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Hydrogen Trucks and New Energy Trucks in Logistics Trunk Lines: Carbon Emission and Cost−Benefit Analysis

Boyu Zhang

School: Hohhot No. 2 Middle School

city: Hohhot, Inner Mongolia

postcode:010010

E-mail:15754946810@163.com

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Abstract

With the escalating environmental harm caused by carbon emissions from road diesel trucks and the global advancement of carbon reduction and carbon neutrality initiatives, enterprises and individuals are compelled to seek greener transportation alternatives. This study focuses on the application of new energy trucks and hydrogen trucks in logistics trunk lines, centering on their roles in reducing carbon emissions and lowering operating costs. By constructing mathematical models, it analyzes different road sections to select appropriate vehicle types and scheduling schemes, thereby optimizing the overall logistics and transportation system for enhanced economic and environmental benefits. The research findings indicate that new energy and hydrogen-powered trucks excel in carbon emission reduction; however, they currently confront challenges such as inadequate infrastructure, high hydrogen fuel costs, and other development constraints. Nevertheless, in the long term, new energy and hydrogen energy are expected to yield substantial economic and environmental benefits (Mao et al., 2022).

Keywords: New energy trucks, hydrogen-powered trucks, logistics, carbon emissions, cost analysis, sustainable development

1. Introduction

1.1 Research Background

Against the backdrop of global carbon neutrality efforts, carbon emissions in the logistics industry have become a top priority for governments and enterprises, requiring urgent attention. The logistics sector contributes significantly to overall carbon emissions, making the reduction of its carbon footprint crucial. Data from the International Energy Agency shows that road transportation, including cars, trucks, and buses, accounts for approximately 17% to 18% of global carbon emissions from energy consumption. Among road transportation, freight trucks are a major source, responsible for 40% to 50% of road transport carbon emissions, which translates to about 6% to 9% of global energy-related carbon emissions. With the implementation of national carbon emission controls and carbon trading systems, enterprises worldwide are pressed to explore sustainable energy alternatives. Currently, new energy is widely adopted in passenger cars but not yet in freight trucks. New energy offers advantages such as mature infrastructure, suitability for short-distance and regional transportation, full-life-cycle emission reduction, high energy efficiency, and cost-effectiveness. Hydrogen energy, on the other hand, has garnered attention due to its suitability for long-distance and heavy-load transportation, fast refueling, good performance in low-temperature and complex environments, and emission reduction potential through industrial synergy. However, new energy trucks face issues like slow charging, limited range, and low load capacity, while hydrogen energy suffers from high costs (currently \$3 to \$5 per kilogram) and slow construction of hydrogen refueling stations. To address these challenges, this study constructs a logistics network cost optimization model based on operations research, integrating hydrogen energy and new energy in logistics trunk lines. This integration leverages the long-range and heavy-load advantages of hydrogen energy and the short-distance and regional transportation strengths of new energy, aiming to optimize both carbon emissions and costs.

1.2 Research Issues

1. When we talk about using hydrogen and new energy sources in logistics trunk lines, we have to see how they affect carbon emissions. These new types of energy can truly make a difference. First, hydrogen-powered vehicles produce zero emissions when they run, which means that they do not release any harmful gases into the air. This is a considerable benefit for reducing the carbon footprint. All the large trucks on the highway run smoothly without polluting the environment. There are also new energy sources, such as electricity and solar power. For example, electric vehicles are becoming increasingly popular. They use batteries to store energy and do not need fossil fuels to run. Solar power, on the other hand, harnesses energy from the sun. It is a clean, renewable resource that can also power vehicles. When we switch from traditional fuels to these cleaner options, we reduce the amount of carbon dioxide and other greenhouse gases released into the atmosphere. This helps slow climate change and keeps our planet healthier. Therefore, in summary, using hydrogen and new energy sources in logistics trunk lines is a great way to reduce carbon emissions. It is cleaner, greener, and better for the environment (Bauer et al., 2020).

2. When we consider energy sources, we must consider whether hydrogen and new energy options are less expensive or more profitable than traditional options are. Simply put, is it worth switching from what we have always used to these newer alternatives? In terms of costs, traditional energy sources such as coal and oil have been around for a long time, and their prices are usually stable. However, with hydrogen and new energies, such as solar and wind, the setup costs can be high. However, over time, these new sources might save money because they do not need as much maintenance and because the fuel is often free or very cheap to obtain. Additionally, we have to think about the environment. Traditional sources can harm the planet, but hydrogen and new energy sources are cleaner. This means they might be better for us in the long run, even if they cost slightly more upfront. In the end, whether hydrogen and new energy sources are economically viable compared with traditional sources depends on many factors. It is not just about the money we spend now but also about what we save in the future and how we take care of our planet.

1.3 Research Innovation Points

1. We plan to build a simple optimization model. This model considers three things: hydrogen energy, new energy, and traditional diesel trucks.

2. Turn carbon emissions into money and include that in the cost estimate. Here's how you can do it in simpler terms: take the carbon emissions, figure out how much they cost, and then add that cost to whatever you're budgeting for.

3. A basic way to change how we think about energy replenishment and its cost in terms of time and money is suggested. This new idea eliminates the simple rule that time is always limited, as in the old models.

2. Literature Review

2.1 Cost Optimization Model Based on the OR Logistics Network

Traditional logistics network optimization aims to reduce costs. It mostly uses operations research methods to build mathematical models for this purpose. Early on, researchers looked into the vehicle routing problem, or VRP. This problem concerns finding the best way to deliver goods. They used linear programming and integer programming to determine the optimal distribution path. As technology has improved, heuristic algorithms, such as genetic algorithms, are now commonly used to address large, tricky problems. However, most of these studies do not consider the costs to the environment. They only look at fuel consumption and time cost when trying to improve things. This makes it difficult to meet the needs for green logistics in a world working towards carbon neutrality (Dantzig & Ramser, 1959).

2.2 Application of the Improved Genetic Algorithm in Path Optimization

Genetic algorithms are often used in logistics for planning complex paths. They are good at searching for the best solution by looking at many possibilities at once. To increase efficiency, researchers have proposed various improvement strategies:

Node priority optimization uses Heap Sort Chen, and his team focused on node priority optimization via heap sorting. They explained that in computer science, managing node priorities is crucial for many algorithms and systems. To do this efficiently, they chose heap sorting because it is well known for its ability to handle priority queues. In their approach, they first set up a heap structure. This structure allows them to quickly add, remove, and update node priorities. They noted that a heap, specifically a max-heap or min-heap, naturally maintains the highest or lowest priority nodes at the top, making it easy to access them. Next, they implemented the heap sort algorithm. This method keeps taking the most important node from the heap, addresses it, and then fixes the heap to keep it in order. To demonstrate their method, Chen et al. present some examples and test cases, which are stated in a simple and direct way: We provide several examples to illustrate the point. For example, we showed how to solve a math problem step-by-step. We also provided test cases to check if the solution works correctly. In one example, we demonstrated how to add two numbers. We wrote the numbers, added them together, and presented the results. For the test cases, we used different sets of numbers to ensure that our method always provided the right answer. We checked both simple cases, such as adding 1 and 1, and more complex cases, such as adding large numbers or numbers with decimals. In this way, we ensure that our solution is accurate and reliable. They proved that their method, which uses heap sorting, was faster and more dependable than other common algorithms for optimizing node priority. It works better in terms of speed and reliability. They also discussed potential applications, such as in scheduling systems, task managers, and network routers. Overall, Chen and his team's work on node priority optimization via heap sort provided a clear and effective solution for managing node priorities in various computer science scenarios. By simplifying the geographic traffic network into a graphical structure and then using heapsort to speed up the sorting of unlabelled nodes in Dijkstra's algorithm, the path search efficiency was improved by 30% (Chen et al., 2018).

Dynamic Adaptation Function Design: In 2020, Wang and Lu designed a function that uses real-time traffic data. They incorporated these data into their genetic algorithm to improve its accuracy and efficiency. They changed the adaptation function when needed and succeeded in making the distribution paths better. This was a straightforward process. This meant that the algorithm worked quickly and well.

Although the new genetic algorithm improves how fast we can perform calculations, it looks mainly at old-fashioned economic costs, such as how far something has to travel and how much time it takes. It does not have a thorough look at the environmental costs. This makes it difficult for it to help with decisions about green logistics.

2.3 The Need for Green Logistics and Carbon Emission Cost

2.3.1 Externality Constraints of Carbon Emissions and Policy Responses

The impact of logistics and transportation on the environment, especially their carbon footprint, is now a major concern in managing the world's climate. In 2022, the International Energy Agency reported that freight trucks are responsible for 11% of global transportation carbon emissions. In China, heavy-duty diesel trucks emit a large amount of carbon dioxide.

Specifically, they produce 1.5 kilograms of CO_2 per kilometer, according to the Ministry of Ecology and Environment's data from 2022. If we do not do anything, logistics carbon emissions might increase by 58% in 2035 compared with those in 2020. This is in accordance with a report by the World Bank in 2023. At the policy level, the European Union has a thing called the carbon border adjustment mechanism (CBAM). This system makes importers pay for the carbon emissions caused by transportation (such as ships and trucks bringing goods in). Moreover, in China, there is this "dual-carbon" goal. Because of this, businesses must consider carbon emission cost when making decisions.

2.3.2 Limitations of existing research

The better genetic algorithm does not include carbon emission cost calculations. Therefore, we add a model for those calculations to the improved genetic algorithm. In this way, we can achieve green optimization for the logistics network.

2.4. Innovative Points of This Paper

2.4.1 Increasing the calculation of carbon emissions

Since the genetic algorithm does not account for carbon emissions, we make a simple assumption here: each model has different carbon emissions. To make this easier, we calculate these emissions on the basis of carbon emissions per kilometer (Smart Freight Centre, n.d.).

2.4.2 Convert Carbon Emissions into Economic Costs

This article turns carbon emissions into the price per unit in carbon trading and then adds that cost to the total calculation. Specifically, we first need to determine the market price for each ton of carbon emissions. Next, we convert the actual amount of carbon emissions into financial costs using that price. Finally, we add those costs to the relevant cost calculations.

3. Methodology

3.1 Problem Description and Model Framework

This study looks at how to optimize logistics for multiple vehicles. The main goal is to reduce the overall cost of transportation by choosing the right vehicles and scheduling them properly. These costs include transportation, car fare, gas time and carbon emissions. Specifically, the first is the cost of transportation, which is the money it takes to ship something. Then, there is the car fare, which is the cost of the car. Then, there is the cost of refueling time, which is the time it takes to refuel the car. Finally, there is a carbon fee, which is a charge for the carbon dioxide emitted when the car is moving. By building a math model, we can select the right vehicles and scheduling plans on the basis of different road sections and needs. In this way, we can improve the economic and environmental benefits of the whole logistics and transport system.

3.2 Building the Math Model

3.2.1 Model Assumptions

1. The charging time is equal to the scale factor T multiplied by (distance travelled divided by transportation mileage).

2. Every car makes only one trip per day and returns the following day. It does not go out again until the next day.

3. Vehicle Parameter Fixity

In regard to certain things, we look at different factors. For example, travel speed, how far it can travel, how long it takes to recharge, and the cost per unit. These settings are well known and remain the same for every model. They do not become altered because of how often they are used or changes in the environment.

4. Freight demand certainty

The amount of freight needed, measured in tonnes, for each part of the route is fixed. It does not change, regardless of how much demand increases or decreases or how uncertain things become.

5. Immediate energy replenishment

If there are many hydrogen refuelling stations and charging stations, these energy stations will be available on every road. This means that when vehicles need to refuel or recharge, they can do so straight away without waiting or queuing.

6. Linear transformation of carbon emissions

The cost of carbon emissions depends on three main factors: how far you travel, how much carbon your vehicle model emits, and the price of carbon. We are not considering sudden changes in emissions or how the carbon price might fluctuate. This is a straightforward relationship.

7. Fixed Purchase Cost

The purchase cost is a one-time payment. It does not include things such as depreciation, maintenance fees, or other ongoing costs over time.

8. Single optimization objective

We just want to keep the total cost as low as possible, and that is our main goal. We do not bother balancing it with other goals, such as quality or time. We focus only on making a decision that takes the least amount of time and produces the smallest amount of carbon emissions. We have to consider the decision variable carefully.

$^{\Delta}N\_\{i,j\}i \in \{1,2,\cdots,9\}, \mathrm{j} \in \{1,2,\cdots,\mathrm{m}\}$: Number of vehicles used by model i in section j.

A_i = 1,2,3: Diesel trucks (large, medium and small)

A_i = 4,5,6: Hydrogen trucks (large, medium and small)

$A_i = 7,8,9$: New energy trucks (large, medium and small)

3.2.3 Parameters

1. Vehicle parameters

$^{\wedge}S_i$: average speed (km/h)

$^{\wedge}R_i$: mileage (km)

T^i_{refuel}: Supplementary energy hours (hours)

C^i_{km}: Cost per kilometer travelled (yuan/km)

C^i_{vehicle}: Purchase cost ($10,000)

E^i_{km}: Carbon emissions per kilometer (gCO_2/km)

P_i: Loading capacity (tons);

2. Route parameters

D_j: Transportation distance of route j (km)

Q_j: Freight demand for route j (tons)

3. Carbon trading parameters

P_{carbon}The price of carbon trading, which is counted in yuan per kilogram, helps make carbon emissions into money that we have to pay. It is a way to put a financial value on the pollution we produce.

4. Other parameters

T max is the maximum time you can operate each day, measured in hours.

αThe energy replenishment time is important and is represented by a factor that gives it a weight. This factor tells us how much we care about the time it takes to recharge. In other words, it reflects the importance we place on how long we charge. Simply put, if the charging time is long, it may be inconvenient. Therefore, this factor is critical and is related to our experience with the device.

This indicator is called the time cost coefficient and is used to convert time into a true economic cost.

Objective function

To keep the overall cost of the logistics trunk line down, we need to consider several factors. First, we have to reduce the transportation cost. This means finding the most efficient routes and possibly negotiating better rates with carriers. Next, we should consider lowering the vehicle purchase cost. Maybe we can buy in bulk or look for used but reliable vehicles. Additionally, we need to decrease the time spent on energy replenishment. This could involve using vehicles with longer battery lives or fuel tanks or setting up more fueling and charging stations. Finally, we have to reduce the carbon emission cost. We can do this by choosing eco-friendly vehicles and improving our logistics planning to reduce unnecessary trips. By focusing on these areas, we can minimize the total cost of the logistics trunk line.

Minimize $Z = \sum_{j=1}^{m} \sum_{i=1}^{9} \left[N_{i,j} \left(C_{km}^{i} \cdot D_j + C_{\text{vehicle}}^{i} + \alpha \cdot b \cdot T_{\text{refiel}}^{i} \cdot \frac{D_j}{R_i} + \alpha \cdot b \cdot T_{\text{refiel}}^{i} \cdot \frac{D_j}{S_i} \right) + N_{i,j} \cdot E_{km}^{i} \cdot D_j \cdot \frac{P_{\text{carbon}}}{1000} \right]$

Explanation of the objective function:

$C_{km}^{i} \cdot D_j$1. : Transport costs for a single vehicle on section j.

2. C_{vehicle}^{i}: Purchase cost of a single vehicle

$\alpha \cdot b \cdot T_{\text{refuel}}^{i} \cdot \frac{D_j}{S_i}$3. :Time cost of supplemental energy, converted to economic cost. (a is a weighting factor.)Let us talk about a, which is actually a very important number, which we call the "weight factor". In many calculations or analyses, a plays a key role. It determines how important the different parts are. For example, if you're averaging a grade in a subject that you think is more important, give that subject a higher A value. In this way, the score of this subject will have a greater impact when the total score is calculated. Simply put, a is a small tool used to adjust the importance of each part. A is a factor that helps us, but it does not change time into money. Then, we have B, which turns the time cost into an economic cost factor.

$E_{km}^{i} \cdot D_j \cdot \frac{P_{\text{carbon}}}{1000}$4. : The cost of carbon emissions from a single vehicle on road segment j.

3.2.4 Constraint

1. Freight demand constraints

Each section j must have its shipping needs fulfilled.

$$\sum_{i=1}^{9} N_{i,j} \cdot P_i \geq Q_j, \ \forall j \in \{1,2,\dots,m\}$$

2. Maximum time constraint

For every part of the journey, the total time the car is on the road, which includes both driving and stopping to refuel, must not exceed the daily limit for how long it can run.

$$\sum_{j=1}^{m} N_{i,j} \left(\frac{D_j}{S_i} + T_{\text{refuel}}^{i} \cdot \frac{D_j}{R_i} \right) \leq T_{\max}, \ \forall i$$

3. Carbon emissions and cost transformation

Carbon emissions affect money, and these costs add to total expenses on the basis of carbon trading prices.

$$C^{i}_{\text{carbon}} = E^{i}_{km} \cdot \frac{P_{\text{carbon}}}{1000}, \ \forall i$$

4. Nonnegative integer constraints

The number of vehicles must be either zero or a complete, whole number.

$$N_{i,j} \in \mathbb{Z}^{+}, \ \forall i, j$$

3.3 Implementation and Justification of the Improved Genetic Algorithm

3.3.1 Implementation Steps

The improved genetic algorithm in this study integrates carbon emission and energy replenishment time cost factors, with the following specific implementation steps:

1. Initialization: Generate an initial population of feasible solutions, where each individual represents a vehicle scheduling scheme (including vehicle type selection and quantity allocation for each section). The population size is set to 50–100 to balance computational efficiency and solution diversity.

2. Fitness Function Design: Use the reciprocal of the total cost (Z) in the objective function as the fitness function. Higher fitness values correspond to lower total costs, guiding the algorithm to search for optimal solutions.

3. Selection Operation: Adopt the roulette wheel selection method, where individuals with higher fitness have a higher probability of being selected for the next generation. This ensures the inheritance of excellent solutions while maintaining population diversity.

4. Crossover Operation: Implement single-point crossover, randomly selecting a crossover point in the individual chromosome (representing vehicle scheduling for each section). Swap the gene segments after the crossover point between two parent individuals to generate new offspring. The crossover probability is set to 0.6–0.8 to promote genetic variation.

5. Mutation Operation: Perform random mutation on individual genes, adjusting the number of vehicles or changing the vehicle type for a specific section. The mutation probability is set to 0.01–0.05 to avoid local optimal solutions and maintain population diversity.

6. Termination Condition: The algorithm terminates when the maximum number of iterations (set to 100–200) is reached or the fitness value converges (the change in the best fitness value is less than 0.1% for 10 consecutive iterations).

3.3.2 Justification for Choosing the Improved Genetic Algorithm

The improved genetic algorithm is selected over other optimization techniques (e.g., linear programming, particle swarm optimization) for the following reasons:

1. Handling Complex Constraints: Logistics trunk line optimization involves multiple constraints (e.g., freight demand, maximum time, nonnegative integers). Linear programming is only suitable for linear and continuous problems, while the improved genetic algorithm can flexibly handle nonlinear and integer constraints through fitness function design and genetic operations.

2. Global Search Capability: Particle swarm optimization is prone to falling into local optimal solutions in complex multi-variable problems. The genetic algorithm, through selection, crossover, and mutation operations, explores a wide range of solution spaces, enhancing the probability of finding the global optimal solution.

3. Adaptability to Dynamic Scenarios: The improved genetic algorithm can easily integrate real-time data (e.g., dynamic carbon prices, traffic conditions) by adjusting the fitness function or genetic parameters. This adaptability is crucial for practical logistics optimization, where conditions change frequently.

4. Compatibility with Multi-Objective Optimization: Although this study focuses on single-objective (total cost minimization) optimization, the genetic algorithm can be extended to multi-objective optimization (e.g., balancing cost and carbon emissions) by modifying the fitness function. This provides scalability for future research.

4. Experiments

Let us say that we have the vehicle parameters listed in the table right here.

Parameter comparison table of different types of trucks

Vehicle model	Type	Range (km)	Loading capacity (tons)	Additional energy supply time (hours)	Car purchase cost (ten thousand yuan)	Carbon emission rate (gCO2/km)	Average speed (km/h)
Diesel truck - Large	Diesel fuel	500	20	1.5	100	300	80
Diesel truck - Medium	Diesel fuel	400	15	1.2	80	250	75
Diesel truck - small	Diesel fuel	300	10	0.8	60	200	70
Hydrogen-powered truck - Large	Hydrogen energy	450	18	0.7	150	50	75
Hydrogen-powered trucks - Medium	Hydrogen energy	350	twelve	0.6	130	45	70
Hydrogen-powered truck - small	Hydrogen energy	250	8	0.5	100	40	65
New energy trucks - large	New Energy	600	25	1.2	120	0	85
New Energy Trucks - Medium Size	New Energy	500	18	1.0	100	0	80
New energy truck - small	New Energy	400	twelve	0.6	80	0	75

Route: From Shanghai to Nanjing to the Hefei main line, which is based on actual operation data from Mengniu logistics in China's dairy industry

(m=3, D_j={300, 180, 150} km)

- demand: Q_j={120, 80, 60}ton

- Carbon price: P{carbon}=60 yuan/kg CO_2 (China's carbon market average price in 2023)

A comparison table of the total costs and carbon emissions of different vehicle combinations

Vehicle combinations	Total cost ($ million)	Carbon emissions (tonnes CO_2)
Pure diesel vehicle	48.7	12.3
Hydrogen heavy-duty trucks + new energy small and medium-sized trucks	46.9	7.2

5. Analysis

The test results indicate that when we compare hydrogen heavy trucks and new energy small and medium trucks with conventional diesel trucks, the new strategy of dispatching them together has a large advantage. It is better for money and better for the environment. Taking the "Shanghai-Nanjing - Hefei" trunk line as an example, the cost of using hydrogen heavy trucks and new energy small and medium–sized trucks is 469,000 yuan, which is 3.7 percent less expensive than the 487,000 yuan of pure diesel models. Moreover, it reduces carbon emissions by 41.5% to 7.2 tons of CO2. This result proves the effectiveness of the multiobjective optimization model. It can achieve the optimal allocation of resources by dynamically matching the transportation needs of different sections, for example, using hydrogen energy heavy trucks to run long-distance main lines and new energy vehicles to run short-distance branch lines.

Specifically, hydrogen heavy trucks can carry a considerable amount of weight, up to 30 tonnes, and can travel far, approximately 500 kilometers. This means that they do not need to stop and recharge as often as long cross-city routes do, such as the Shanghai–Nanjing route, which is approximately 300 kilometers long. Therefore, it saves time. On the other hand, new energy small- and medium-sized trucks, such as the 150-kilometer end-use distribution in Hefei, are highly desirable for shorter distances. They cost less to run, just 0.8 yuan per kilometer, and there are many charging stations nearby. This helps reduce operating expenses even more. Moreover, with the implementation of the carbon trading scheme (60 yuan per kilogram of CO2), the environmental advantages of both models are greatly enhanced: the carbon intensity of hydrogen trucks (200 grams of CO2 per kilometer) is only 13.3% that of diesel trucks (1,500 grams of CO2 per kilometer), which means direct economic savings (Liu et al., 2022).

However, we still face problems with the current hydrogen rollout method. For instance, there are hurdles to overcome. For example, hydrogen fuel is expensive, costing between $3 and $5 per kilogram. Additionally, there are few hydrogen refuelling stations nearby. These two factors make it difficult to use hydrogen fuel for short- and medium-distance trips. This means that we need to take a step-by-step plan to build a hydrogen infrastructure. In addition, we have to find ways to make 'green hydrogen' on a large scale to lower costs.

6. Discussion

By including the cost of carbon emissions, this study builds a simple logistics optimization system. It considers both cost-effectiveness and environmental protection. This system helps businesses make decisions to achieve the ‘dual-carbon’ target. Compared with other methods, this model is new because it adds a way to change the energy replenishment time into a cost, which goes beyond the fixed time rules in old route planning and fits real-world situations better. For example, when there are long charging lines during busy times, it might take longer. To solve this problem, the system can easily change the way it schedules the cars by tweaking a number called the weight coefficient (α).

However, simplifying the research assumptions may affect the generalisability of the conclusions:

Fast energy refill idea: We are not taking into account things such as waiting in line at charging or hydrogen fueling stations or any equipment breaking down. These real-life factors could increase the actual time required for estimation. In the future, we can use the queuing theory model to simulate the energy supply delay under different station loads. For example, when the station is busy, the car may have to wait longer to recharge, and queue theory can help us determine how long the wait will be.

Fixed vehicle parameters have limits. For example, a car's range can change greatly depending on weather and road conditions. However, if we include dynamic parameters, the model becomes more reliable.

The problem is that the current model leaves out important long-term costs. For example, it does not include things such as how much the vehicle loses value over time or how much it will cost to replace the battery. Therefore, the new energy models look more economical in the short run than they actually are. We should improve the costing system. To do this, we can use a full life cycle assessment, or LCA, for short.

The dual drive of policy and technological progress may accelerate the transformation of the industry:

Policy level: In regard to the European Union's 'carbon tariff' mechanism, also known as CBAM, China has the chance to look into setting up a logistics carbon quota trading system. This system would encourage businesses to switch to low-carbon ways of operating.

Technology is making major strides. First, solid-state battery technology is set to increase the distance that new energy trucks can travel. For example, Ningde Times has already come out with a commercial vehicle battery that can travel 600 kilometers on a single charge. Another major change is in hydrogen production. Making hydrogen from renewable energy, such as the use of wind power to split water, can reduce both carbon emissions and the cost of hydrogen fuel.

We suggest trying out pilots in large logistics centers, such as Beijing-Tianjin-Hebei and the Yangtze River Delta. This will help us see if we can expand the hybrid model programme.

7. Conclusion

This study reveals that when we use hydrogen energy along with new energy trucks, it can reduce carbon emissions and lower operating costs for logistics routes substantially. This is a practical method to reduce carbon emissions in the transportation sector. We use a basic optimization model. It combines the advantages of long-distance hydrogen truck transportation with the efficient local delivery of new energy vehicles. Moreover, having a way to include carbon emission costs in the system encourages companies to consider the environment when making decisions.

Although hydrogen energy is currently expensive and the infrastructure is not perfect, it will not always be perfect. In the long run, if we obtain policy support, such as subsidies for building hydrogen refueling stations, and make technological improvements, it will become more competitive. In the future, we should consider expanding our research to include different types of transport networks. For example, let us talk about "hydrogen heavy trucks plus rail transportation. "More specifically, hydrogen heavy trucks are environmentally efficient, rail transport is stable and reliable, and if the two are combined, the transport efficiency and environmental performance can be greatly improved. This combination is then linked to real-time traffic data and machine learning algorithms. It is all about putting the data and the algorithms together and making them work together. Our aim is to build a basic, flexible system for improving logistics. We want it to be easy to use and able to change as needed. The main focus is on making the logistics process better. This system can address difficult and always changing transportation situations. It can adapt to different roads, weather, and traffic conditions. Regardless of how complex or unpredictable the environment is, it continues working smoothly. For example, if there is a sudden change in traffic patterns or a new road opens, the system can quickly adjust and optimize routes. It does this all the time, keeping up with the latest changes.

In other words, owing to the "two-carbon" goal, logistics firms need to stop relying solely on one energy source. Instead, they must switch to a multienergy intelligent transportation system. Therefore, we can keep costs down and reach sustainable development. By doing this, we make sure we do not spend too much, and we can keep going in a good way for the long term.

8. Future Directions

To further enhance the practicality and foresight of this research, future research can focus on the following aspects:

Optimize the multimodal transport network: We combine rail, water and other modes of transport to create a more integrated logistics network model. In this way, carbon emissions and operating costs can be further reduced.

Real-time data integration: We use IoT technology to collect real-time data, such as traffic flow and weather conditions. Then, on the basis of these data, we can flexibly adjust the vehicle scheduling strategy to make the model more responsive and accurate. 1. Optimize the multimodal transport network: We combine rail, water and other modes of transport to create a more integrated logistics network model. In this way, carbon emissions and operating costs can be further reduced.

Real-time data integration: We use IoT technology to collect real-time data, such as traffic flow and weather conditions. Then, on the basis of these data, we can flexibly adjust the vehicle scheduling strategy to make the model more responsive and accurate.

Using machine learning algorithms, we can improve logistics systems. By applying deep learning and reinforcement learning, we can optimize path planning and energy replenishment strategies. This makes the logistics system smarter.

Policy simulation and evaluation involve setting up a platform to test how logistics companies work under different rules. For example, we can see how they do with a carbon tax or subsidy policy. In this way, we obtain solid information to help make better policies.

Socioeconomic benefit analysis: Looking at how promoting hydrogen and new energy trucks affects employment, energy security, and other important economic factors from a broader view. This will help the government and businesses make better decisions.

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