An Optimization Framework for the Selection of Battery and Fuel Cell Electric Trucks in Long-Haul Freight Transport

Angelina Krendeleva[1], Michele Roccotelli[1], *Senior Member, IEEE*,
Agostino Marcello Mangini[1], *Senior Member, IEEE*, and Maria Pia Fanti[1], *Fellow, IEEE*

***Abstract*— This paper analyzes the efficiency of Battery Electric Vehicles (BEV) and Fuel Cell Electric Vehicles (FCEV) in delivering parcels for long distance trips. A Mixed-Integer Linear Programming (MILP) problem is formulated for the joint optimization of route energy planning and vehicle type. In a case study from Bari to Milan, the model compares travel time, cost, and operational feasibility using real vehicle specifications and infrastructure constraints. The analysis explicitly accounts for payload-dependent energy consumption and a gradual reduction of the carried load. Simulation results show that fuel cell trucks are advantageous when minimizing delivery time is the primary objective, whereas battery electric trucks provide a more cost-stable and infrastructure-compatible solution when operational energy expenditure is prioritized.**

I. INTRODUCTION

The freight sector, particularly in the high-volume and long-haul segments, remains one of the slowest to decarbonize. Despite the focus on light-duty electric vehicles [1], [2], the freight industry remains largely diesel-powered in many countries, resulting in high greenhouse gas emissions. According to Sun *et al.* [3], while battery electric vehicles (BEVs) have demonstrated their effectiveness in modern conditions, their scalability in the freight segment remains limited due to long charging times, large battery masses, and the need for portable batteries.

Against this backdrop, hydrogen fuel cell electric vehicles (FCEVs) are seen as a promising alternative for long-haul transportation due to their high energy density, fast refueling times, and better low-load cycle performance [4]. Moreover, recent studies emphasize that FCEVs offer clear operational advantages on routes with high mileage and tight delivery windows, especially when supported by well-planned refueling infrastructure and favorable hydrogen prices [5], [6].

A growing body of literature relies on the Total Cost of Ownership (TCO) framework to objectively compare electric propulsion technologies. TCO takes into account both capital (CAPEX) and operating (OPEX) costs, as well as energy costs, maintenance, equipment depreciation, residual value, and even emissions [7].

For example, Magnino *et al.* [8] found that for cold climates such as Finland, FCEVs and hydrogen internal combustion engines (H2-ICE) could be more profitable than BEVs on several heavy-duty routes. The authors also use a levelled cost of transportation (LCOT) metric that normalizes TCO by transport volume, allowing for more accurate technology comparisons.

The study by Rout *et al.* [9] suggests that FCEVs could reach TCO parity with diesel trucks as early as the 2030s, assuming hydrogen and fuel cell costs decrease sufficiently. The authors also reinforce the need for subsidies, tax incentives, and scale-ups to accelerate cost reductions.

Mu et al. [10] extend the TCO comparison of fuel cell and battery electric heavy-duty trucks to 2035, showing that although FCEVs currently exhibit a significantly higher TCO than BEVs, the gap narrows substantially with declining hydrogen and renewable electricity prices. Their results suggest that cost parity becomes feasible for 49-ton long-haul trucks under favorable energy scenarios.

Lee *et al.* [6] developed models to optimize the placement of hydrogen fueling stations based on the projected FCEV penetration rate and TCO. This reduces infrastructure risks and ensures more sustainable technology adoption.

Dash *et al.* [4] provide a comprehensive review of hydrogen as a possible future mobility fuel, highlighting its advantages in terms of energy density, rapid recharging, and zero exhaust emissions. Although BEVs have operational limitations, the authors note that FCEVs have a lot of potential for long-haul freight transportation. However, they also admit that FCEVs currently face challenges with infrastructure, production costs, and hydrogen distribution.

A recent report by Basma *et al.* [5] provides one of the most comprehensive estimates of the total cost of ownership for fuel cell electric trucks (FCETs) in a European context. The study concludes that FCETs could reach TCO parity with diesel trucks by 2030, provided that green hydrogen is available at competitive prices. The study also highlights that the TCO gap will narrow significantly by 2030 due to the falling cost of fuel cell systems, improved hydrogen fuel efficiency and economies of scale.

Sharpe and Basma [11] conducted a comprehensive meta-analysis of zero-emission truck purchase costs. Their study shows that the initial costs of BEVs and FCEVs can vary by up to four times, largely due to the size of the battery pack or hydrogen system. Batteries account for approximately 60% of the BEV purchase price, while fuel cell systems and hydrogen storage dominate FCEV costs. The authors estimate that both technologies will significantly reduce costs by 2030. Basma et al. [12] and Liu et al. [13] quantify how energy consumption of heavy-duty trucks scales with payload, supporting the linear formulation adopted in this

The authors are with the department of Electrical and Information Engineering of the Polytechnic University of Bari, Italy. E-mail address: angelina.krendeleva@poliba.it, michele.roccotelli@poliba.it, agostinomarcello.mangini@poliba.it, mariapia.fanti@poliba.it.

paper.

Recent operational studies also explore how delivery scheduling, energy planning, and station positioning impact the performance of zero-emission fleets. Coordinated optimization of routing and charging has proven to significantly reduce energy waste and delivery time in logistics with BEVs, while integrated consideration of hydrogen infrastructure is crucial for FCEV viability [7], [3]. Mathematical programming has also been applied to multi-stage logistics systems [14].

Overall, the literature indicates that the choice between BEVs and FCEVs depends on route characteristics, infrastructure, energy costs, and policy conditions. Unlike existing studies, this work proposes a joint MILP framework that simultaneously selects the propulsion technology and optimizes the energy replenishment strategy along a real Italian freight corridor, serving as a decision-support tool for freight logistics companies.

The remainder of this paper is organized as follows: Section II presents the proposed methodology and the optimization model. Section III describes the case study, including the simulation scenarios and the results analysis. Finally, Section IV concludes the paper and outlines future research directions.

II. METHODOLOGY

This section presents a mixed-integer linear programming (MILP) model that jointly selects the truck type (BEV or FCEV) and optimizes the associated charging/refuelling strategy to minimize operational energy cost.

The novelty of this model lies in the integration of:

- Optimal route energy planning.
- Automated truck selection among BEV and FCEV candidates.
- Payload-dependent energy consumption.
- Cost minimization for electricity and hydrogen.
- Realistic operational and capacity constraints.

The current model assumes unlimited station capacity and zero waiting time. Congestion, queuing, and charging at unloading locations will be considered in future work.

A. Optimization Model

1) Sets and Indices:

- $I = \{i = 1, \ldots, N\}$: set of cities (nodes), where 1 is the origin and N the destination.
- $J = \{j = 1, \ldots, N-1\}$: set of road segments, where segment j connects city i to city $i+1$.

Candidate fleet

- $V^B = \{v = 1, \ldots, N_B\}$: set of candidate BEV models, with $N_B = |V^B|$.
- $V^H = \{v = 1, \ldots, N_H\}$: set of candidate FCEV models, with $N_H = |V^H|$.
- Total fleet: $V = V^B \cup V^H$, $|V| = N_B + N_H$.

Infrastructure

- $CP^B = \{s = 1, \ldots, S_B\}$: set of BEV charging stations, $S_B = |CP^B|$.
- $CP^H = \{s = 1, \ldots, S_H\}$: set of hydrogen stations, $S_H = |CP^H|$.
- $CP_j^B \subseteq CP^B$: charging stations available along segment j.
- $CP_j^H \subseteq CP^H$: hydrogen stations available along segment j.

We assume that each station is uniquely associated with exactly one road segment. Formally, the segment–station incidence sets are mutually disjoint:

$$CP_j^B \cap CP_{j'}^B = \emptyset \qquad \forall j \neq j'$$

$$CP_j^H \cap CP_{j'}^H = \emptyset \qquad \forall j \neq j'$$

and

$$\bigcup_{j \in J} CP_j^B \subseteq CP^B, \qquad \bigcup_{j \in J} CP_j^H \subseteq CP^H.$$

Under this assumption, each charging or refueling station belongs to exactly one segment, while each segment may include one or more stations. Therefore, energy decision variables are indexed only by station (x_s, h_s), and their contribution to the energy balance of segment j is captured through the subsets CP_j^B and CP_j^H.

2) Parameters:

Route

- D_j [km]: distance of segment j.

Payload dynamics

- m_1 [kg]: initial transported load.
- $l_i \in [0, 1]$: unloaded load fraction at city i.

Energy prices

- p_s [€/kWh]: electricity price at charging station s.
- c_s [€/kWh-eq]: hydrogen price at station s.
- $\eta = 33.3$ [kWh/kg]: hydrogen energy equivalence factor.
- P_s [kW]: charging power at station $s \in CP^B$.

Vehicle technical parameters

For each $v \in V^B$ (BEV):

- $E_v^{\max}$: maximum battery capacity of vehicle v.
- $E_v^{\min}$: minimum admissible battery level of vehicle v.
- E_v^{start}: initial battery level of vehicle v.
- E_v^{end}: required minimum battery level at destination.
- $E_{0,v}$: base energy consumption coefficient of vehicle v.
- k_v: payload-dependent energy coefficient of vehicle v.

For each $v \in V^H$ (FCEV):

- $H_v^{\max}$: maximum hydrogen storage capacity of vehicle v.
- $H_v^{\min}$: minimum admissible hydrogen level of vehicle v.
- H_v^{start}: initial hydrogen level of vehicle v.

- H_v^{end}: required minimum hydrogen level at destination.
- $E_{0,v}$: base energy consumption coefficient of vehicle v.
- k_v: payload-dependent energy coefficient of vehicle v.

Energy consumption (payload dependent)

For BEVs:

$$e_{jv} = \frac{E_{0,v} + k_v m_j}{100}. \tag{1}$$

For FCEVs:

$$h_{jv} = \frac{E_{0,v} + k_v m_j}{\eta \cdot 100}. \tag{2}$$

The linear consumption model is consistent with VECTO-based analyses [13], [12], though road gradient, temperature, and traffic may introduce nonlinearities in real-world.

3) Decision variables:

Vehicle selection

- $y_v^B \in \{0,1\}, \quad \forall v = 1,\ldots,N_B$
- $y_v^H \in \{0,1\}, \quad \forall v = 1,\ldots,N_H$

Let us define:

$$y^B = \sum_{v=1}^{N_B} y_v^B, \qquad y^H = \sum_{v=1}^{N_H} y_v^H \tag{3}$$

Energy decisions

- $x_s \in \mathbb{R}_+$ [kWh]: energy charged at station $s \in CP^B$.
- $h_s \in \mathbb{R}_+$ [kg]: hydrogen refueled at station $s \in CP^H$.

State variables

- $E_i \in \mathbb{R}_+$ [kWh]: battery energy level at city i.
- $H_i \in \mathbb{R}_+$ [kg]: hydrogen level at city i.

Charging time

- $t_s^{chg} \in \mathbb{R}_+[h]$: charging time at station s.

4) Objective function:

$$\min \sum_{s=1}^{S_B} p_s x_s + \sum_{s=1}^{S_H} \eta\, c_s\, h_s \tag{4}$$

The objective minimises energy cost; travel time is evaluated post-optimisation via equation (20).

5) Constraints:

Unique vehicle selection

$$\sum_{v=1}^{N_B} y_v^B + \sum_{v=1}^{N_H} y_v^H = 1 \tag{5}$$

Payload dynamics

$$m_{j+1} = (1 - l_{j+1})\, m_j, \qquad \forall j \in J. \tag{6}$$

BEV energy balance

$$E_{j+1} = E_j - D_j \sum_{v=1}^{N_B} e_{jv} y_v^B + \sum_{s \in CP_j^B} x_s, \quad \forall j \in J \tag{7}$$

FCEV hydrogen balance

$$H_{j+1} = H_j - D_j \sum_{v=1}^{N_H} h_{jv} y_v^H + \sum_{s \in CP_j^H} h_s, \quad \forall j \in J \tag{8}$$

Since m_j is computed deterministically, e_{jv} and h_{jv} are known parameters, preserving the MILP linearity.

Initial conditions

$$E_1 = \sum_{v=1}^{N_B} E_v^{start} y_v^B \tag{9}$$

$$H_1 = \sum_{v=1}^{N_H} H_v^{start} y_v^H \tag{10}$$

Terminal requirements

$$E_N \geq \sum_{v=1}^{N_B} E_v^{end} y_v^B \tag{11}$$

$$H_N \geq \sum_{v=1}^{N_H} H_v^{end} y_v^H \tag{12}$$

Capacity and safety constraints

$$\sum\nolimits_{v=1}^{N_B} E_v^{min} y_v^B \leq E_i \leq \sum\nolimits_{v=1}^{N_B} E_v^{max} y_v^B, \quad \forall i \in I \tag{13}$$

$$\sum\nolimits_{v=1}^{N_H} H_v^{min} y_v^H \leq H_i \leq \sum\nolimits_{v=1}^{N_H} H_v^{max} y_v^H, \quad \forall i \in I \tag{14}$$

Technology activation constraints

$$x_s \leq M y^B, \quad \forall s = 1,\ldots,S_B \tag{15}$$

$$h_s \leq M y^H, \quad \forall s = 1,\ldots,S_H \tag{16}$$

Charging time

$$t_s^{chg} = 1.05 \frac{x_s}{P_s}, \quad \forall s = 1,\ldots,S_B \tag{17}$$

The factor 1.05 accounts for a conservative 5% overhead due to charging losses.

$$t_s^{chg} \leq \bar{T}\, y^B, \quad \forall s = 1,\ldots,S_B \tag{18}$$

While constraints (5)-(14) are intuitive, let us remark that constraints (15) and (16) activate charging/refueling decisions consistent with the selected propulsion technology, preventing electricity or hydrogen purchases when an FCEV or BEV is respectively chosen. In addition, constraints (17) and (18) ensure that the charging time is zero if BEV is not selected, and a time cap $\bar{T} \in \mathbb{R}_+[h]$ applies only when BEV is selected to avoid excessively long charging stops.

III. CASE STUDY

For the sake of clarity and ease of interpretation, the proposed approach is illustrated through a small-scale case study. However, the formulation itself is general and scalable, and can be applied without modification to larger fleets, extended transport corridors, and more complex infrastructure configurations, as the model grows polynomially with the number of vehicles, segments, and stations.

In this case study, the proposed formulation is applied to a set of candidate truck models, including two BEVs and two FCEVs. The optimization selects the most suitable vehicle configuration and the corresponding charging or refuelling strategy along the delivery corridor. The objective is to determine the most efficient strategy to deliver parcels from Bari to Milan (Italy), with unloading stops in Naples, Rome, and Florence. The segment distances are: Bari–Naples (265 km), Naples–Rome (225 km), Rome–Florence (275 km), and Florence–Milan (305 km). The total route length is approximately 1,070 km. The company operates a mixed BEV–FCEV fleet and seeks the most advantageous configuration in terms of delivery time and operational energy cost (Fig. 1).

Fig. 1. Delivery route using BEV and FCEV trucks

The numerical values of the key model parameters adopted in the case study are reported in Table I.

TABLE I

MODEL PARAMETERS USED IN THE CASE STUDY

Parameter	Value	Unit
Initial payload m_1	20000	kg
Unloading fraction	0.25	–
Hydrogen lower heating value η	33.3	kWh/kg
Charging time cap $\bar{T}$	1	h
Hydrogen price	0.36	€/kWh-eq

The hydrogen price of 12 €/kg is converted into an equivalent cost of 0.36 €/kWh-eq using the lower heating value $\eta = 33.3$ kWh/kg. In the considered case study, node 1 corresponds to Bari and node N corresponds to Milan. BEV trucks have access to seven public charging stations located 30 km before and after the unloading cities; each station provides two charging points, except Stations 5 and 6, which provide one. FCEV trucks have access to seven hydrogen stations positioned under the same distance criteria, each providing one refuelling point. All stations are assumed to be operational along the corridor. The truck departs with an initial payload of 20000 kg. At each city 25% of the remaining cargo is delivered, leading to a progressive reduction in energy demand along the route. The considered truck models are Volvo FH Electric, Mercedes-Benz eActros 600 (BEVs), Nikola TRE FCEV and Hyundai Xcient Fuel Cell (FCEVs). Their main specifications are summarized in Table II.

TABLE II

TRUCK SPECIFICATIONS

Type	Model	Average cruising speed (km/h)	Range	Capacity
BEV1	Volvo FH Electric	87.5 km/h	300 km	540 kWh
BEV2	MB eActros 600	83.5 km/h	500 km	621 kWh
FCEV1	Nikola TRE FCEV	88.5 km/h	800 km	70 kg H_2
FCEV2	Hyundai Xcient FC	83.5 km/h	400 km	32 kg H_2

Figures 2 and 3 illustrate the charging and refuelling infrastructure available along the corridor for BEVs and FCEVs, respectively.

Fig. 2. Location of charging points (CPs) for BEV trucks along the delivery route

Fig. 3. Location of hydrogen refuelling points (RPs) for FCEV trucks along the delivery route

Energy Consumption and Price Calibration from Literature

Since operational feasibility and cost performance strongly depend on energy consumption and fuel prices, representative values for BEV and FCEV heavy-duty trucks were calibrated from recent European long-haul studies, assuming a payload of approximately 20 tons, consistent with the developed case study.

The consumption ranges summarized in Table III were derived from manufacturer reports, public road tests, and independent sector analyses. For BEVs, consumption estimates are based on official Volvo road tests of 40 tons vehicles and independent ICCT assessments [15], [16]. For FCEVs, hydrogen consumption values were extracted from ICCT tractor-trailer technical reviews and OEM test data [12].

Energy prices are consistent with recent ICCT Total Cost of Ownership analyses for heavy-duty BEVs and FCEVs,

TABLE III

ENERGY CONSUMPTION PER 100 KM FOR BEV AND FCEV MODELS

Vehicle model	Energy type	Consumption
Volvo FH Electric	kWh	110–130 kWh/100 km
Mercedes eActros 600	kWh	95–120 kWh/100 km
Nikola TRE	H_2	8–10 kg/100 km
Hyundai Xcient	H_2	7–9 kg/100 km

together with current public infrastructure tariffs in Europe [11], [5]. For cost calibration, the following European price ranges were considered:

- Electricity price for public High Power Charging (HPC): **0.55–0.90 €/kWh**
- Hydrogen station price: **10–20 €/kg**

Price variability and its impact on results will be explored in future work.

A. Simulation scenarios

For FCEV trucks, the energy cost is obtained with a fixed conversion factor of 33.3 kWh per 1 kg of H_2. For BEV trucks, the power and price tariffs at each charging station are listed in Table IV.

TABLE IV

TARIFFS AND CHARGING POWER FOR BEV CHARGING POINTS

Station	Location	CP	Power (kW)	Price (€/kWh)
S1	Before Naples	CP1	350	0.60
S1	Before Naples	CP2	150	0.55
S2	After Naples	CP3	350	0.60
S2	After Naples	CP4	150	0.55
S3	Before Rome	CP5	350	0.60
S3	Before Rome	CP6	450	0.65
S4	After Rome	CP7	350	0.60
S4	After Rome	CP8	150	0.55
S5	Before Florence	CP9	450	0.65
S6	After Florence	CP10	350	0.60
S7	Before Milan	CP11	350	0.60
S7	Before Milan	CP12	150	0.55

The values shown in Table II refer to the representative average cruising speeds used in the simulation. For each segment j, the applied speed v_j is selected within a narrow realistic interval around the reported average value in order to reflect highway operating conditions.

Travel time is calculated using the formula:

$$T_{\text{travel}} = \sum_{j \in J} \frac{D_j}{v_j}, \qquad (19)$$

where D_j denotes the length of segment j, and v_j is the cruising speed used for that segment.

The total delivery time is computed as:

$$T_{\text{total}} = T_{\text{travel}} + T_{\text{energy}} + T_{\text{unloading}} \qquad (20)$$

where T_{energy} represents the charging time for BEVs or the refuelling time for FCEVs, depending on the selected vehicle technology.

The unloading time is assumed constant and equal to 0.5 hours per intermediate city:

$$T_{\text{unloading}} = N_{\text{cities}} \cdot 0.5 \qquad (21)$$

For each truck, the optimization will provide travel time, number of stops, total duration, and operational costs.

B. Results analysis

The optimization results highlight clear performance differences between BEV and FCEV technologies in terms of travel time, charging/refuelling behavior, and operational energy cost. Table V reports the charging times for BEV models at the used stations.

TABLE V

CHARGING TIME AT EACH CHARGING POINT (CP) FOR BEVS

CP	Location	BEV 1 (h)	BEV 2 (h)
CP2	Before Naples	1.00	0.15
CP4	After Naples	1.00	1.00
CP7	After Rome	0.28	–
CP8	After Rome	1.00	1.00
CP12	Before Milan	0.76	0.87

As shown in Table V, both BEV models use multiple charging points distributed along the corridor. The Volvo FH Electric performs five charging sessions, resulting in a total charging time of approximately 4.04 hours. The Mercedes-Benz eActros 600 requires four charging sessions, with a cumulative charging time of approximately 3.02 hours.

TABLE VI

REFUELLING TIME AT HYDROGEN STATIONS FOR FCEVS

Station	Location	FCEV 1 (h)	FCEV 2 (h)
Station 2	After Naples	–	0.05
Station 4	After Rome	–	0.19
Station 6	After Florence	0.06	0.19
Station 7	Before Milan	0.12	0.07

Table VI reports the refuelling times for the FCEV models. The Nikola TRE requires only two refuelling stops, while the Hyundai Xcient depends more heavily on hydrogen infrastructure, requiring four refuelling stops along the corridor to satisfy reserve constraints.

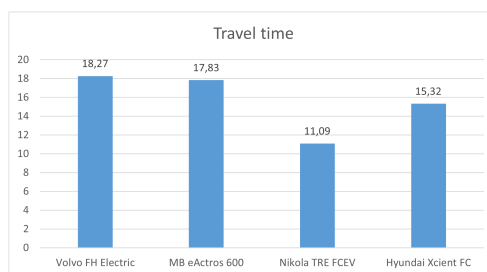

Fig. 4. Total travel time for each truck model

Figure 4 compares the total travel time for each vehicle. The Nikola TRE FCEV achieves the shortest duration (11.09 h), followed by the Hyundai Xcient (15.32 h). Among BEVs, the eActros 600 and the Volvo FH Electric show comparable total times (17.83 h and 18.27 h, respectively), with the Volvo slightly slower due to higher cumulative charging time.

Figure 5 compares the total en-route energy cost. The Mercedes-Benz eActros 600 achieves the lowest cost

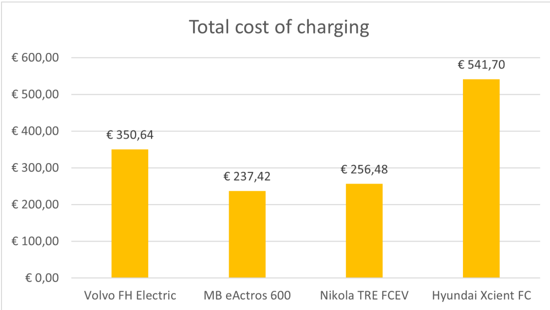

Fig. 5. Total en-route energy cost for each truck model

(€237.42), followed by the Volvo FH Electric (€350.64), mainly due to differences in battery capacity and charging frequency. Among FCEVs, the Nikola TRE incurs a hydrogen cost of €256.48, while the Hyundai Xcient records the highest cost (€541.70) due to its smaller tank capacity and more frequent refuelling stops.

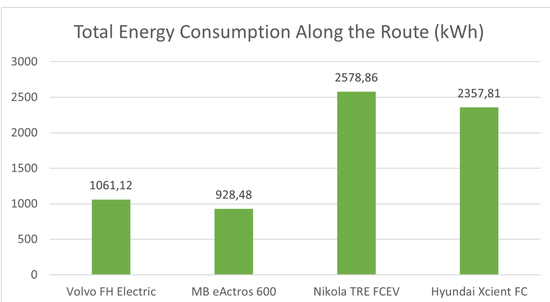

Fig. 6. Total Energy Consumption Along the Route (kWh)

Figure 6 shows the total energy consumption for each vehicle. The Mercedes eActros 600 achieves the lowest consumption (928.48 kWh), followed by the Volvo FH Electric (1061.12 kWh). Conversely, the Nikola TRE FCEV records the highest (2578.86 kWh), while the Hyundai Xcient reaches 2357.81 kWh. This gap is consistent with the lower well-to-wheel efficiency of FCEVs (40–50%) compared to BEVs (85–90%), due to losses in hydrogen production, storage, and conversion.

IV. CONCLUSIONS

This paper proposes a MILP framework for joint vehicle selection and charging/refueling optimization along a delivery corridor. In a case study with four real heavy-duty vehicles across five Italian cities, the Volvo FH Electric provides zero emissions and moderate costs but requires five charging stops. The Nikola TRE FCEV achieves the shortest delivery time with its 70-kg tank and only two refuelling stops. In contrast, the Hyundai Xcient Fuel Cell offers competitive performance versus BEVs, but its 32-kg tank leads to four stops and the highest hydrogen cost.

In conclusion, fuel cell trucks are advantageous for minimizing delivery time, whereas battery electric trucks provide a more cost-stable and infrastructure-friendly solution when energy expenditure is prioritized. The proposed framework is a powerful decision-support tool for vehicle technology selection in freight logistics. In future work, a comprehensive total cost of ownership (TCO) analysis will be investigated, along with sensitivity studies examining the impact of electricity and hydrogen price variability, infrastructure availability, and payload dynamics.

REFERENCES

[1] M. P. Fanti, A. M. Mangini, M. Roccotelli, M. Nolich, and W. Ukovich, "Modeling virtual sensors for electric vehicles charge services," in *Proc. 2018 IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, 2018, pp. 3853–3858.

[2] M. P. Fanti, A. M. Mangini, M. Roccotelli, and W. Ukovich, "Optimal energy management integrating renewable energy, energy storage systems and electric vehicles," in *Proc. 2017 IEEE 14th Int. Conf. Netw., Sens. Control (ICNSC)*, 2017, pp. 519–524.

[3] R. Sun, V. A. Sujan, and G. Jatana, "Systemic decarbonization of road freight transport: A comprehensive total cost of ownership model," arXiv:2410.21026, 2024.

[4] S. K. Dash, S. Chakraborty, M. Roccotelli, and U. K. Sahu, "Hydrogen fuel for future mobility: Challenges and future aspects," *Sustainability*, vol. 14, no. 14, p. 8285, 2022.

[5] H. Basma, Y. Zhou, and F. Rodríguez, "Fuel-cell hydrogen long-haul trucks in Europe: A total cost of ownership analysis," International Council on Clean Transportation (ICCT), Sep. 2022. [Online]. Available: https://theicct.org/publication/eu-hvs-fuels-evs-fuel-cell-hdvs-europe-sep22/

[6] H. Lee, A. Kim, A. Lee, B. Lee, and H. Lim, "Optimized H_2 fueling station arrangement model based on total cost of ownership (TCO) of fuel cell electric vehicle (FCEV)," *Int. J. Hydrogen Energy*, vol. 46, no. 69, pp. 34116–34127, 2021.

[7] Z. Wang *et al.*, "A total cost of ownership analysis of zero emission powertrain solutions for the heavy goods vehicle sector," *J. Cleaner Prod.*, vol. 434, p. 139910, 2024.

[8] A. Magnino, P. Marocco, A. Saarikoski, J. Ihonen, M. Rautanen, and M. Gandiglio, "Total cost of ownership analysis for hydrogen and battery powertrains: A comparative study in Finnish heavy-duty transport," *J. Energy Storage*, vol. 99, p. 113215, 2024.

[9] C. Rout, H. Li, V. Dupont, and Z. Wadud, "A comparative total cost of ownership analysis of heavy duty on-road and off-road vehicles powered by hydrogen, electricity, and diesel," *Heliyon*, vol. 8, e12417, 2022.

[10] Z. Mu, F. Zhao, F. Bai, Z. Liu, and H. Hao, "Evaluating fuel cell vs. battery electric trucks: Economic perspectives in alignment with China's carbon neutrality target," *Sustainability*, vol. 16, no. 6, p. 2427, 2024.

[11] B. Sharpe and H. Basma, "A meta-study of purchase costs for zero-emission trucks," International Council on Clean Transportation (ICCT), Feb. 2022. [Online]. Available: https://theicct.org/publication/purchase-cost-ze-trucks-feb22/

[12] H. Basma and F. Rodríguez, "Fuel cell electric tractor-trailers: Technology overview and fuel economy," International Council on Clean Transportation (ICCT), Jul. 2022. [Online]. Available: https://theicct.org/publication/fuel-cell-tractor-trailer-tech-fuel-jul22/

[13] F. Liu, Q. Zhu, Y. Wang, J. Zhang, and X. Li, "Energy consumption analysis of fuel cell commercial heavy-duty truck with waste heat utilization under low-temperature environment," *Energies*, vol. 18, no. 11, p. 2711, 2025.

[14] M. Gam, O. Hayane, and D. Lefebvre, "Optimization of a two-stage logistic system using hybrid filtered beam search algorithm," in *Proc. 20th Annu. Ind. Simul. Conf. (ISC)*, Dublin, Ireland, 2022.

[15] Volvo Trucks, "Volvo's heavy-duty electric truck is put to the test: Excels in both range and energy efficiency," Jan. 2022. [Online]. Available: https://www.volvotrucks.com/en-en/news-stories/press-releases/2022/jan/volvos-heavy-duty-electric-truck-is-put-to-the-test-excels-in-both-range-and-energy-efficiency.html

[16] S. Mao, Y. Zhang, F. Rodríguez, and S. Wang, "Real-world performance of battery-electric heavy-duty vehicles in China: Energy consumption, range, and charging patterns," International Council on Clean Transportation (ICCT), Apr. 2023. [Online]. Available: https://theicct.org/publication/hdv-china-real-world-performance-apr23/