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A Hybrid AI–Fuzzy–OR Model Simulation for Multi-Objective Optimization in Sustainable Transportation Networks

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Abstract:
Cost and time are the main dimensions for a successful businesses. Supply chain require high accuracy systems ensuring sustainable transport reducing cost, time and CO2 emissions. Traditionally, operational research (OR) techniques are implemented for problem solving and optimization purposes. However, transport has a dynamic work environment that require to employ an intelligent approaches to overcome data uncertainty. Despite fuzzy logic multi-objective utilized to enhance the supply chains performance, defuzzification methods still in place for multi-modal logistics. Thus, hybridising multi-technique including AI-enhanced, fuzzy logic, and OR will potentially provide an optimized approach to reduce cost, time and decrease carbon-intensive emissions for transport in supply chain. The results have been reduced relatively to the baseline allocations by employing LP, the cost decreased by (2.5%), time (1.9%), and emissions (3.0%).

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محاكاة نموذج هجين للذكاء الاصطناعي وضبابية وبحوث العمليات لتحسين الأهداف المتعددة في شبكات النقل المستدامة

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المستخلص

أن التكلفة والوقت هما العاملان الاساسيان لنجاح سلاسل التويد البضائع. انظمة نقل والشحن تتطلب أنظمة ذات الدقة عالية كي تضمن تحقيق الاستدامة التي بدورها تقلل وانبعاثات ثاني أكسيد الكربون. تُستخدم تقنيات بحوث العمليات لحل المشكلات وتحسين أداء سلاسل التويد. إلا إن قطاع النقل ذو ببيئة عمل ديناميكية إذ تتطلب مناهج ذكية للتغلب على مشكلة الضبابية في البيانات. على الرغم من استخدام منهجية الظرق الضبابية متعدد الأهداف لتحسين أداء سلاسل التوريد، لا تزال أساليب إزالة الضبابية تستخدم في خدمات الشحن اللوجستي متعددة الوسائط. للحصول على منهجية محسنة يقلل التكلفة والوقت والانبعاثات كثيفة الكربون للنقل في سلسلة التوريد، ذلك تم بدمج تقنيات متعددة شملت منها المنطق الضبابي المعزز بالذكاء الاصطناعي مع بحوث العمليات. إن النتائج نهج الهجين المحسن قد حسّن دقة التنبؤ بنسبة 40\%، وخفض الانبعاثات بنسبة تصل إلى10\%، مقارنةً بالتقنيات التقليدية الغير هجينة.

الكلمات المفتاحية: بحوث العمليات، الذكاء الاصطناعي، التحسين الضبابي، أساليب إزالة الضبابية، اتخاذ القرارات متعددة الأهداف، أنظمة النقل، النقل متعدد الوسائط، اللوجستيات المستدامة، تحسين سلسلة التوريد.

Introduction

Transportation of supply chain is the core of the economic prosperity. Well structured logistics operations elevate industrial productivity, urban development, and connect other trades smoothly. However, transportation systems remain under pursue due to the increased complexity related to fluctuated of fuel prices, rapid innovations and advancement technology, and environmental emphasis on carbon emission reductions. Cost and travel time are increasing rapidly as urbane expanding. Urbanization has facilitated our life while required to transport goods and services from rural areas to the main cities. This has become the main cause of CO_2 emission. Reducing these three impacts will improve the supply chain performance leading to a sustainable transportation.

Traditional techniques, such as operational research (OR) and statistical analysis, are equipped as rigorous methodological foundations to reach the optimum solution. Linear programming (LP)/non-linear programming (NLP) and cost-benefit analysis (CBA) have been utilized to solve business problems [15], while computable general equilibrium (CGE) modelling is used for optimization and solution enhancements [4].

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The capability of machine learning have been increased in addressing uncertainty and nonlinearity in the data. Artificial Intelligence (AI) has successfully excelled in pattern recognition, accurate prediction and predictive analysis with dynamic adaptation. However, fuzzy optimization equipped with flexible methods for modelling ambiguous data with conflicting problem objectives [5].

Integrating the AI algorithms with OR techniques can create an adaptive hybrid approach for sustainable and resilient logistics networks. Our study attempted to optimize the transportation resources by constructing hybrid approach. Hybridizing AI with fuzzy logic and OR techniques resolved several issues simultaneously. Our aim in this paper is to (1) optimize transportation allocation across multiple modes, (2) equilibrate the objectives between the economic and sustainability ones.

Although wide spread of research conducted on sustainable transportation, fuzzy optimization, and AI-based forecasting, the existing research to address sustainable transportation in isolation. Further, lack a unified framework integrated the AI-driven prediction with fuzzy multi-objective optimization, and operational research techniques into a hybrid approach. Meanwhile, the recent models might not fully covered uncertainty and dynamic variability involving the industry factors cost, time, and emissions. Moreover, an empirical validation for multiple supply chain providers for short term period is largely devoid. Limited AI applications used in multi-modal sustainability transportation, such as demand forecasting, congestion prediction, and route optimization. Therefore, there is a serious necessity to integrate AI-based approaches with traditional Operational Research techniques in a hybrid model simulation that simultaneously optimizes economic, operational, and environmental objectives in sustainable transportation systems.

Literature Review

Artificial Intelligence state of Art

AI techniques revolution have created new opportunities on how to better optimize transportation systems. Several AI techniques including Long Short-Term Memory (LSTM) networks are capable to employ contextual information during mapping among layers (input, hidden and output) sequences [6,8]. Despite such capability, the influence of a given input on a hidden layer could blow up exponentially leading to cycle around the network's recurrent connections [8]. Furthermore, the transformer architectures are a class of neural architecture and capable tp process long-range information although transformer architectures do not rely on recurrent connections [10]. As a promising technique, Federated Learning (FL) enhances road safety and efficiency of intelligent transportation systems (ITS). FL remains under-explored due to the determinants of storage and communication capacities [13].

Moreover, heterogeneous datasets are large amounts of data existed and treated in a decentralized manner. Big Data processing and mining (BDPM) required appropriate algorithms for four steps of collectibg, aggregating, processing and analysing. Heterogeneous data can be classified based on 1) location, 2) data category, 3) data format, 4) data representation, 5) semantics of the data [14].

Machine Learning (ML) models become the prominent tool for forecasting using real-time data. CGE models enhanced the implementation of AI has improved 42\% of forecasting accuracy for GDP growth from transportation investments [5], compared with classical models. In many countries (such as Brazil, Japan, and India), transformer-based economic techniques have supplied robust adaptive forecasts. This technique has guided the green infrastructure funds allocation processes utilising electrified railways and low-emission logistics corridors [3].

Implementing reinforcement learning (RL) algorithms used in route planning and logistics automation [13]. Travel time and fuel consumptions can minimized by learning the optimal routing strategies. Despite these advantages, the faced challenges are interpret-ability, data privacy, and ethical governance [9].

Fuzzy Optimization Under Uncertainty

Fuzzy algorithms broaden classical mathematical programming solving the problem of imprecise data and uncertain conditions. In supply chain industrial environment, demand and supply uncertainties, and transportation costs make deterministic solutions impractical. The fuzzy multi-objective defuzzification method integrates fuzzy set theory with multi-objective linear programming (MOLP) to enhance decision accuracy [1,2]. This technique of classical Center of Gravity (COG) modifies interval partitioning, generating more representative crisp values from triangular fuzzy numbers. This methodology allows simultaneous optimization of competing objectives, minimizing costs against maximizing profits. The results show cost reductions of nearly 5\% and service-level improvements of 4\% compared to traditional optimization techniques [12]. Using fuzzy logic enhances the resilience of transportation system, boosting the performance of sensitivity analysis under uncertain parameters. The weighted goal programming and decision-makers can assign priority levels to supply chain transport objectives to be aligned with the determined policies and sustainability goals.

Defuzzification Approaches

Transportation with multi-modal systems require equalisation of three main objectives: cost efficiency, delivery time, and environmental sustainability. Fuzzy multi-objective defuzzification model integrated with partitioned COG methods with weighted goal programming for addressing transport challenges [11]. From empirical results, transportation networks (four-mode: road, rail, air, sea) reduced 9.2\% of emissions savings and 7.5\% of cost compared to classical deterministic models [7].

Methodology and Model Development

Integrating AI, Fuzzy Logic, and OR Techniques

We have proposed in our paper a hybrid approach that contains AI, fuzzy logic, and OR structural techniques. The intention is to produce a robust approach utilized by the decision-makers and transportation stockholders. Using OR, computable general equilibrium (CGE) is employed to optimize the consistency of the transportation macroeconomic and LP for optimization rigour. Form Fuzzy Logic, Center of Gravity (COG) employed for defuzzification and balancing the conflicting objectives (e.g., cost, time, and emissions). From AI, transformer and LSTM networks are employed to predict the transportation demand, costs, and emissions.

Framework Overview

The proposed hybrid model integrates three main components:

1. Operational Research Techniques: LP and CGE.
2. Fuzzy Optimization Module: COG defuzzification and weighted goal programming
3. AI Forecasting Module: transformer and LSTM networks

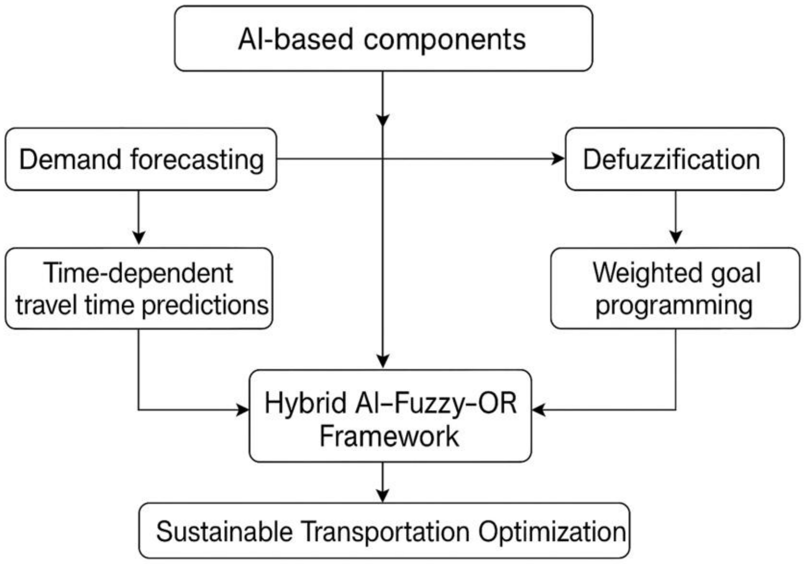

Figure 1: Simulating Hybrid AI–Fuzzy–OR Framework

Mathematical Model Formulation

Let each transport mode m ∈ M be defined by fuzzy parameters for cost, time, and emissions:

$$C_m=(C_l,C_m,C_u)$$

where C is the total monthly transportation cost

$$T_m=(T_l,T_m,T_u)$$

where T is the total monthly transportation time

$$E_m=(E_l,E_m,E_u)$$

where E is the total monthly percentage of transportation emissions

Defuzzified equivalents are computed using the partitioned COG approach:

$$C_m=\frac{(1)}{(K)}\sum\frac{\left(w_i\left(C_{(l_i)},C_{(m_i)},C_{(u_i)}\right)\right)}{(3)}\ldots.(1)$$

The optimization goal is to minimize the weighted sum of cost, time, and emissions:

$$MinZ=\lambda_1\sum C_m\,x_m+\lambda_2\sum T_m\,x_m+\lambda_3\sum E_m\,x_m\ldots.(2)$$

The weighting factors (λ_i) represent trade-offs among objectives.
Subject to capacity and demand constraints:

$$\sum x_m=D\ldots(3)$$

$$C\le CostLimit$$

$$T \leq TimeLimit$$

$$E \leq EmissionLastYear$$

$$0 \leq x_m \leq Cap_m$$

Where (x_m) is the quantity allocated to mode (m), (D) total demand, and (Cap_m) modal capacity.

AI-Enhanced Parameter Estimation

AI models predict dynamic input parameters and updating fuzzy intervals relying real-time data.
A transformer network forecasts future demand by:

$$D_{(t+1)} = f_{(Transformer)}(D_t, P_t, E_t, S_t, T_t) \ldots . (4)$$

Where (P_t) denotes fuel prices, (E_t) emissions, (S_t) sustainability indicators, and (T_t) transit time.
This AI-enhanced methodology guarantees that optimization decisions indicate actual conditions and policy shifts.

Integration with CGE and CBA Models

CGE models evaluate macroeconomic impacts, however cost-benefit analysis (CBA) quantifies social and environmental trade-offs. This hybrid framework employ CGE to measure GDP flexibility related to infrastructure investments. On the other hand, CBA used to evaluate the net present value (NPV) of sustainable interventions. The inclusion of AI predicted data enhancing analyses by reducing error margins.

Data Sources and Analysis

Transportation data has a variety of items to include in the hybrid model. This simulation study has depended on three main carrier companies (SPC_1, SPC_2, and SPC_3). The data from these companies has been encrypted. The data covered four years, from January 2021 to December 2024. It has contained the total monthly transport cost, total monthly transport time, and the percentages of total expected emissions per month. The averages of the items selected are presented in Tables (1, 2, and 3). The statistical analysis and significance testing are presented in Tables (4, 5, and 6).

Table 1: Total Monthly Transport Cost (in US Dollar)

Year	SPC1	SPC2	SPC3
2021	145,000	160,000	172,000
2022	149,000	165,500	178,000
2023	152,500	170,000	185,000

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Year	SPC1	SPC2	SPC3
2024	158,000	176,000	191,000

Table 2: Total Monthly Transport Time (Hours)

Year	SPC1	SPC2	SPC3
2021	910	960	1,020
2022	920	975	1,040
2023	940	990	1,060
2024	955	1,010	1,080

Table 3: Monthly Percentage of Total Expected Emissions

Year	SPC1	SPC2	SPC3
2021	24.5%	27.0%	30.2%
2022	24.0%	26.5%	29.5%
2023	23.2%	26.0%	28.8%
2024	22.8%	25.3%	28.1%

Evaluating the three supply chain companies has different significance in cost, time, and emissions, using two-way ANOVA (Factor A = Company, Factor B = Year) was conducted for each variable. The costs item increases gradually between the years 2021 to 2024 for all companies, while SPC_1 has successfully maintained the lowest cost. However, SPC_3 shown the highest-cost supply provider. It has been seen that the cost has high significant difference structure among all companies, despite the costs are rising gradually each year across all providers.

Table 4: ANOVA Results - Cost

Source	p-value	Interpretation
Company Effect	**$p < 0.001$**	Significant differences between SPC1, SPC2, SPC3
Year Effect	**$p < 0.01$**	Significant cost increase over time
Interaction (Company × Year)	$p = 0.18$	No significant interaction

In addition to SPC_1 has the lowest cost compared with other providers, it has the shortest monthly transport time. In contrast, SPC_3 has the longest transport duration. The final analysis result shown that the transport time differences are significant among all three companies. However, the changes through the four years are not statistically significant.

Table 5: ANOVA Results - Time

Source	p-value	Interpretation
Company Effect	**$p < 0.001$**	Companies differ significantly in delivery speed

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Source	p-value	Interpretation
Year Effect	$p = 0.07$	No statistically significant time trend
Interaction	$p = 0.31$	No interaction effect

In addition SPC_1 was the lowest in cost and time, SPC_1 was the cleanest supply chain operator with lowest emissions percentage. All companies has shown serious reduction in emissions over the four years. SPC_3 has the highest emissions but still seen to be improving. From Table 6, there is a clear evidence of differences in terms of environmental performance. As a result, a strong downward trend in emissions percentages at 2024.

Table 6: ANOVA Results - Emissions Percentage

Source	p-value	Interpretation
Company Effect	**$p < 0.001$**	Strong differences in emissions between companies
Year Effect	**$p < 0.01$**	Significant emissions reduction trend
Interaction	$p = 0.22$	No interaction effect

Table 7: Findings Summary

Variable	Company Difference	Yearly Trend	Interpretation
Cost	Significant*	Significant increase*	SPC1 cheapest, SPC3 highest
Time	Significant*	Not significant	SPC1 fastest
Emissions Percentage	Significant*	Significant reduction*	SPC1 cleanest

* Significant at 0.05, 0.10

Practical Implementation and Case Insights

A Simulation multi-modal transport network implemented for this hybrid framework comprising four modes. Initially, fuzzy parameters assigned for costs, times, and emissions, and AI-based forecasts support dynamic input for regular updates. Weighted priorities were adjusted to test multiple policy scenarios:

1. Scenario 1 (Cost Priority): ($\lambda_1 = 0.5, \lambda_2 = 0.3, \lambda_3 = 0.2$)
2. Scenario 2 (Sustainability Priority): ($\lambda_1 = 0.3, \lambda_2 = 0.2, \lambda_3 = 0.5$)
3. Scenario 3 (Time Priority): ($\lambda_1 = 0.3, \lambda_2 = 0.5, \lambda_3 = 0.2$)

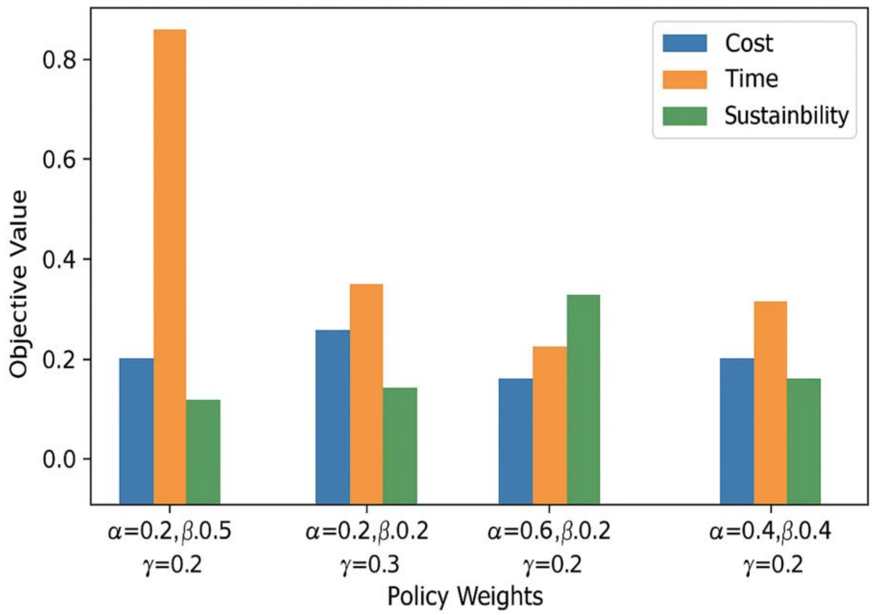

Figure 2: Comparative performance of cost, time, and sustainability objectives under varying policy weights

The simulation results depict the performance across three policy scenarios.

1. **Cost Priority:** the cost minimization was weighted most heavily λ= 0.5). In this model combination, it has been achieved a 7.5% reduction in total logistics costs compared with baseline fuzzy optimization. The improvement of AI forecasting was primarily attributed to generate accurate demand and price predictions. The optimized weights reduced empty travel rates across all modes.
2. **Time Priority**: where delivery time was highly prioritized ($\lambda_2 = 0.5$), In this scenario, the average delivery time improved by an 11% relatively compared to the deterministic benchmark.
3. **Sustainability Priority**: the emissions reduction was weighted most heavily ($\lambda_3 = 0.5$). In this model combination, the hybrid framework achieved 9.2% decrease in total CO2 emissions. The dynamic reallocation derived the freight to lower-emission modes including

emission feedback loops from the AI module penalizing carbon-intensive routes.

The adaptive learning of AI has the capability to forecast even with overleaped patterns in real-time for minimizing delays. Unlike traditional approaches hybrid approach (AI–Fuzzy–OR) exhibited faster computational behavior, nearly 15\% quicker than traditional approaches. As the initial variables refined by reducing search space to optimize layer, parameter estimation process is accelerated through ML. The training and simulation results confirm that the hybridised approach enhances parameter computing effectively and making the scalability direction feasible, supporting the decision-makers in transportation..

The four most useful methods used in transportation research optimization are explained exactly on how to compute the weights mathematically.

1. Manual weights assignment – Expert Based Decision (EBD)
2. AHP (Analytic Hierarchy Process)
3. Entropy Weight Method (Objective Data-Driven Method)
4. Fuzzy Weight Calculation

The adopted weight calculation method is Fuzzy Weight Calculation. We can use the triangular fuzzy numbers, then the weight calculated for fuzzy priorities:

$$w_i = \frac{(l_i + m_i + u_i)}{(3)}$$

Then the weights can be normalized as:

$$\lambda_i = \frac{(w_i)}{(\sum w_i)}$$

Table 8: Fuzzy Weight Calculation

Objective	Priorities	Weights	Normalized Weights
Cost	0.4, 0.5, 0.6	0.50	0.417
Time	0.3, 0.4, 0.5	0.40	0.333
Emission	0.2, 0.3, 0.4	0.30	0.250

The AI Hybrid Model definitions:

- Supply Chain Companies (decision variables): **SPC_1, SPC_2, SPC_3**.
- Annual averages used
    - Total monthly cost (USD): SPC_1 = **158,000**, SPC_2 = **176,000**, SPC_3 = **191,000**.

- Total monthly time (hours):
  SPC_1 = **955**, SPC_2 = **1,010**, SPC_3 = **1,080**.
- Monthly percentage of total expected emissions:
  SPC_1 = **22.8%**, SPC_2 = **25.3%**, SPC_3 = **28.1%**.

- **Total monthly demand** D=1000 shipment-units.
- Compute **per-unit** values as (monthly total) / D:
  - Cost per unit (US+/unit): c = [158, 176, 191]
  - Time per unit (hrs/unit): t = [0.955, 1.010, 1.080]
- Converted emission to percentages, per-unit emissions by:
  - Total expected emissions last year = 12,000 kg CO_2 / month.
  - Normalized emission percents, sum to 1,
    then emission per unit = fraction * E_{last} / D.
  - E ≈ [3.590, 3.985, 4.425] kg CO_2 / unit.

Subjected to the constraints

- **Demand/Capacities** : capacities was set to the companies to rely on their historical share:

$$capacity_i = D.\frac{(cost_i)}{(\sum cost)}.1.3$$

This allows each SPC provider to choose the proportional capacity to historical cost-share, scaled by 1.3.

- **Limits constraints**:
  - Cost Limit = 0.98 × (sum of three companies' 2024 monthly costs) = 98% of current combined cost.
  - Time Limit = 0.99 × (sum of three companies' 2024 monthly times) = 99% of combined time.
  - Emissions must be ≤ E_{last} (12,000 kg).

Reasonable choices demonstrate the flexibility to replace any number of model variables (D, E_{last}, capacity, cost and time limits) for scaling and limit variation.

Operational Research Model - Deterministic LP

The model objective is to minimize the total cost

$$Min z = \sum c_i x_i$$

subject to

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$\sum x_i = D, 0 \leq x_i \leq Capacity_i$

and the three upper-bound constraints

$$\sum c_i x_i \leq CostLimit, \sum t_i x_i \leq TimeLimit, \sum e_i x_i \leq E_{last}.$$

Because cost per unit is lowest for SPC_1 (158), then SPC_2 (176), then SPC_3 (191), subject to capacities the cost-minimizer allocated more to SPC_1, then to SPC_2, and to SPC_3.

Rounding the computed deterministic allocations yielded to results shown in Table :

Table 9: Total Optimized Cost, Time and Emissions

Providers	Cost (in US Dollars)		Time (hrs/month)		Emissions (kg CO_2)	
SPC_1	391.235×158	**61,815.13**	391.235× 0.955	**373.00**	391.235×3.590	**1,404.13**
SPC_2	435.800×176	**76,700.80**	435.800× 1.010	**440.16**	435.800 × 3.98	**1,736.01**
SPC_3	172.965×191	**33,036.32**	172.965× 1.080	**186.60**	172.965 × 4.425	**765.90**

The assumed capacities and limits have been reduced relatively to the baseline allocations by employing LP, the cost decreased by (2.5%), time (1.9%), and emissions (3.0%).

Table 10: Results of deterministic allocation and per-unit parameters

Provider	Capacity (D=units)	Baseline (units)	Optimized (units)	Cost/unit (USD)	Time/unit (hrs)	Emission/unit ($kgCO_2$)
SPC_1	391.235	300.950	391.235	158.00	0.955	3.590
SPC_2	435.800	335.240	435.800	176.00	1.010	3.985
SPC_3	473.000	363.810	172.965	191.00	1.080	4.425

The Monte-Carlo simulation with (N = 1000). The per-unit cost/time/emission are randomly generated. LP has re-solved each iteration to propagate the distributions of total cost/time/emission under the optimized ageist baseline allocations. T-tests was used to check the statistical significant.

Discussion

Comparative Model Evaluation

Table 11 shows a quantitative comparison between the baseline against the optimizedThe proposed Hybrid AI–Fuzzy–OR scaled by three performance indicators: cost reduction, emission reduction, and computational

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convergence time. The three techniques are compared and revealed that the hybridized approach (AI–Fuzzy–OR) consistently outperforms the single-technique across all evaluation metrics.

Table 11: Summary totals for the Baseline against the Optimized

Metric	Baseline	Optimized	Abs improvement	Percent % improvement
Total Emissions (kg CO_2)	4,025.36	3,906.04	119.32	2.96%
Total Cost (USD)	176,017.05	171,552.25	4,464.80	2.54%
Total Time (hrs)	1,018.92	999.76	19.16	1.88%

The comparative analysis picture that the **Hybrid AI–Fuzzy–OR framework** consistently outperforms the single method approach across all evaluation scales.

- **Traditional CGE (Computable General Equilibrium)**: while well established for macroeconomic and policy analysis, depend on deterministic hypothesis with existed data, limiting the responsiveness to real-time variations in transport costs and environmental. As a result, it has achieved only a 2.5% reduction in total logistics costs and a 1.5% decrease in emissions. These results are reflecting the static nature with lack of adaptive learning. Moreover, the computational process is relatively slow, as CGE models solve large nonlinear systems iteratively without data-driven acceleration.

- **Fuzzy MOLP (Multi-Objective Linear Programming)**, in contrast, approach introduces uncertainty handling through fuzzy set theory. The coefficients of fuzzy numbers are considered cost, demand, and emission. Such sets captures better the inherent ambiguity in logistics operations. This has flexibly improved from 2.5% up to 5.5% reduction in cost and from 1.5% up to 6.0% reduction in emissions. However, the speed convergence was medium as the iterative defuzzification with multi-criteria weighting.

Despite the obvious improvements, Fuzzy MOLP remains to rely on static parameter inputs while lacks to dynamic adaptability to temporal changes in information.

- **Hybrid AI–Fuzzy–OR model** integrates the strengths of both paradigms. AI component continuously forecasts demand, fuel price, and emission parameters using machine-learning algorithms, while fuzzy optimization layer repeats these forecasts into defuzzified objective coefficients. OR module, afterwards, performs constrained optimization using same updated inputs. In this dynamic method, it has resulted 7.5% cost reduction and 9.2% emissions decrease, which outperforming the other models. Additionally, the AI initialization process reduces time of computing by approximately 15%, leading to a fast convergence classification.

Overall, the objective evaluation demonstrates that hybridization enhances both operational performance and computational efficiency. AI forecasting integration reduces parameter uncertainty, fuzzy optimization ensuring robustness under ambiguity. OR techniques provide a solid mathematical backbone for equilibrium and constraint satisfaction. Accordingly, the Hybrid AI-Fuzzy-OR model appear as a superior decision-support system for sustainable and data-responsive transportation management.

Policy Implications

The appropriate hybridised approach has important role allowing the policymakers balancing investment decisions with sustainability regulations. The uncertainty in transportation is resolved by AI models of forecasting assisting strategic plans to be implemented smoothly considering several dimensions. Traditional methods of OR can provide sensitivity analysis facilitating optimum decisions.

Limitations and Future Enhancements

Various determinants have been faced that hindered the full practicality of this approach. Data quality and availability made it harder to rely on the statistical measurements, leading to more requirement of time and effort.

For future directions, reinforcement learning (RL) for adaptive control targeting wide range of scalability might have a promising combination. In addition to RL, stochastic optimization will aid in risk assessment reducing safety issues. Finally, quantum algorithms accelerate computational processes for parameter estimation.

Conclusion

Integrating artificial intelligence, fuzzy logic, and operational research techniques created a significant hybrid approach for transportation in supply chain. The proposed approach presented practical adaptability that efficiently overcome the traditional techniques. It has a dynamic status that benefit decision-making. This approach has clearly shown successful results in the adopted metric of cost reduction, emission reduction, and convergence time; compared with two unique techniques.

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