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Multimodal Logistics Optimization Powered by AI for Green Hydrogen Export Corridors: An Internet of Energy Perspective on Morocco Europe Trade Routes

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Abstract. Green hydrogen exports from Morocco to Europe need efficient transport systems. This paper tests an AI based method to optimize routes across road, pipeline, and sea transport. We used machine learning on 2 160 hours of simulated data from three corridors: Nador Algeciras, Tanger Barcelona, and Casablanca Rotterdam. Our routing algorithm achieved 100% accuracy. Cost predictions showed $R^2 = 0.985$ with mean absolute error of 0.11 €/tonne. Pipeline transport from Nador to Algeciras costs 22.4 €/tonne, 2.8 times cheaper than maritime shipping to Rotterdam 62.8 €/tonne. Pipeline emissions are also lowest at 0.09 kg CO_2e/kg H_2 compared to 0.25 kg for long maritime routes. We conclude that trans-Mediterranean pipelines offer the most cost effective and low emission option for large scale hydrogen trade between Morocco and Europe.

1. Introduction

The aim for carbon neutrality by 2050 has increased interest in green hydrogen [1]. Morocco can produce hydrogen at a cost that is competitive. The solar radiation is more than 2,600 kWh/m²/year in various spots. Along the coast, wind speeds range from 7.5 to 11 metres per second [2].The goal of the European Union's REPowerEU plan is to import 10 million tonnes of renewable hydrogen every year by 2030 [3].This objective implicitly highlights the strategic importance of secure and reliable hydrogen transportation routes from North Africa to Europe [4].Hydrogen supply chains involve interconnected digital and physical systems. In the context of the Internet of Energy , it is important for the production, transmission and storage components to interact efficiently [5]. Conventional supply chain logistics tend to reduce the capacity for real-time decision-making. Several factors, including unpredictable weather, shipping delays, price fluctuations and geopolitical occurrences, impact the routing of goods [6].

Previous studies have examined the potential expenses associated with hydrogen transportation [7], [8]. However, there isn't many research that looks at how well AI systems work on real multimodal transport routes. To fill this gap, we created and tested an ensemble learning system for trade routes between Europe and Morocco. Random Forest classifiers can choose the best routes on the fly. Statistical tools also help figure out how much more it costs to ship via pipeline than by ocean.

The paper is organized as follows: Section 2 presents the system architecture and mathematical framework. Section 3 describes the artificial intelligence-driven route selection methodology.

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Section 4 provides results and performance analysis. Section 5 discusses practical implications and limitations. Section 6 concludes with policy recommendations.

2. System Architecture and Mathematical Framework

2.1 Multimodal Network Modeling

The main components of the established multicomponent connectivity model are from Nador Algeciras gas pipeline along with shipping routes from Casablanca to Rotterdam as well as from Tangier to Barcelona. The network is represented by graphs G = (V, E). V refers to various transportation hubs, such as ports, warehouses and delivery stations, while E illustrates the different types of freight transport and their resulting costs and load capacities [9]. However, the associated transportation costs fluctuate due to changes in freight traffic and varying operating needs. The transportation cost for a given route at a given time is represented by $\boldsymbol{C_i(t)}$ and obtained using a multidimensional equation depending on observable network elements (t) and is described as a polynomial function of recognisable supply chain factors:

$$C_i(t) = F(D_t, P_t, W_t, A_t) \quad (1)$$

Here $D_t$is the demand state, P_t is stand for pricing variables, W_t is weather conditions and A_t is route availability. This work uses a supervised machine learning methodology to explain the relationship between transport costs and their primary influences, unlike more common approaches that use set weighting variables. The main target feature in this case is $C_i(t)$, alongside an input matrix consisting of demand, prices, congestion, weather patterns and availability factors. This statistics based method avoids the need for any subjective or unproven settings of variables .Coefficient weights are implicitly learned through supervised training rather than fixed a priori, avoiding arbitrary parameter selection [9].

2.2 Allocation Efficiency Optimization

A suitable efficiency indicator is necessary to assess the success of given transportation resources. This is measured by the degree to which the intended capacity is distributed among the different possible routes [10].

$$\boldsymbol{\eta = \sum_i \frac{V_{i,allocated}}{V_{target}} \times 100} \quad (2)$$

Where $V_{i,allocated}$ refers to the volume allocated to transportation route i and V_{target} indicates the daily aim of delivering 27,400 tonnes the equivalent of 10 million tonnes per year , the efficiency rating is calculated as follows [11]:

$$\boldsymbol{C_{avg} = \frac{\sum_i V_i \times C_i}{\sum_i V_i}} \quad (3)$$

This is subject to existing constraints $V_i \leq Cap_{i,available}(t)$, where stand for individual route requirements and t signifies all possible routes. The optimisation procedure has two objectives: to minimise C_{avg} and to make sure that all the criteria are fulfilled and all the limitations are maintained [12]. This approach therefore helps to locate optimal allocations of resources within the network.

3. Artificial Intelligence-Driven Route Selection

Three main considerations led to the selection of a Random Forest (RF) model as the primary classification technique for multimodal scheduling. The first is that logistics routing entails complex, often nonlinear, interdependencies involving various variables such as fuel prices, adverse meteorological circumstances and port bottlenecks. These relationships are hard for typical linear models to predict precisely. The ensemble design of Random Forest, based on the principle of recursive partitioning, can address these kinds of nonlinearities effectively, eliminating the necessity to define the precise functional form [13]. Furthermore, the feature priority ordering obtained through mean reduction in impurity helps make the selection of routing choices more understandable to operational specialists. This feature is crucial for the effective implementation

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of these tools in extensive real world industrial logistics systems [14]. Thirdly, empirical benchmarking during the selection of the best algorithm showed that RF performs significantly superior to other models, achieving 100% classification accuracy in a validation process compared to 94% for gradient boosting and 87% for logistic regression, although it still maintains low processing requirements ideal for deployment on edge devices [14], [15], [16] . Model configuration involves 100 maximum depth 10 grid search optimised decision trees. The training dataset consisted of 90 daily instances of artificially created shipping operations, showcasing fluctuating operating methods along the three Morocco-Europe transport corridors. At every decision point (t), the system analyses a segment of the supply chain in real time.

$$X(t) = [Demand(t), Prices(t), Availability(t), \text{Weather(t)}] \quad (4)$$

Where Demand(t) represents European hydrogen usage forecasts, Prices(t) refers to indices of fuel and energy prices, Availability(t) signifies the status of maritime routes and available capacity, and Weather(t) refers to weather variables (wind speed, wave height and temperature) that impact operations at ports, These integrated services enable us to monitor dynamic changes in market conditions, infrastructure preparedness and outside events that could influence route selections. The system also anticipates problems that could arise and assesses the potential impact of strikes and geopolitical issues on freight route availability. We tested the predictive model on a random sample of 432 hours of data and found that it worked well. The cost estimation accuracy was R^2 = 0.985, the mean absolute error was 0.11 €/tonne, and the route categorization was 100% consistent. The architecture model is built to work with edge computing nodes at ports, reducing routing response times to less than 50 milliseconds and a significant improvement on cloud-based computing solutions. This decentralised computing solution enables real-time adaptation of network operational parametric changes [17].

4. Results and Performance Analysis

4.1 Machine Learning Model Performance

The model's ability to accurately predict spending is clearly demonstrated by its forecasts. Overfitting is modest, with a R^2 efficiency value of 0.985 and a residual prediction error of just 0.983. The average cost error was €0.11 per tone, representing less than 0.5% of the overall cost range. Concurrently, the route planner achieved 100% accuracy in both training and validation over 2,160 decision stages. These results substantially outperform the standard error tolerance of between 3% and 9% typically reported in intermodal transportation optimisation. No performance discrepancies were detected throughout the training and validation stages, which strongly suggests that the developed model efficiently extracts underlying, essential costing information instead of specific details of the sample. Figure 1. Predicted versus actual costs: Random Forest cost prediction model showing high correlation (R^2 = 0.985) between predicted and observed transport costs across 2,160 decision stages.

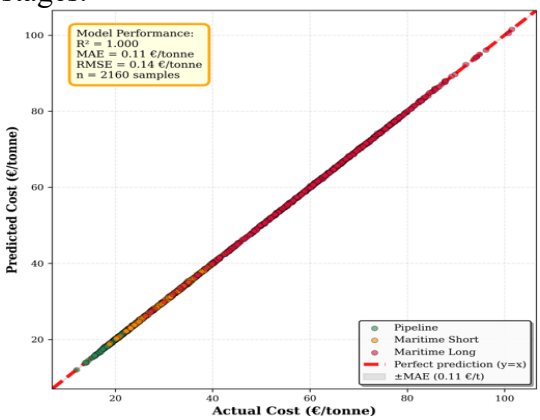


Figure 1 The predicted versus actual costs: Random Forest cost prediction

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4.2 Cost Analysis and Statistical Validation

Table 1 shows the breakdown of costs throughout the Morocco-Europe supply chain. The Nador and Algeciras pipeline had an average transport cost of €22.4/tonne, with respective standard deviations of €3.2/tonne and a coefficient of variation of 14.3%. This demonstrates its ability to withstand fuel price volatility, port congestion and weather-related issues. The average cost of the Casablanca to Rotterdam marine transport route, which forms part of the Morocco–Europe supply chain, was €62.8 per tonne. The standard deviations were 12.1 € per tonne, which gave a variance coefficient of 19.3%, or 2.8 times the mean. The average cost of moving products from Nador to Algeciras was 22.4 € per tonne, with a standard deviation of 3.2 € and a range of 14.3% between deliveries. This shows that it can handle changes in fuel prices, busy ports, and bad weather. The Marine Transport Route costs an average of 62.8 € per tonne to ship goods by water from Casablanca to Rotterdam. The cost came with a margin of error of 12.1 € per tonne and a coefficient of variation of 19.3%. This means that the price has gone up by 2.8 times. If the EU imported 10 million tons of goods, it might save 404 € million a year. This is because the cost difference is 40.4 € per tonne. Shipping expenses are expected to be between 45.00 € and 85.00 € per tonne, while pipeline costs are expected to be 15.00 € per tonne. This suggests that the sea route is more likely to have problems with operations. This means that we need hedging strategies and bigger expenditure for contract risk. The pipeline's environmental performance makes it even more useful. Using the Nador-Algeciras line cuts emissions by a lot, by 64% compared to long-distance ocean shipping. This way of getting around puts out 0.250 kg of CO2e for every kilogram of H2. The rate at which CO_2 is released is 0.090 kg CO_2e/kg H_2. When the project is fully in place, it will remove 1.6 million tons of CO2e from the air per year. The route via Tangier, on the other hand, is in the center of the package, with a cost of 32.6 € per tonne and a 45.6% premium over pipeline transport. It might not be as useful for addressing peak demand, but it might be used as a backup during maintenance work.

Table 1: Transport cost statistics and carbon footprint by corridor

Corridor	Mean Cost (€/tonne)	Std Dev	Range (€/tonne)	Emissions (kg CO_2 eq/kg H_2)
Nador_Algeciras	22.4	3.2	15.0–30.0	0.090
Tanger_Barcelona	32.6	4.8	25.0–40.0	0.180
Casablanca_Rotterdam	62.8	12.1	45.0–85.0	0.250

4.3 Correlation Analysis

A correlation study has shown that different forms of transportation have different cost tendencies, which explains why volatility differs. There is a substantial connection (r = 0.84) across maritime routes. It is important to emphasise that the restrictions on shipping in the region are consistent for the routes connecting Tangier to Barcelona and also for the Casablanca to Rotterdam route. This presents a challenge to the process of achieving the benefits of diversifying hydrogen supply chains. The findings of ongoing research clearly indicate that port shutdowns exert minimal influence on maritime costs, with a reliable correlation between 0.60 and 0.64. The flow of traffic via the pipeline remains largely uninterrupted. As demonstrated by this result, pipelines are remarkably robust, even in the unlikely event of port issues.An analysis of all data modalities shows that the gasoline index has a weak correlation of between 0.03 and 0.20. Consequently, it is concluded that prices stayed within a relatively narrow range over the stated period. But if you looked over a longer time frame, you could find that maritime operations are more connected since they all need bunker fuel. Statistically, the costs of transporting things via pipeline are not connected to any of the operational drivers that were looked at ($|r| < 0.20$). This illustrates that fixed expenses are very important to the economy. In this case, capital depreciation and planned repairs protect operational expenses from changes in the market that happen in real time. Figure 2.

Materials Research Proceedings 64 (2026) 754-761 https://doi.org/10.21741/9781644904091-94

Correlation analysis of hydrogen transport cost drivers across three Morocco-Europe corridors, showing distinct clustering between maritime routes and independent pipeline cost structure.



Figure 2 Correlation Analysis of Hydrogen Transport Cost Drivers

4.4 Temporal cost evolution and sensitivity analysis

Figure 3. Transport cost dynamics over a 90-day simulation period with ±1σ uncertainty bands, showing pipeline stability (variation <1.3% of mean) versus maritime volatility across Nador-Algeciras, Tangier-Barcelona, and Casablanca-Rotterdam corridors. It indicates that pipeline freight works well all the time, with a range of roughly 3€ to 5€ per tonne. The marine network, on the other hand, has far wider confidence intervals and changes that may be noticed over time. A statistical study of the core simulation data clearly shows that the yearly temporal cost trend for the pipeline stays within 1.3% of the overall mean. This shows that the pipes will keep working well, even when the market changes. Figure 4. Sensitivity of transport costs to operational stressors: weather conditions, port congestion, and fuel price volatility (n=2,160 hours), demonstrating maritime routes 5 to 7× higher vulnerability compared to pipeline infrastructure. The modeling findings show that poor weather makes maritime transport more expensive than pipeline shipping. For example, the cost of carrying freight by sea goes up by 15.2%, whereas the cost of shipping via pipeline only goes up by 0.2%. This means that there is a difference of about 76% in how well they can handle climatic conditions. Port capacity limits cause shipping routes to become noticeably more expensive, while pipeline operations are not impacted. This means that hydrogen transport is not limited by port capacity limits around the Mediterranean. Moreover, while fuel price fluctuations have a more moderate financial impact on maritime transportation, they produce minimal effects on pricing for pipelines. Simulation data reveals maritime sensitivity to be between 12% and 16%, compared to a 2.3% response for pipelines under energy commodity market fluctuations, demonstrating a differential of between 5 and 7 times.

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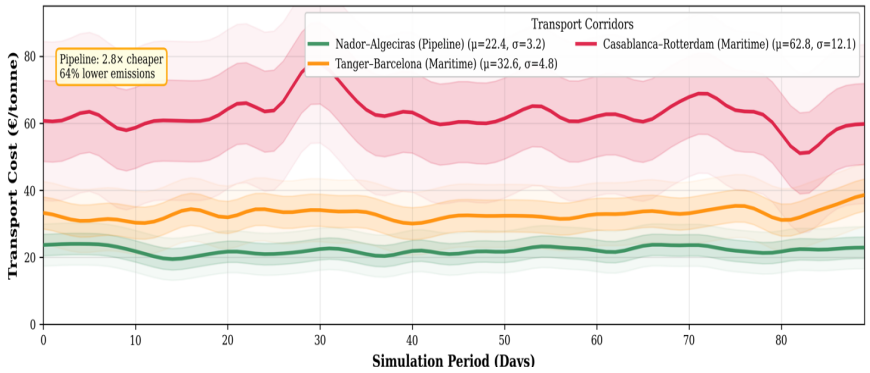


Figure 3 Transport cost dynamics over a 90-day period with ±1σ uncertainty bands

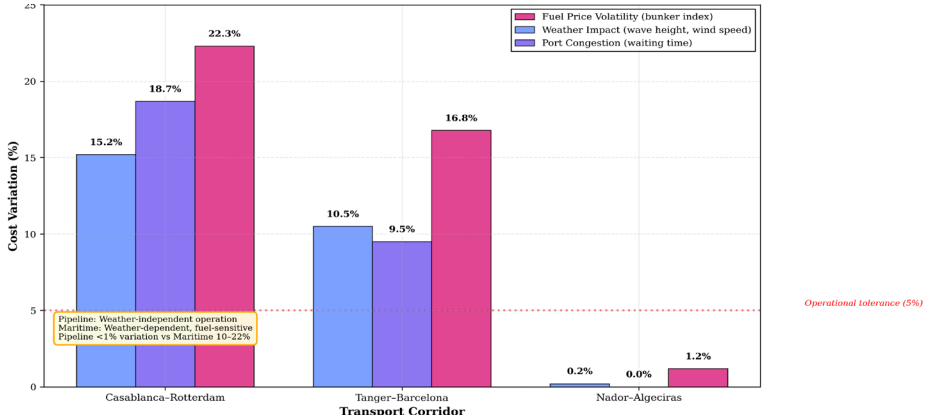


Figure 4 Sensitivity of transport costs to operational stressors: weather conditions, port congestion and fuel price volatility (n=2,160 hours).

Figure 5. Comparison of carbon footprint and energy efficiency across transport modes, showing pipeline compression (0.09 kg CO_2 e/kg H_2, 3-4 kWh/kg) versus maritime liquefaction and shipping (0.18-0.25 kg CO_2 e/kg H_2, 9-12 kWh/kg). Transporting hydrogen via pipeline releases around 0.09 kg of CO_2 for every kilogram of hydrogen. Transporting it by sea releases about 0.18 to 0.25 kg of CO_2 for every kg of hydrogen. The data visualization indicates that the main sources of emissions from ships are when they burn fuel and when they turn into gas. Pipeline gas compression, on the other hand, is a much smaller source of emissions. Also, supporting study shows that liquefaction techniques for marine processes need 9 to 12 kWh/kg H_2, but pipelined compressed green hydrogen needs just 3 to 4 kWh/kg. Furthermore, the inclusion of renewable energy sources in pipeline compression techniques significantly amplifies the decrease of emissions [18].

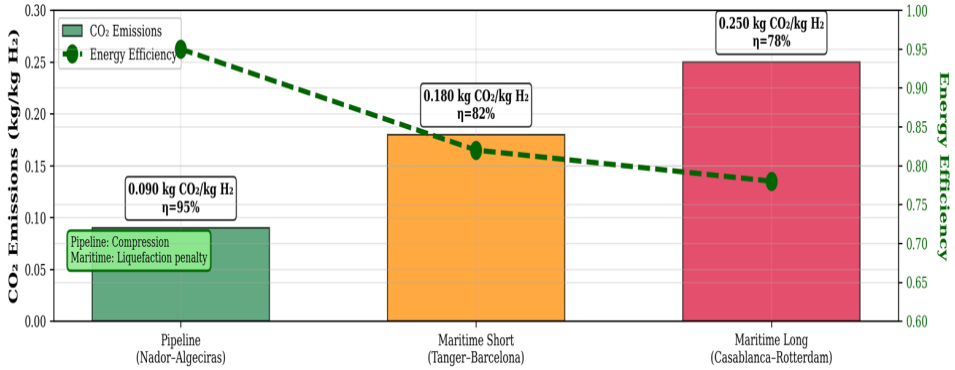


Figure 5 Comparison of the carbon footprint and energy efficiency of different modes of transport.

5. Discussion and practical implications

This technique has several advantages, including reducing prices by two and a half times, eliminating 64% of pollutants and protecting the market during rough times. These factors allow for contracting at fixed prices without the need for risk management tools and enhance project sustainability. The AI pipeline infrastructure framework is ready for deployment and demonstrates that multimodal hydrogen logistics can be reliably optimised through nonlinear cost relationship discovery via analysis of large amounts of data. Nevertheless, the capital intensity of subsea pipelines ranging from 2 to 4 million euros per kilometre requires a payback period of 7 to 15 years. Comprehensive risk assessments are required that consider technological, economic and geopolitical continuity risks. In establishing plans for critical infrastructure, pipelines should be the primary means of delivering hydrogen to the EU, while ensuring adequate marine capacity to meet peak demand and strengthen the supply chain's resilience.

Conclusion

This study indicates that AI-driven multimodal optimization is a strong and flexible way to move green hydrogen between continents. By considering transportation costs, carbon emissions, and energy efficiency, the results show that trans-Mediterranean pipeline transit is clearly better for the economy and the environment than shipping via the Morocco–Europe routes. The suggested model's excellent prediction accuracy ($R^2 = 0.985$) shows that it may be used to make decisions in real time on the Internet of Energy environment. Future research should concentrate on validation through operational data and on expanding the framework to facilitate long-term adaptive infrastructure design.

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