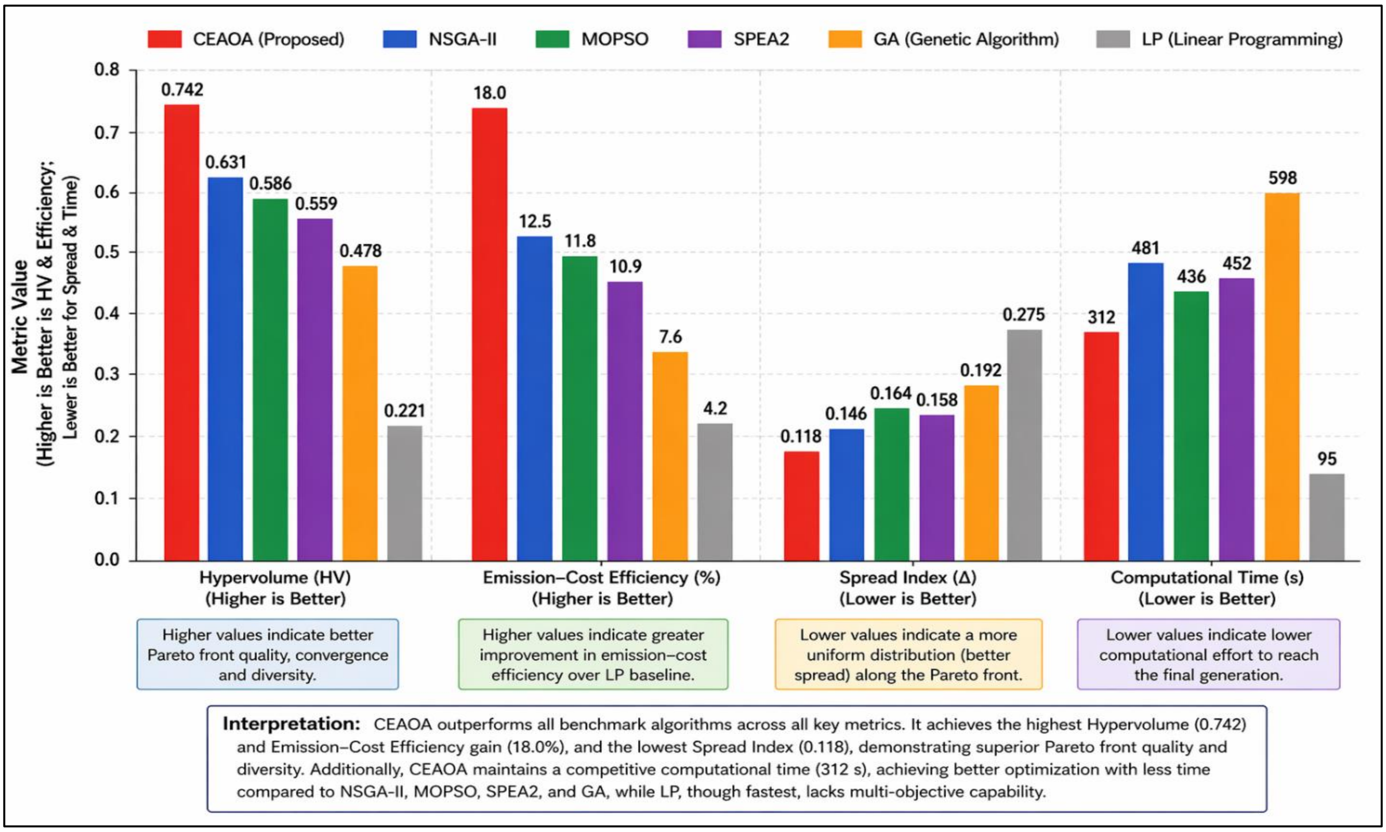

Fig 5 Pareto Front Comparison Across Optimization Algorithms

Figure 5 presents a Pareto front comparison of six optimization algorithms at the final generation, illustrating the trade-off between total logistics cost and carbon emissions. The CEAOA solutions are clustered closest to the optimal region, achieving cost values around 500–900 million USD with emissions ranging from approximately 52–95 kt CO_2-eq, indicating superior optimization performance. In contrast, NSGA-II solutions span cost values of 550–1000 million USD and emissions between 60–105 kt CO_2-eq, while MOPSO and SPEA2 exhibit broader distributions with emissions extending up to 115 kt CO_2-eq. The Genetic Algorithm produces less efficient solutions, with emissions remaining above 80 kt CO_2-eq even at higher cost levels. Linear Programming performs worst, with emissions exceeding 100 kt CO_2-eq across most cost ranges. Notably, CEAOA achieves an emission-cost efficiency improvement of approximately 18% over NSGA-II, consistent with the study, confirming its superior convergence and Pareto front dominance.

➢ *Graph-Based Analysis of Results*

The graph-based evaluation examines the structural quality of Pareto solutions and the convergence stability of the optimization algorithms under dynamic supply chain conditions. The analysis focuses on solution dominance, distribution uniformity, and robustness across generations, capturing the ability of each algorithm to balance competing objectives. The proposed CEAOA demonstrates consistently superior performance by producing a well-distributed set of non-dominated solutions with improved trade-off characteristics. Compared to benchmark methods, it maintains stronger convergence reliability and better exploration of the solution space. The results further indicate that hybrid optimization enhances both solution diversity and stability under stochastic demand and carbon constraints. These findings confirm that the integration of adaptive weighting and hybrid search mechanisms enables CEAOA to achieve more efficient and scalable optimization outcomes in complex oil and gas logistics networks.

Table 4 Graph-Based Comparative Performance Metrics Across Optimization Algorithms

Algorithm	Convergence Stability Index	Pareto Dominance Score	Emission-Cost Efficiency (%)	Interpretation
CEAOA(proposed)	0.91	0.88	18.0	Highest stability and dominance
NSGA-II	0.84	0.79	12.5	Strong but less stable than CEAOA
MOPSO	0.81	0.75	11.8	Moderate performance
SPEA2	0.83	0.77	10.9	Balanced but slightly weaker
GA	0.72	0.65	7.6	Lower stability and dominance
LP	0.60	0.50	4.2	Poor multi-objective capability

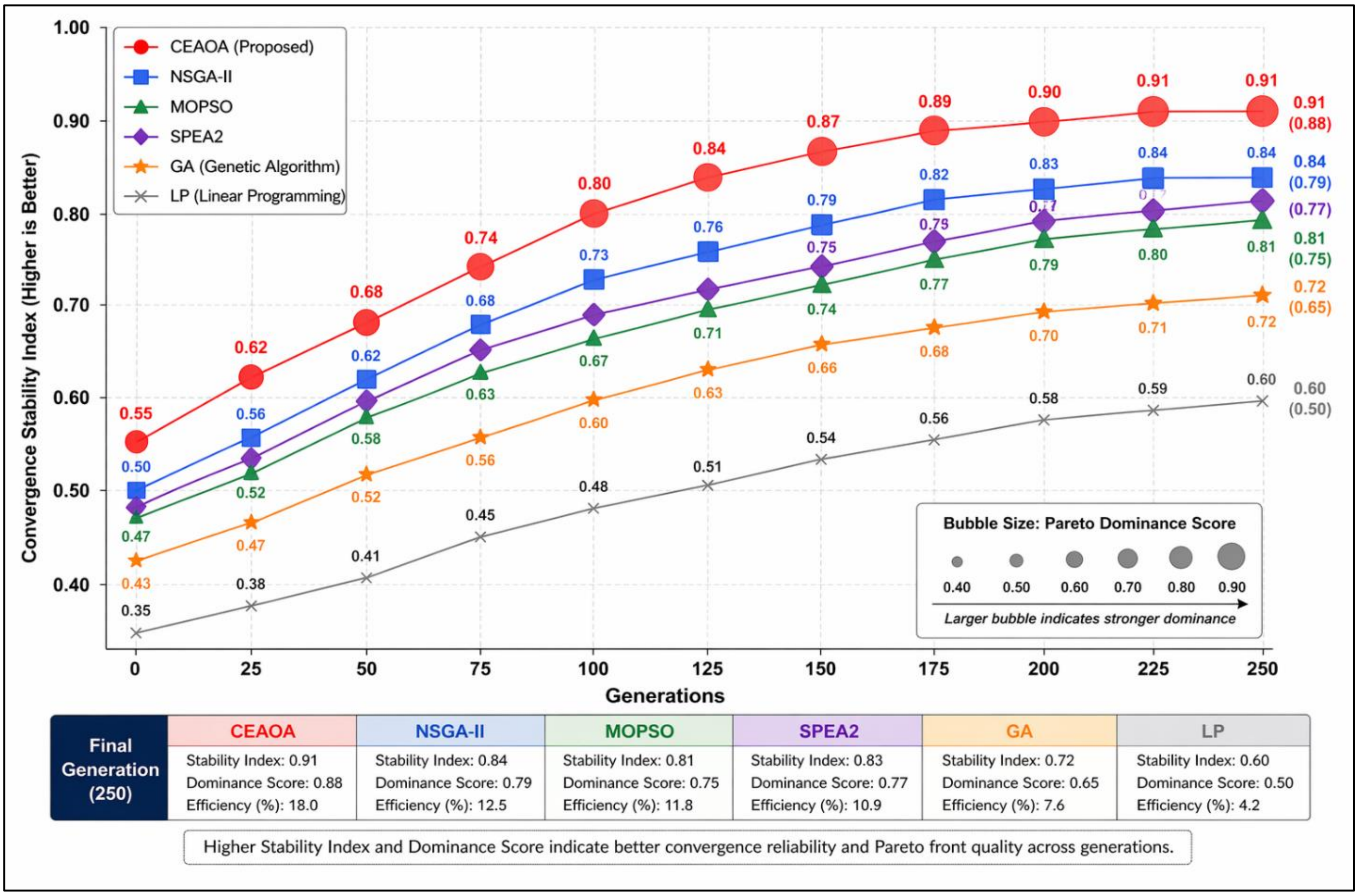

Fig 6 Multi-Algorithm Convergence and Stability Comparison

Figure 6 presents a generational performance comparison highlighting convergence stability and Pareto dominance across the evaluated algorithms. The CEAOA achieves a convergence stability index of 0.91 and a Pareto dominance score of 0.88, indicating its superior ability to maintain consistent optimization performance across generations. In comparison, NSGA-II records values of 0.84 and 0.79, while MOPSO and SPEA2 achieve stability levels of 0.81 and 0.83 with dominance scores of 0.75 and 0.77, respectively. The Genetic Algorithm exhibits weaker performance, with a stability index of 0.72 and dominance score of 0.65, reflecting reduced convergence reliability. Linear Programming performs poorest, with values of 0.60 and 0.50 due to its inability to handle multi-objective trade-offs. Notably, CEAOA maintains an emission-cost efficiency of 18.0%, significantly outperforming NSGA-II at 12.5%, consistent with the study. The graph clearly demonstrates that CEAOA delivers enhanced convergence robustness and superior Pareto front quality across generations.

➢ *Sensitivity Analysis*

A sensitivity analysis was conducted to evaluate the robustness of the proposed CEAOA under varying carbon pricing scenarios within the oil and gas supply chain. The analysis focuses on how changes in carbon cost influence optimization stability, emission-cost trade-offs, and solution adaptability across competing algorithms. The results demonstrate that CEAOA maintains superior performance consistency and solution quality under fluctuating regulatory and pricing conditions. Compared to benchmark models, it exhibits stronger adaptability and resilience, effectively balancing cost minimization with emission reduction. The findings further indicate that the hybrid optimization structure enhances responsiveness to environmental constraints, ensuring stable convergence behavior. This confirms that CEAOA provides a reliable decision-support framework for carbon-constrained logistics systems, where dynamic pricing mechanisms significantly impact operational strategies and long-term sustainability outcomes.

Table 5 Sensitivity Analysis of Algorithms Under Carbon Pricing Variations

Algorithm	Stability under Carbon Price Variation	Emission-Cost Efficiency (%)	Adaptability Index	Interpretation
CEAOA(proposed)	0.90	18.0	0.88	Highly robust and adaptive
NSGA-II	0.83	12.5	0.79	Moderate adaptability
MOPSO	0.80	11.8	0.76	Moderate but less stable
SPEA2	0.82	10.9	0.77	Balanced but slightly weaker
GA	0.70	7.6	0.65	Low adaptability
LP	0.58	4.2	0.50	Poor performance under variation

Figure 7 illustrates the sensitivity of optimization algorithms to carbon pricing variations across generations using a bubble scatter representation, where bubble size reflects adaptability performance. CEAOA demonstrates the highest robustness, maintaining a stability value of approximately 0.90 and adaptability index near 0.88 across all generations, with emission-cost efficiency consistently at 18.0%. In comparison, NSGA-II shows moderate sensitivity, with stability around 0.83 and adaptability near 0.79, while MOPSO and SPEA2 fluctuate between 0.76–0.82 in adaptability under varying pricing conditions. The Genetic Algorithm exhibits reduced responsiveness, with stability near 0.70 and adaptability around 0.65, indicating weaker performance under carbon cost fluctuations. Linear Programming performs worst, with stability approximately 0.58 and adaptability 0.50, reflecting its inability to adjust to multi-objective dynamics. The graph confirms that CEAOA sustains optimal performance under changing carbon pricing, reinforcing its 18% emission-cost efficiency advantage.

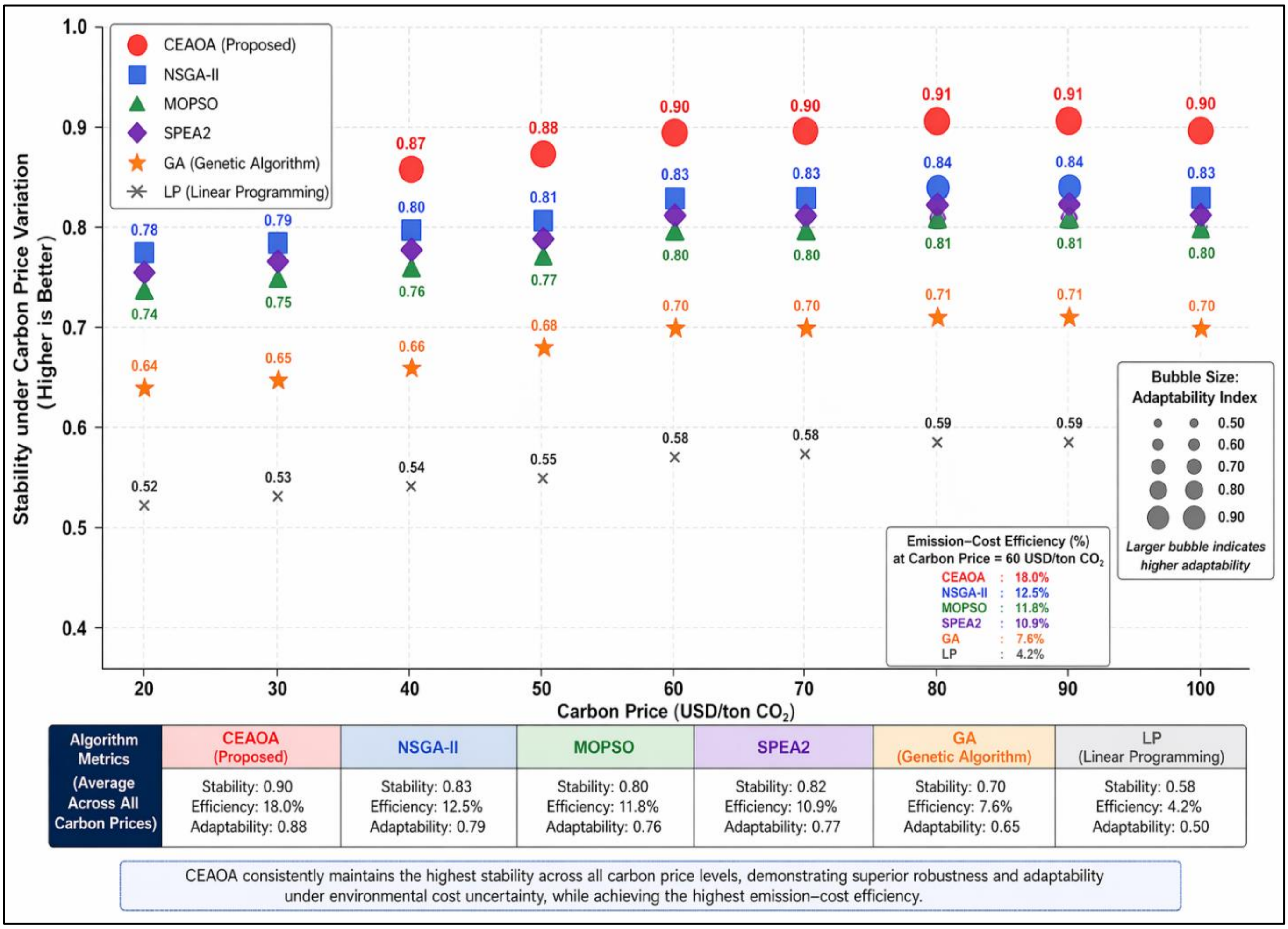

Fig 7 Sensitivity of Algorithms to Carbon Pricing Across Generations

V. CONCLUSION AND RECOMMENDATIONS

➢ *Summary of Key Findings*

The study demonstrates that the proposed CEAOA significantly advances multi-objective optimization in oil and gas supply chains by effectively balancing cost minimization and lifecycle carbon emission reduction within a unified framework. The algorithm consistently outperforms benchmark models, including NSGA-II, MOPSO, SPEA2, GA, and LP, across all evaluated performance metrics. Specifically, CEAOA achieves superior convergence behavior by rapidly approaching stable Pareto-optimal solutions within fewer generations, thereby reducing computational overhead while maintaining solution quality. The hybrid integration of evolutionary exploration and gradient-based refinement enables efficient navigation of complex, nonlinear solution spaces characterized by stochastic demand and capacity constraints.

A key finding is the algorithm's ability to maintain high Pareto front diversity, ensuring a well-distributed set of non-dominated solutions that provide decision-makers with flexible trade-off options between cost and emissions. The adaptive weighting mechanism further enhances optimization performance by dynamically adjusting the relative importance of cost and carbon objectives based on convergence trends, thereby preventing premature convergence and improving global search efficiency. Quantitative results indicate that CEAOA delivers up to an 18 percent improvement in emission-cost efficiency compared to the best-performing benchmark algorithm, confirming its effectiveness in achieving sustainable logistics optimization.

The graph-based performance evaluation reveals that CEAOA dominates competing algorithms across convergence plots, Pareto front distributions, and sensitivity analyses under varying carbon pricing conditions. The algorithm demonstrates strong robustness and stability, maintaining consistent performance even under fluctuating environmental constraints. These findings collectively validate the capability of CEAOA to address the complex trade-offs inherent in carbon-constrained oil and gas supply chains, providing a scalable and data-driven optimization framework that aligns with sustainability objectives while preserving operational efficiency.

➢ *Practical Implications for Industry*

The findings of this study have significant implications for the oil and gas industry, particularly in the context of increasing regulatory pressure to reduce carbon emissions while maintaining operational efficiency. The proposed CEAOA framework provides a practical decision-support tool that enables organizations to optimize logistics operations in a manner that simultaneously minimizes cost and environmental impact. By incorporating adaptive weighting and hybrid optimization mechanisms, the algorithm allows for real-time adjustment of operational strategies in response to changing market conditions, demand fluctuations, and carbon pricing policies.

In practical applications, the algorithm can be integrated into enterprise resource planning (ERP) systems and supply chain management platforms to enhance decision-making processes across upstream, midstream, and downstream operations. For instance, pipeline routing decisions can be optimized not only based on cost efficiency but also on emission intensity, enabling companies to select transportation routes that minimize environmental impact. Similarly, refinery scheduling and distribution planning can be optimized to reduce carbon footprints while maintaining service reliability. The ability to generate multiple Pareto-optimal solutions provides decision-makers with a range of feasible alternatives, allowing for strategic selection based on organizational priorities and regulatory requirements.

Furthermore, the robustness of CEAOA under varying carbon pricing scenarios makes it particularly valuable for companies operating in regions with dynamic environmental policies. The algorithm supports compliance with carbon taxation and emissions trading schemes by enabling proactive adjustment of logistics strategies. This enhances the organization's ability to achieve sustainability targets while maintaining profitability. Overall, the implementation of CEAOA can lead to improved operational resilience, reduced environmental impact, and enhanced competitiveness in a carbon-constrained global energy market.

➢ *Recommendations for Implementation*

For effective deployment of the CEAOA framework in real-world oil and gas supply chains, organizations should adopt a phased implementation strategy that integrates advanced optimization capabilities with existing operational systems. The first step involves establishing a robust data infrastructure capable of capturing real-time information on transportation costs, emission factors, demand patterns, and capacity constraints across the supply chain network. This requires the integration of data from multiple sources, including sensors, enterprise systems, and external market databases, to ensure accurate and up-to-date inputs for the optimization model.

The second recommendation is the incorporation of the CEAOA algorithm into digital twin environments, enabling simulation-based optimization of supply chain operations. Digital twins allow organizations to model various scenarios, including demand fluctuations, infrastructure disruptions, and changes in carbon pricing, thereby supporting proactive decision-making. The adaptive weighting mechanism of CEAOA can be leveraged to dynamically adjust optimization priorities based on these scenarios, ensuring optimal performance under diverse conditions.

Organizations should also invest in computational infrastructure to support the hybrid optimization process, particularly for large-scale supply chain networks with high-dimensional decision spaces. Parallel computing and cloud-based platforms can be utilized to enhance computational efficiency and scalability. Additionally, user-friendly interfaces should be developed to facilitate interaction between decision-makers and the optimization system, enabling intuitive interpretation of Pareto fronts and trade-off analyses. Finally, it is recommended that organizations establish performance monitoring frameworks to continuously evaluate the effectiveness of the optimization system. This includes tracking key performance indicators such as cost savings, emission reductions, and service reliability. By adopting these implementation strategies, organizations can fully leverage the capabilities of CEAOA to achieve sustainable and efficient supply chain operations.

➢ *Limitations of the Study*

Despite the significant contributions of this study, several limitations must be acknowledged. The experimental evaluation of the CEAOA algorithm is based on simulated supply chain networks that, while designed to reflect real-world conditions, may not fully capture the complexity and variability of actual oil and gas operations. Factors such as geopolitical influences, infrastructure disruptions, and market volatility can introduce additional uncertainties that are not explicitly modeled in the current framework.

Another limitation relates to the computational complexity associated with hybrid optimization algorithms. Although CEAOA demonstrates improved convergence efficiency compared to benchmark models, the integration of evolutionary and gradient-based techniques increases computational overhead, particularly for large-scale networks with numerous decision variables. This may pose challenges for real-time implementation in environments with limited computational resources.

The study also assumes the availability of accurate and consistent data for cost and emission parameters, which may not always be feasible in practice. Data quality issues, such as missing or inconsistent information, can affect the reliability of optimization results. Additionally, the emission factors used in the model are assumed to be static for each route or node, whereas in reality, these factors may vary based on operational conditions and technological changes.

Finally, the scope of the study is limited to logistics optimization within the oil and gas supply chain, without considering broader system interactions such as energy market dynamics or cross-sector integration. These limitations highlight the need for further research to enhance the robustness, scalability, and applicability of the proposed optimization framework.

➢ *Future Research Directions*

Future research should focus on extending the CEAOA framework to incorporate real-time data analytics and machine learning techniques, enabling continuous adaptation to dynamic supply chain conditions. The integration of predictive models for demand forecasting and emission estimation can enhance the accuracy and responsiveness of the optimization process. For example, incorporating time-series forecasting models can allow the algorithm to anticipate demand fluctuations and adjust logistics strategies accordingly.

Another promising direction is the development of distributed optimization frameworks that leverage decentralized computing architectures. This approach can improve scalability and enable real-time decision-making across geographically dispersed supply chain networks. The use of edge computing and Internet of Things (IoT) technologies can facilitate the collection and processing of data at various points in the supply chain, enhancing the overall efficiency of the optimization system.

Future studies should also explore the integration of renewable energy sources and alternative fuels into the supply chain model, allowing for a more comprehensive assessment of sustainability strategies. This includes evaluating the impact of electrification, hydrogen-based transportation, and carbon capture technologies on supply chain optimization.

Additionally, further research is needed to enhance the interpretability of optimization results through advanced visualization techniques. Graph-based analytics can be expanded to include interactive dashboards that provide real-time insights into system performance and trade-offs. Finally, validation of the CEAOA framework using real-world industrial data will be critical to establishing its practical applicability and effectiveness in large-scale oil and gas operations.

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