Advances in Industrial Engineering, December 2026, 60(2): 305-322
DOI: 10.22059/aie.2026.405098.1957

RESEARCH PAPER

Optimizing Container Drayage with Multi-Mode Hybrid Electric Trucks: Model, Experiments, and Insights

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Received: 27 October 2025, Revised: 29 April 2026, Accepted: 14 May 2026
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Abstract

Container drayage is a key component of maritime intermodal logistics, yet it is associated with high operational costs and considerable greenhouse gas emissions due to the extensive use of diesel trucks. This study develops an optimization framework for container drayage operations using hybrid electric trucks. We introduce the Hybrid Electric Container Drayage Problem (HECDP), which incorporates multiple propulsion modes, pure electric, internal combustion, charging, and boost, within a unified routing and scheduling model. A mixed-integer linear programming formulation is proposed to jointly determine vehicle routes, pickup–delivery operations, propulsion-mode selection, and battery state-of-charge dynamics while satisfying container loading and operational constraints. The model is first validated through a small numerical example and then applied to a real-world case study based on the Inland Container Terminal (ICT) Tilburg in the Netherlands. Computational experiments compare three fleet configurations: a conventional diesel fleet, a fully hybrid fleet, and a mixed fleet scenario. Results show that a fully hybrid fleet can reduce operational costs by about 30% and CO_2 emissions by nearly 60% compared with the diesel benchmark. Furthermore, even a partial transition to hybrid trucks (e.g., 30% fleet penetration) captures a substantial portion of these benefits. Sensitivity analyses examining battery capacity, travel speed, and terminal location indicate that operational conditions significantly influence system performance. Overall, the findings suggest that integrating propulsion characteristics of hybrid trucks into routing decisions can simultaneously improve operational efficiency and environmental performance in container drayage systems.

Keywords:
Container Drayage Problem, Multi-Mode Hybrid Electric Vehicle, MILP Optimization, Emission Reduction, Battery Efficiency.

1. Introduction

Maritime intermodal container transportation forms a fundamental component of global supply chains, enabling the large-scale movement of goods across continents [1]. Within this system, container drayage represents the short haul trucking operation that connects maritime terminals with inland shippers and distribution centers, completing the door-to-door logistics chain. Despite relatively short travel distances, drayage accounts for approximately 25–40% of total container transport costs [2] and contributes significantly to greenhouse gas emissions due to

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the widespread use of diesel-powered heavy-duty trucks. As global freight volumes continue to grow, improving both the economic efficiency and environmental sustainability of drayage operations has become increasingly important.

Environmental concerns further intensify this challenge. Recent studies indicate that heavy-duty trucks are responsible for nearly half of transport-related CO_2 emissions in several major economies [3]. In response, many governments have introduced ambitious policies aimed at transitioning freight transport toward zero emission technologies, with some targeting a fully-zero emission truck market by 2040 [4]. Consequently, increasing attention has been directed toward alternative propulsion technologies, particularly electric and hybrid trucks in port-related logistics systems [5].

Although fully electric trucks offer substantial environmental benefits, their large-scale adoption in drayage operations remains constrained by high acquisition costs, limited driving range, and insufficient fast charging infrastructure [6, 7]. Hybrid electric vehicles (HEVs) represent a practical transitional solution, combining the operational flexibility of internal combustion engines with the energy efficiency and emission reductions of electric propulsion. Empirical evidence suggests that hybrid drayage trucks can significantly reduce fuel consumption and emissions without requiring extensive new charging infrastructure [8].

Parallel to these technological developments, vehicle routing research has increasingly focused on modeling hybrid propulsion systems and multi-mode driving behavior. Several studies incorporate energy consumption and propulsion mode decisions within routing models [9]. However, these models typically assume that battery recharging occurs only at dedicated charging stations and do not allow charging during combustion mode operation. Other studies explore concepts such as charging while driving [10, 11], yet they are generally developed within simplified logistics contexts that do not capture the operational characteristics of container drayage systems.

Meanwhile, classical formulations of the Container Drayage Problem (CDP) primarily focus on diesel-powered fleets and routing efficiency. Drayage operations are strongly influenced by standardized container dimensions and chassis capacities, which determine feasible loading combinations. For example, a 40 ft chassis can transport either one 40 ft container or two 20 ft containers, allowing up to four customer visits within a single trip. Such operational characteristics frequently generate multiple short-haul trips between terminals and inland customers, motivating multi trip daily schedules to improve asset utilization [12-16]. Fig. 1 illustrates a typical feasible solution of the CDP serving both import (negative) and export (positive) demands.

Despite these developments, an important research gap remains. Existing HEV routing studies rarely consider the pickup–delivery structure, container-loading constraints, and multi trip scheduling requirements that characterize drayage operations. Conversely, traditional CDP models do not account for hybrid propulsion modes or battery energy dynamics. As a result, the interaction between hybrid multi-mode energy management and container drayage routing decisions has not yet been systematically investigated in the literature.

To address this gap, this study introduces the Hybrid Electric Container Drayage Problem (HECDP), a novel optimization framework tailored to hybrid truck operations in container pickup and delivery systems. In the proposed model, each hybrid truck can operate under four propulsion modes: (i) pure electric mode, (ii) pure combustion mode, (iii) combustion mode with battery charging, and (iv) boost mode. Each mode exhibits distinct characteristics in terms of energy consumption, travel speed, and battery charge or discharge dynamics. The objective is to minimize total operational cost while satisfying all export and import demands within a daily planning horizon.

The main contributions of this research are summarized as follows:

- The study extends the classical container drayage problem by incorporating hybrid electric

trucks with four propulsion modes, enabling a realistic representation of energy aware drayage operations.

- A mixed integer linear programming model is developed to jointly optimize routing decisions, pickup–delivery operations, propulsion mode selection, fuel consumption, and battery charge dynamics.
- A real-world case study from the Inland Container Terminal in Tilburg, the Netherlands, is used to evaluate the performance of diesel fleets, fully hybrid fleets, and mixed fleet configurations under identical operational conditions.
- Sensitivity analyses investigate how key operational parameters, including battery capacity, travel speed, and terminal location, affect routing feasibility, operational costs, and energy usage.

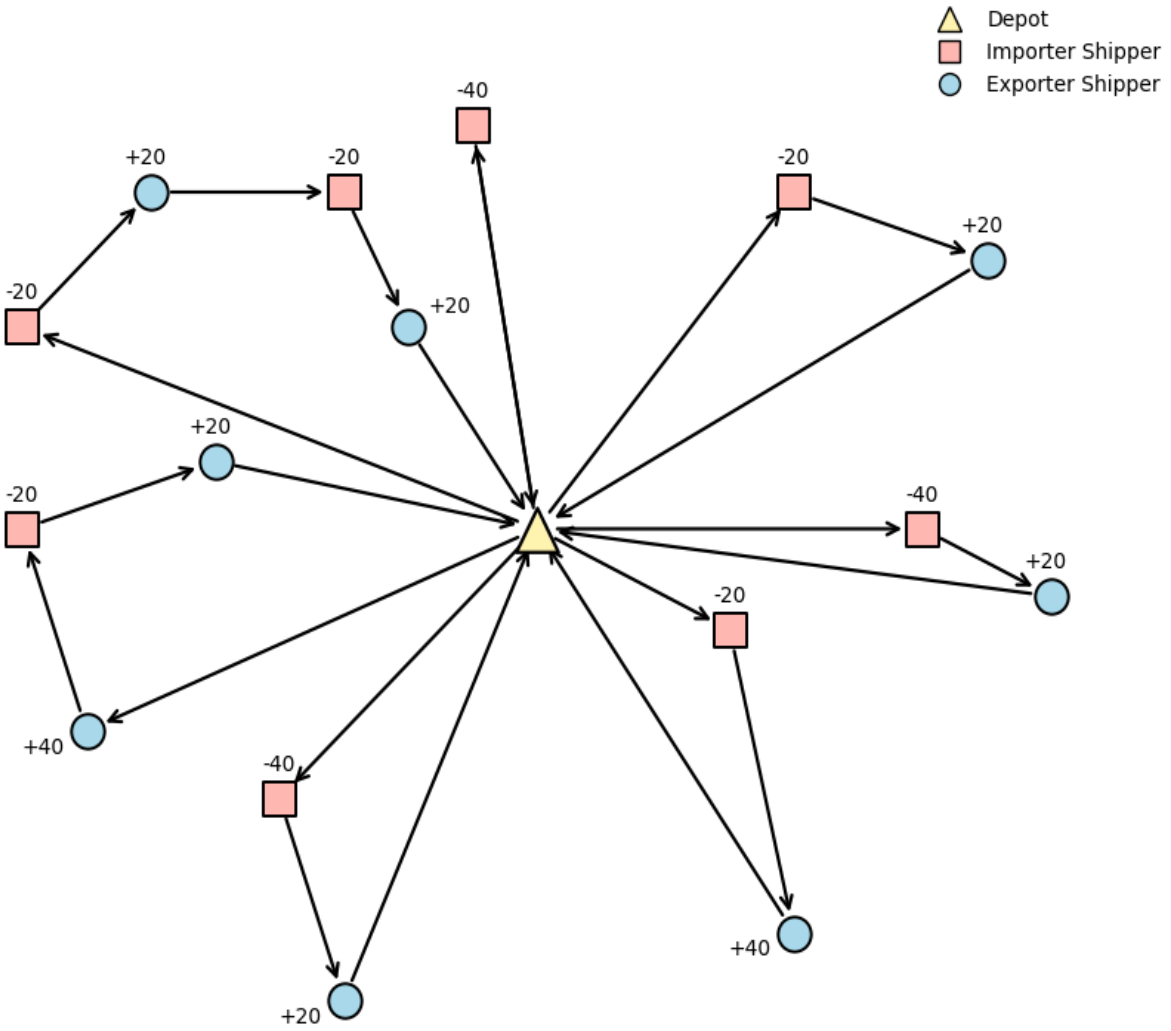

Fig. 1. An example of feasible solution of the CD.

Overall, the results demonstrate that hybrid fleets can significantly reduce operational costs and emissions without compromising service reliability, highlighting their potential as an effective transitional solution toward sustainable container drayage systems. The remainder of this paper is organized as follows. Section 2 reviews the related literature and positions the proposed model within existing research streams. Section 3 presents the mathematical formulation of the Hybrid Electric Container Drayage Problem. Section 4 reports the computational experiments, including the case study and sensitivity analyses. Finally, Section 5 concludes the paper and outlines managerial implications and future research directions.

2. Literature Review

This section reviews the relevant literature in two major domains: (i) the Container Drayage Problem (CDP), which focuses on optimizing container pickup-and-delivery operations, and (ii) the Hybrid Electric Vehicle Routing Problem (HEVRP[†]), emphasizing the integration of multi-mode hybrid trucks into sustainable freight transport networks.

2.1. Container Drayage Problem (CDP)

The Container Drayage Problem (CDP), a port-oriented variant of the Pickup and Delivery Problem within the VRP family [17,18], addresses short-haul container transfers among terminals, depots, and customer sites under time-window and capacity constraints. Early work progressively incorporated practical elements such as heterogeneous container types, time windows, and handling requirements to better reflect port operations [19]. Later contributions expanded CDP's temporal structure through multi-trip and multi-period planning with release and due dates, supporting multi-day operations, driver-hour rules, and customer-specific availability intervals [12]. As operational environments became more dynamic, additional studies incorporated time-dependent travel and uncertainty, including stochastic arrivals, variable service times, and multi-period interactions, thereby enhancing the temporal and stochastic realism of CDP models [20–22].

Parallel to these modeling advances, extensive research examined operational strategies aimed at improving equipment utilization and reducing port-related inefficiencies. Key studies analyzed tractor–trailer separation to lower labor and handling costs [13], emission-aware routing to reduce empty repositioning [23], and comparisons of Stay-with versus Drop-and-Pick policies [24]. Other innovations explored truck platooning for fuel savings [25], as well as multi-resource or multi-trailer configurations to increase productivity and flexibility [26,27]. Coordination-focused extensions further investigated synchronized tractor–trailer exchanges [28], heterogeneous multi-depot settings [29], and alternative handling mechanisms, such as chassis exchange or barge-based operations [30–31]. Collectively, these works improved operational realism and coordination capabilities, though most treat modeling and operational strategies separately and give limited attention to energy-related considerations.

Growing environmental regulations and decarbonization goals have recently increased interest in electrified drayage systems. Early studies mainly addressed policy aspects, emphasizing environmental benefits and infrastructure requirements for electric drayage fleets [33]. More recent work highlights operational challenges, especially the limitations of depot-only charging and the need for opportunity charging within ports [34]. Subsequent research integrates electric-fleet characteristics by jointly modeling fleet composition, charging infrastructure, and operational scheduling [35,2]. Despite these contributions, CDP formulations seldom consider hybrid or multi-mode energy use; interactions among routing, scheduling, and energy-mode flexibility in hybrid or mixed-energy fleets remain largely unexplored, which underscores the need for models that represent energy-diverse drayage systems while capturing the coordination constraints inherent in port logistics.

2.2. Electric and Hybrid Electric Vehicle Routing Problem (HEVRP)

Research on electric vehicle routing has progressively moved toward more realistic representations of battery behavior and charging operations. Early studies examined feasibility under simplified assumptions and typically relied on full-recharging policies and linear charging processes [36]. Subsequent work improved realism by introducing nonlinear charging

[†] Hybrid electric vehicle Routing Problem

functions and more detailed energy-replenishment decisions within routing models [37,38]. Later studies emphasized operational strategies such as partial-charging, which increases routing flexibility and improves overall efficiency [39]. More recent contributions incorporated infrastructure-related constraints, including station congestion, limited charger availability, and waiting times, thereby embedding charging resources directly into routing formulations [40].

Tanvir et al. [6] evaluated the operational feasibility of electric drayage trucks and showed that, with base charging only, fleets could complete just 62% of trips. Building on these insights, modeling work gradually extended to freight transportation and heavy-duty electric trucks, where limited battery capacity, nonlinear charging, and scheduling constraints interact in complex ways [41]. In port-related logistics, where freight flows are concentrated and charging infrastructure is scarce, the availability and capacity of chargers become operationally critical. Accordingly, recent studies have incorporated these infrastructure limitations into container drayage models, emphasizing the importance of charging-aware routing and scheduling in port environments [2]. Despite these efforts, most existing formulations remain focused on fully electric fleets and do not explicitly address mixed or hybrid propulsion systems.

In parallel, hybrid electric vehicles (HEVs) have emerged as an important transitional technology for sustainable freight transport. Prior research analyzed dynamic in-route charging strategies for plug-in hybrid trucks and highlighted both operational benefits and infrastructure constraints [42]. More recent work modeled propulsion-mode selection under joint fuel and battery constraints, capturing the trade-offs inherent in hybrid systems [11]. Hybrid technologies are increasingly recognized as a practical option for reducing emissions in freight and port operations where full electrification is constrained by limited infrastructure [43,8]. Within this context, the multi-mode hybrid electric vehicle routing problem formalizes propulsion-mode selection as an explicit routing decision, allowing vehicles to switch energy sources depending on operating conditions [44]. Follow-up studies enhanced these formulations by incorporating advanced energy-management mechanisms to improve hybrid fleet efficiency [45]. However, hybrid routing has largely been studied independently of container drayage, and the interaction between propulsion-mode decisions, routing, and temporal scheduling in port-oriented freight systems remain underexplored.

To address this gap, this study develops a container drayage modeling framework that explicitly incorporates the operational characteristics of hybrid electric vehicles. The proposed formulation captures the interaction among routing, temporal scheduling, and propulsion-mode decisions while accounting for energy-consumption dynamics and drayage-specific operational constraints. By integrating multi-mode energy usage with the structural features of container transport, the model provides a realistic representation of hybrid electric drayage fleets in infrastructure-constrained port environments and connects previously separate research streams on drayage operations, energy-constrained routing, and hybrid propulsion systems.

3. Problem Formulation

In this section, we define the problem under investigation by outlining the essential settings and key assumptions. We begin by presenting the setting along with the main assumptions. Next, we provide the mathematical formulation. Finally, we examine the validation of the proposed model by investigating a numerical example.

3.1. Problem Setting

The Container Drayage Problem involves serving a set of predetermined shippers using a fleet of hybrid electric vehicles (HEVs) with limited range. The goal is to minimize the total travel cost while considering varying energy consumption, cost, and travel time across different driving modes (combustion, electric, charging, and boost). Since each truck can carry either

one 40-foot container or two 20-foot containers, the possible trip types are defined as follows:

Definition 1: Type of trips

1- customer trip: {0, *i*, 0}, with $r_i \in \{40, -40, 20, -20\}$;
2- customer trip: {0, *i*, *j*, 0}, with $(r_i, r_j) \in \{(-20, -20), (20, 20), (20, -20), (-20, 20), (-40,20), (-20, 40), (-40, 40)\}$;
3- customer trip: {0, *i*, *j*, *k*, 0}, where $(r_i, r_j, r_k) \in \{(-20, -20, 20), (-20, 20, 20), (-20, 20, -20), (20, -20, 20), (-20, -20, 40), (-40, 20, 20)\}$;
4- customer trip: {0, *i*, *j*, *k*, *v*, 0}, where $(r_i, r_j, r_k, r_v) \in \{(-20, 20, -20, 20), (-20, -20, 20, 20)\}$.

Fig. 2 presents a representative instance of the problem in which two hybrid electric trucks depart from the depot to execute multiple trip types. Each arc represents a distinct driving mode, and the highlighted routes illustrate a feasible solution where vehicles switch between modes while completing their assigned trips before returning to the depot.

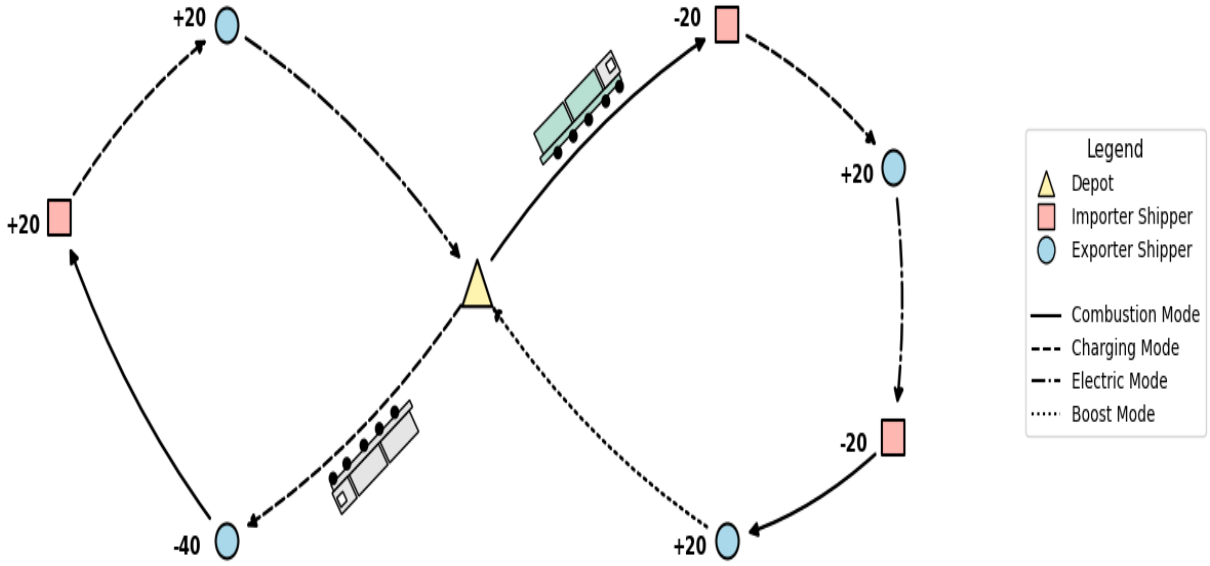

Fig. 2. An illustrative example for problem

3.2. Mathematical Formulation

We consider a network $G(N, A)$, where (A) represents the set of arcs, and(N) denotes the set of nodes. The set (N) includes a depot (denoted as node 0) and a node for each shipper, belonging to the subset (S). Thus, the universal set (N) comprises both the ICD (0) and the shipper nodes in (S). The set of trucks is defined as (K), consisting of individual trucks $(k \in K)$, each based at the depot. A maximum limit on the number of trips is established, denoted by (R), with a corresponding sequence of trips from 0 to (R).

In parameters, The demand for containers for each shipper i is represented by an integer variable. Specifically, Q_i represents the total loading capacity of a truck, while D_i denotes the total demand quantity of shipper i, $i \in S$. The decision variables include u^+ the integer variable representing the total quantity of pickups at node i since the last departure from node 0, $\forall i \in N$ and u^- denotes the integer variable representing the total quantity of deliveries at node i since the last departure from node 0, $\forall i \in N$. x_{ij}^k, a binary routing variable that indicates whether truck k uses arc (i, j). The sets, parameters, and decision variables are further detailed in Table. 1 .

Table. 1. Sets, Parameters and Decision Variables

Set	**Meaning**
N	Set of all nodes
A	Set of arcs
S	Set of shippers
K	Set of trucks
R	Set of trips
Parameter	**Meaning**
D_i	Demand of node i
C_{ij}	Distance between node i and j, where $i, j \in N$
τ_i	Service time at shipper i
T	Time horizon
Q	Loading truck capacity
l_{max}	Battery capacity
Parameter	**Meaning**
α_m	Cost factor associated with drive mode $m \in M$
R_m	Charging (discharging) factor of mode $m \in M$ (0 in for combustion mode, a negative value for electric and boost modes, and a positive value for charging mode)
v_m	Speed on drive mode $m \in M$
M	A large value
Decision variables	**Meaning**
x_{ij}^{kr}	Binary variable that takes the value 1 if truck k in trip r travels from node i to j, 0 otherwise
u_i^+	An integer variable indicating the total quantity of pickups at node i since the last departure from node 0, $\forall i \in N$
u_i^-	An integer variable indicating the total quantity of deliveries at node i since the last departure from node 0, $\forall i \in N$
l_i	Battery SoC upon the arrival at customer i ($i \in S$)
G_k	Battery SoC upon the arrival of vehicle k ∈ K at the depot

The problem is formulated as follows:

$$\boldsymbol{min} \sum_{\boldsymbol{i,j\epsilon N}} \sum_{\boldsymbol{k\epsilon K}} \sum_{\boldsymbol{m\epsilon M}} \boldsymbol{\alpha_m C_{ij} y_{ijm}^k} \tag{1}$$

Subject to:

$$\sum_{\boldsymbol{i\in N}} \sum_{\boldsymbol{k\in K}} \boldsymbol{x_{ij}^k = 1} \qquad \forall i \in S, i \neq j \tag{2}$$

$$\sum_{\boldsymbol{j\epsilon N}} \boldsymbol{x_{ji}^k} = \sum_{\boldsymbol{j\epsilon N}} \boldsymbol{x_{ij}^k} \qquad \forall i \in N, k \in K \tag{3}$$

$$\sum_{\boldsymbol{j\in S}} \boldsymbol{x_{0j}^k \leq 1} \qquad \forall k \in K \tag{4}$$

$$\sum_{\boldsymbol{m\in M}} \boldsymbol{y_{ijm}^k} = \boldsymbol{x_{ij}^k} \qquad \forall i, j \in N, k \in K \tag{5}$$

$$\boldsymbol{l_0 = 0} \tag{6}$$

$$\boldsymbol{l_j \leq l_{max}} \qquad \forall j \in N \tag{7}$$

$$\boldsymbol{l_j \leq l_i + R_m v_m^{-1} d_{ij} y_{ijm}^k + l_{max}(1 - y_{ijm}^k)} \qquad \forall i \in N, j \in S, i \neq j, k \in K, m \in M \tag{8}$$

$$\boldsymbol{G_k \leq l_i + R_m v_m^{-1} d_{i0} y_{i0m}^k + l_{max}(1 - y_{i0m}^k)} \qquad \forall i \in S, k \in K, m \in M \tag{9}$$

$$\sum_{\boldsymbol{i\in N}} \sum_{\boldsymbol{j\in N, j\neq i}} \sum_{\boldsymbol{m\in M}} \boldsymbol{(v_m^{-1} c_{ij} + \tau_i) y_{ijm}^k \leq T} \qquad \forall k \in K \tag{10}$$

$$\boldsymbol{u_0^+ = u_0^- = 0} \tag{11}$$

$$u_j^+ \geq u_i^+ + \max\{D_j, 0\} - (Q + (\max\{D_j, 0\})(1 - \sum_{k \in K} x_{ij}^k) \quad \forall i, j \in N, j \neq 0 \quad (12)$$

$$u_j^- \geq u_i^- - \min\{D_j, 0\} - (Q - \min\{D_j, 0\})(1 - \sum_{k \in K} x_{ij}^k) \quad \forall i, j \in N, j \neq 0 \quad (13)$$

$$x_{ij}^{kr} \leq u_i^- - u_i^+ \quad \forall k \in K, r \in R, i, j \in N, i \neq 0, j \neq 0, i \neq j, D_i = D_j = -20 \quad (14)$$

$$x_{ij}^{kr} \leq Q - u_i^+ \quad \forall k \in K, r \in R, i, j \in N, i \neq 0, j \neq 0, i \neq j, D_i = 20, D_j = -20 \quad (15)$$

$$u_i^- \leq Q \quad \forall i \in S \quad (16)$$

$$u_i^+ \leq Q \quad \forall i \in S \quad (17)$$

$$\sum_{k \in K} x_{0i}^k = 1 \quad \forall i \in S, D_i = -40 \quad (18)$$

$$\sum_{k \in K} x_{i0}^k = 1 \quad \forall i \in S, D_i = +40 \quad (19)$$

$$x_{j0}^k \geq x_{ij}^k \quad \forall i, j \in S, i \neq j, D_i = D_j = 20, k \in K, \quad (20)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall i, j \in N, k \in K \quad (21)$$

$$u_i^+, u_i^- \geq 0 \ \ integer \quad \forall i \in S \quad (22)$$

$$l_i \geq 0 \quad \forall i \in N \quad (23)$$

$$G_k \geq 0 \quad \forall k \in K \quad (24)$$

The objective function outlined (1) is formulated to minimize the total travel cost in different driving modes. Constraint (2) ensures that each shipper is visited exactly once, while Constraint (3) enforces flow conservation. Constraint (4) imposes that the depot may be visited no more than once by each truck during a trip. Constraint (5) Ensures that if arc $(I, j)$is traversed by truck k, a driving mode must be assigned. Constraint (6) sets initial battery SoC (state of charge) at depot to zero. Constraint (7) guarantees that The battery state of charge must not exceed its capacity. Constraints (8) and (9) track the battery SoC of the HEVs during their tours. Constraint (10) guarantees the availability time for each truck. Constraint (11) establishes the quantity of both pickups and deliveries at depot as zero, while Constraints (12) and (13) address the quantities of pickups and deliveries at each node, respectively. Since these constraints apply to all arcs except those entering the terminal, they also guarantee that any sub-tours not including a visit to the terminal are infeasible. Constraint (14) ensure that no two consecutive deliveries of 20 ft containers occur immediately after a 20 ft pickup. Specifically, trip sequences such as $\{0.\,e.\,i.\,j.\,0\}$, where $D_e = 20$, $D_i = D_j = -20$, are prohibited. Similarly, constraints (15) prevent consecutive pickups and deliveries of 20 ft containers from occurring immediately after a sequence involving a 20 ft delivery and pickup. For example, a trip configuration such as $\{0.\,f.\,e.\,i.\,j.\,0\}$, where $D_f = D_j = -20$, $D_e = D_i = 20$, is also considered infeasible. The constraints (16) and (17) ensure that the truck's maximum loading capacity is never violated. For trips involving a customer $i \in S$ with $D_i = -40$ft, that customer must be served first, as enforced by constraint (18). Conversely, constraint (19) insure any customer $i \in S$ with $D_i =$

+40 ft must be served last. Additionally, after consecutively visiting two shippers i and j with $D_i = D_j = 20$, the truck is required to return to the terminal, as specified in constraint (20). Finally, constraints (21) to (24) clearly define the permissible ranges for all decision variables, preserving the integrity of the solution space.

3.3. Model Validation

To validate the proposed model, numerical experiments were conducted on a small instance. All tests were performed on a PC with an i5-2450 processor, 8 GB RAM, using CPLEX Studio IDE 22.1.1.0 in Python with a one-hour time limit per instance. The instance includes 10 randomly distributed shippers with a centrally located depot. Distances were calculated using the Euclidean metric and scaled by 100 to represent kilometers. Vehicle capacity was set to 40, and HEV battery capacity to 30 kWh based on Scania specifications. The planning horizon was 24 hours [46], with 6 trucks and trips considered. Other parameters are reported in Appendix Tables A.1–A.4.

The optimal solution requires 4 trucks to satisfy all shippers under routing, capacity, time, and battery SoC constraints. Detailed variable values are reported in Appendix Tables A.5–A.8. The optimized routes (Fig. 3), with arcs colored by propulsion mode, are as follows: Truck 1 ([0,10,5,0]), Truck 2 ([0,1,0]), Truck 4 ([0,4,8,2,0]), and Truck 5 ([0,6,9,3,7,0]). As illustrated in Fig. 3, Truck 1 starts in combustion mode due to zero initial SoC and short travel distance, then switches to charging mode, and finally completes its return in electric mode. The other trucks begin in charging mode and continue in electric mode once sufficient charge is reached. Truck 5 briefly uses charging mode mid-route to enable electric operation for the remainder of its trip.

To validate the solution, we examine Truck 5's tour with demands (−20, +20, −20, +20). The truck departs the depot carrying two 20-ft containers. At node 6 (−20), it delivers one container, giving $u_6^- = 20$and $u_6^+ = 0$. It then moves to node 9 (+20), picks up one container, updating the pickup load to $u_9^+ = 20$, remaining within the capacity $Q = 40$. At node 3 (−20), another delivery is made ($u_3^- = 40$). Finally, at node 7 (+20), it picks up one container, reaching $u_7^+ = 40$. The truck then returns to the depot, satisfying all capacity limits, flow-conservation constraints, and 20-ft container sequencing rules.

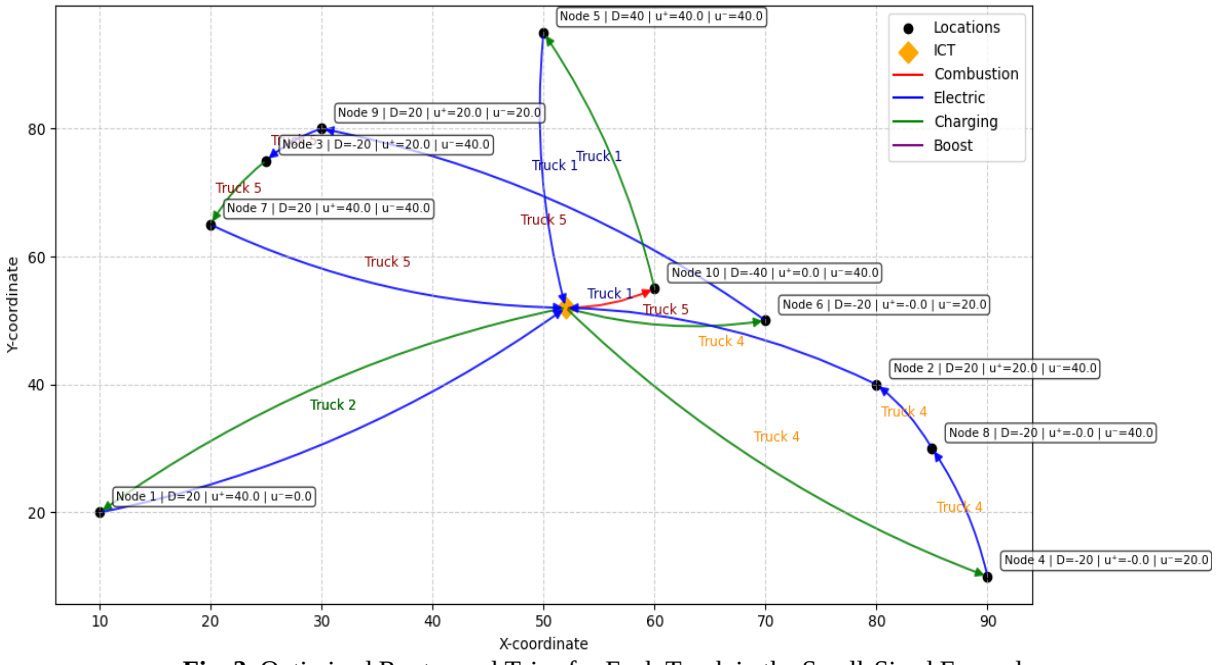

Fig. 3. Optimized Routes and Trips for Each Truck in the Small-Sized Example

4. Computational Experiments

This section evaluates the proposed HECDP model through a case study of ICT Tilburg in the Netherlands, serving as the depot. Three scenarios, diesel, hybrid, and mixed fleets, are solved with CPLEX to compare cost, fuel consumption, and CO_2 emissions. Sensitivity analyses on battery capacity, speed, and terminal location are also conducted, followed by managerial insights.

4.1. Experiments on Case Study

This section evaluates the proposed model using a case study of the ICT terminal in Tilburg, the Netherlands, based on operational data from Fazi et al. [47]. The terminal (ICT Tilburg – BTT, Vossenberg) functions as a hinterland depot connected to the Port of Rotterdam and operates a truck fleet serving regional shippers. Fig. 4 illustrates the transport system using Euclidean distance coordinates. Most pickup and delivery activities occur within the Netherlands, particularly in dense industrial zones [41]. For the case-study setup, 10 industrial demand points were identified using Google Maps coordinates and adjusted accordingly. In Fig. 4, the terminal is marked with a triangle and the demand region is outlined by a circle. Container demand was randomly assigned, and all operational parameters follow the assumptions in Section 3.3.

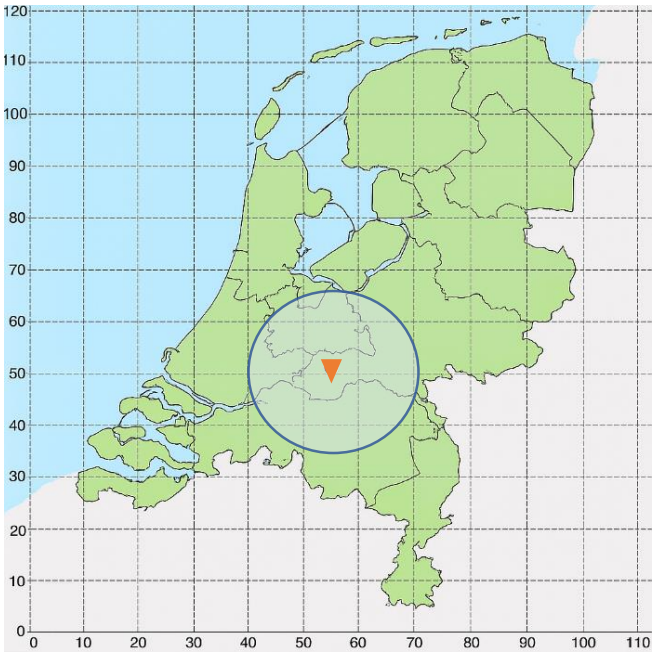

Fig. 4. The geographical context of the case study is represented, with the numbers indicating the axes used to plot the coordinates.

The proposed optimization model was implemented to evaluate economic and environmental performance. Using IBM ILOG CPLEX, solutions were analyzed to assess the benefits of hybrid-electric truck integration. Three scenarios were compared (Table. 2): the Diesel scenario (all diesel trucks), the HEV-Full scenario (all hybrid-electric trucks), and the Mixed Fleet scenario (a combination of hybrid and diesel units). All scenarios were assessed under identical service and scheduling constraints to compare total cost, fuel consumption, and CO_2 emissions.

To ensure methodological consistency, environmental indicators such as carbon dioxide emissions and fuel consumption were quantified using recognized European standards. The carbon dioxide emission factor for a heavy-duty diesel truck was taken as 724.9 (g/km),

validated against the HBEFA database and consistent with the COPERT methodology [48]. Following the EEA [49] formulation, total hot emissions per vehicle are computed as Eq. (25), where Dist is the total mileage (km) and EF_{hot} is the CO_2 emission factor (g/km).

$$E_{hot} = Dist \times EF_{hot} \tag{25}$$

For hybrid heavy-duty trucks, the diesel baseline is adjusted by the relative reduction observed for hybrid configurations. Let R_{HEV} denote the fractional reduction (e.g., 0.16 for 16%) derived from Zacharof et al. [50] over VECTO driving missions (urban, regional, and long-haul). The hybrid total emissions are then obtained as Eq. (26).

$$E_{hot,HEV} = Dist \times EF_{hot,Diesel} \times (1 - R_{HEV}) \tag{26}$$

In addition to CO_2 emissions, fuel consumption was evaluated as a complementary environmental indicator. According to HBEFA v5.1 [51] and EEA [49], the representative fuel consumption for long-haul heavy-duty diesel trucks in Europe is approximately 30 (L/100 km) (0.30 L/km), which aligns with the baseline reported by Delgado et.al study [52] In that study, the reference tractor-trailer tested under the VECTO Long Haul cycle exhibited an average fuel consumption of 33.1 (L/100 km). Following the GLEC Framework v3 [50], which applies an "activity × intensity" logic, total fuel use is given by Eq. (27), where Mis the total mileage (km) and FC_{spec} is the specific fuel consumption (in L/km).

$$FC_{TOT} = Dist \times FC_{spec} \tag{27}$$

For hybrid vehicles, the diesel reference is scaled by the same reduction factor R_{HEV}, yielding Eq. (28).

$$FC_{\mathrm{TOT,HEV}} = Dist \times FC_{\mathrm{spec,Diesel}} \times (1 - R_{\mathrm{HEV}}) \tag{28}$$

The findings highlight the potential of hybrid-electric fleets for sustainable freight transport. As shown in Table. 2, the HEV-Full scenario reduces total fuel consumption from 2,027 to 806 L and total CO_2 emissions from 4,439 to 1,766 kg, corresponding to an overall reduction of about 60%. The specific fuel consumption decreases from 33.1 to 27.8 L/100 km, representing a 16% improvement in energy intensity. These reductions are primarily attributed to propulsion-mode allocation and improved vehicle efficiency rather than changes in route length. Likewise, the CO_2 emission factor falls from 724.9 to 608.9 g/km, consistent with COPERT and HBEFA baseline values for European long-haul trucks.

Table. 2. Comparative performance of diesel and hybrid-electric truck fleet scenarios

Scenario	Total Cost	Distance (km)	fuel combustion factor (L/100 km)	Fuel Consumption (L)	CO_2 emission factor (kg/km)	CO_2 Emission Total (kg)	Trips	Trucks Used
HEV	3159	2900.84	27.804	806.55	0.608916	1766.37	9	5
Diesel	4474	6124	33.1	2027.04	0.7249	4439.29	19	5
HEV (30%) & Diesel (70%)	4050	4286.8	31.5112	1350.82	0.6901048	2958.34	14	5

Note: For HEV-based scenarios, distance refers to travel in non-pure electric modes; pure electric travel is excluded. For diesel-only scenarios, distance represents total travel distance.

The Mixed Fleet scenario (30% HEV, 70% diesel) represents a realistic transition option, reducing fuel consumption and CO_2 emissions by about 33% while maintaining the same fleet size. It also reduces required trips from 19 (diesel scenario) to 9 (HEV scenario), indicating improved consolidation and fleet utilization. Overall, partial electrification with about 30% HEV penetration can provide significant environmental benefits while remaining operationally feasible for terminal freight operations.

4.2. Sensitivity Analyses

Expanding the Section 4.1 case study, we analyze 10-node scenarios to investigate how battery size, speed, and ICT location affect operational efficiency. Shipper locations and demands are randomly generated to match the dataset, with other parameters consistent with Section 3.3. This sensitivity analysis highlights the impact of these factors on logistics performance in more complex urban and semi-rural scenarios. Results are detailed in the following sections.

4.2.1. Battery Size Analysis

To evaluate the impact of battery capacity, we varied capacity from −100% to +50% in 10% increments and re-solved all ten instances. Results are summarized in Table. 3. Overall, larger batteries yield modest average cost reductions, but effects differ substantially across instance types. Type-3 instances (Inst7–Inst10) show the highest sensitivity. For example, in Inst10, removing the battery (−100%) increases cost by 11.16%, while a +50% increase reduces cost by 6.76%. In contrast, Type-1 instances (Inst1–Inst3) are largely insensitive to capacity reductions, with near-zero changes across −10% to −100%, and only limited savings under expansion (e.g., Inst3: −1.53% at +50%). Type-2 instances display intermediate behavior; effects remain small overall, with Inst6 ranging from +0.39% (−100%) to −1.48% (+50%).

The higher responsiveness of Type-3 cases suggests that battery capacity is a binding resource in these networks, likely due to longer effective routes or tighter energy budgets. When capacity is limited, the model shifts to more expensive propulsion modes, increasing costs; additional capacity enables greater electric or hybrid usage and reduces total cost. By contrast, Type-1 instances appear constrained by other operational factors, making them less sensitive to battery size, while Type-2 cases lie between these extremes.

Table. 3. Impact Analysis of Change in Battery Capacity

Instance	Type	-100%	-90%	-80%	-70%	-60%	-50%	-40%	-30%	-20%	-10%	10%	20%	30%	40%	50%
Inst1	Type1	0	0	0	0	0	0	0	0	0	0	-0.18	-0.35	-0.53	-0.7	-0.88
Inst2	Type1	0.11	0.1	0.09	0.08	0.06	0.05	0.04	0.03	0.03	0.01	-0.09	-0.2	-0.28	-0.38	-0.48
Inst3	Type1	0	0	0	0	0	0	0	0	0	0	-0.3	-0.61	-0.92	-1.23	-1.53
Inst4	Type2	0	0	0	0	0	0	0	0	0	0	-0.07	-0.14	-0.22	-0.29	-0.36
Inst5	Type2	0	0	0	0	0	0	0	0	0	0	-0.2	-0.4	-0.61	-0.81	-1.01
Inst6	Type2	0.39	0.36	0.31	0.28	0.23	0.21	0.16	0.13	0.08	0.04	-0.29	-0.6	-0.89	-1.19	-1.48
Inst7	Type3	5.17	4.66	4.14	3.62	3.1	2.59	2.06	1.55	1.03	0.51	-0.41	-0.81	-1.22	-1.62	-2.03
Inst8	Type3	4.6	4.14	3.68	3.22	2.76	2.31	1.84	1.37	0.91	0.46	-0.33	-0.67	-1.01	-1.34	-1.68
Inst9	Type3	6.29	5.66	5.04	4.4	3.78	3.14	2.52	1.89	1.26	0.63	-0.47	-0.94	-1.4	-1.88	-2.34
Inst10	Type3	11.16	10.03	8.92	7.8	6.69	5.57	4.46	3.35	2.23	1.12	-1.36	-2.7	-4.06	-5.41	-6.76

4.2.2. Truck Speed Analysis

Electric-mode speed was varied by ±10% to ±50% in 10% increments, and the same proportional change was applied to boost-mode speed through the electric contribution ratio. Table. 4 reports the resulting percentage changes in total cost. The impact of speed is geometry-dependent. Type-1 instances (Inst1–Inst3), where customers are clustered near the depot, show the highest sensitivity: slower speeds substantially increase costs (up to +7.9% at

−50% in Inst2), while higher speeds yield notable reductions (down to −7.5% at +50% in Inst2 and −5.6% in Inst3). With short inter-node distances, tour duration becomes binding, so lower speeds force costlier propulsion mixes whereas higher speeds create time slack that enables cheaper mode combinations. Type-2 instances (Inst4–Inst6) show milder responses, with Inst6 ranging from +0.9% (−50%) to −1.5% (+50%), while Inst4–Inst5 remain within roughly ±1%. Type-3 instances (Inst7–Inst10) exhibit minimal sensitivity overall: cost increases at −50% remain small (about +0.3% to +0.8%) and savings at +50% are modest (around −0.8% to −1.4%), as longer inter-node legs provide sufficient in-motion time to balance propulsion modes even when speed changes.

Table. 4. Impact Analysis of Changing in Truck speed

Instance	Type	-50%	-40%	-30%	-20%	-10%	10%	20%	30%	40%	50%
Inst1	Type1	5.4	5	4.2	2.3	1.2	-1.1	-2.1	-3.4	-4.9	-6.2
Inst2	Type1	7.9	7.2	6	3.4	1.6	-1.3	-2.7	-4.6	-6.1	-7.5
Inst3	Type1	4.6	4.3	3.6	1.9	1	-0.9	-1.8	-3	-4.2	-5.6
Inst4	Type2	0.6	0.6	0.5	0.3	0.2	-0.2	-0.4	-0.7	-0.9	-1.2
Inst5	Type2	0.4	0.4	0.3	0.2	0.1	-0.2	-0.3	-0.5	-0.7	-0.9
Inst6	Type2	0.9	0.8	0.7	0.4	0.3	-0.3	-0.6	-0.9	-1.2	-1.5
Inst7	Type3	0.5	0.5	0.4	0.2	0.1	-0.2	-0.3	-0.5	-0.7	-0.9
Inst8	Type3	0.3	0.3	0.2	0.1	0.1	-0.1	-0.2	-0.4	-0.6	-0.8
Inst9	Type3	0.7	0.6	0.5	0.3	0.2	-0.3	-0.5	-0.8	-1	-1.3
Inst10	Type3	0.8	0.7	0.6	0.3	0.2	-0.3	-0.6	-0.9	-1.1	-1.4

4.2.3. Location of ICT Analysis

To assess the effect of ICT location, we modified ICT–customer distances and re-solved all ten instances (Inst1–Inst10) under two scenarios: moving the ICT 70% closer (Scenario 1) and 30% farther (Scenario 2). Table. 5 reports the resulting percentage changes in total cost relative to the baseline. Overall, bringing the ICT closer generates substantial savings (mean −9.75%), whereas moving it farther increases costs (mean +5.65%). However, responses vary by instance type. Type-1 cases (Inst1–Inst3) show the strongest sensitivity; for example, in Inst1 the −70% shift reduces cost by 18.0%, while a +30% increase raises it by 12.0%. Type-3 cases (Inst7–Inst10) exhibit smaller changes (e.g., Inst10: −6.5% vs. +3.0%), while Type-2 instances are intermediate (e.g., Inst6 ranges from −10.0% to +6.0%). This pattern likely reflects spatial structure: when shippers are concentrated near the ICT (Type-1), ICT proximity strongly affects deadhead travel and tight tour-duration feasibility, so moving it closer reduces empty repositioning and enables cheaper propulsion mixes. In contrast, Type-3 instances involve longer inter-node travel, providing greater routing and mode flexibility and therefore smaller cost variations, with Type-2 falling between these behaviors.

Table. 5. Impact Analysis of Location of ICT

Instances	Inst1	Inst2	Inst3	Inst4	Inst5	Inst6	Inst7	Inst8	Inst9	Inst10
Senario 1	−18.0	−16.5	−14.0	−9.0	−7.5	−10.0	−6.0	−4.5	−5.5	−6.5
Senario 2	12	10.5	9	5	4	6	2.5	2	2.5	3
Type	Type1	Type1	Type1	Type2	Type2	Type2	Type3	Type3	Type3	Type3

4.3. Managerial Insight

The results show that hybrid-electric integration in drayage can be economically attractive and operationally transformative when aligned with network characteristics. Partial hybridization already delivers a large share of the attainable benefits: adopting only 30% HEVs

cuts fuel use and CO_2 emissions by about one third (Table. 2) without requiring additional vehicles, suggesting that meaningful decarbonization does not depend on full-fleet electrification. For capital-constrained operators, a staged rollout can reduce risk while still yielding substantial environmental gains. Moreover, environmental improvement and cost efficiency are structurally aligned; the fully hybrid configuration lowers total operational cost by roughly 30% relative to the diesel baseline, driven mainly by propulsion-mode optimization and lower energy consumption rather than shorter routes. Hybrid adoption therefore represents both a sustainability and an efficiency strategy. It also reshapes service structure: the number of required trips drops by more than 50% in the fully hybrid case (Table. 2), indicating higher consolidation and vehicle utilization, which can translate into reduced terminal congestion, better use of driver hours, and improved asset productivity.

Sensitivity analyses confirm that the value of hybrid technology depends on network geometry. Battery capacity becomes cost-critical in longer-haul structures (Type-3), where insufficient capacity can increase cost by more than 10% (Table. 3). Urban or clustered networks (Type-1) are more sensitive to electric-mode speed, with cost deviations near ±8% (Table. 4). Terminal–customer proximity exerts the strongest structural influence: relocating the ICT closer can reduce cost by up to 18% in clustered layouts (Table. 5), implying that spatial design choices may, in some settings, yield greater efficiency gains than incremental vehicle-technology improvements. Overall, hybrid-electric deployment should be network-aware and spatially coordinated. Operators should implement moderate HEV penetration early, prioritize battery capacity in extended routing environments, improve operating conditions in dense urban networks, and integrate terminal-siting decisions with technology investment. Such coordinated planning enables simultaneous improvements in cost, environmental performance, and operational robustness.

5. CONCLUSION

This study introduced the Multi-Mode Hybrid Electric Vehicle Routing Problem (MM-HEVRP), extending the classical container drayage problem by modeling four propulsion modes (Electric, Hybrid, Boost, Combustion) with distinct fuel and emission characteristics and integrating them into a MILP that links vehicle-level energy dynamics to network-level routing decisions. Applied to the ICT Tilburg case, the model showed that hybridization delivers substantial and robust benefits: the fully hybrid configuration reduces total operational cost by about 30% and CO_2 emissions by nearly 60% relative to diesel, while a mixed fleet with 30% HEVs captures roughly one-third of these gains—confirming the viability of incremental adoption under capital or infrastructure constraints. Hybrid routing also improves service structure through fewer trips and more efficient propulsion-mode allocation, and the reliance on COPERT and GLEC v3 parameters ensures that fuel and emission outputs remain compatible with international carbon-accounting frameworks.

Overall, the MM-HEVRP contributes to sustainable freight transportation by explicitly linking hybrid-vehicle propulsion dynamics with routing optimization, showing that hybrid-electric trucks can simultaneously enhance environmental performance and operational efficiency when propulsion behavior is integrated into routing decisions. Future research may extend the model by incorporating empty-container repositioning, richer drayage flow structures, stochastic travel times and demand variability for improved robustness, and more detailed battery and charging behavior to better represent hybrid-vehicle energy management in real operational settings.

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APPENDIX

Table A.1. Shippers parameters as Demand, Time window of shipper, Servicetimes

Node	0	1	2	3	4	5	6	7	8	9	10
Demand	0	20	20	-20	-20	40	-20	20	-20	20	-40
Service times (h)	0.25	0.32	0.32	0.45	0.47	0.25	0.3	0.37	0.44	0.39	0.22

Table A.2. Shippers parameters as coordinates

Node	0	1	2	3	4	5	6	7	8	9	10
x	50	10	80	25	90	50	70	20	85	30	60
y	50	20	40	75	10	95	50	65	30	80	55

Table A.3. Driving mode parameters

Node	1	2	3	4
v_m	49	46	43	53
α_m	1	0.2	1.1	1.2
R_m	0	-12	48	-12

Table A.4. The value of the variable G_k

Truck	1	2	3	4	5
G_k	0	0	0	0	0

Table A.5. The value of the variable x_{ij}^k

Source (*i*)	0	5	10	0	1	0	2	4	8	0	3	6	7	9
Destination (*j*)	10	0	5	1	0	4	0	8	2	6	7	9	0	3
Truck (*k*)	1	1	1	2	2	4	4	4	4	5	5	5	5	5
Value	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table A.6. The value of the variable y_{ijm}^k

Source (*i*)	0	5	10	1	0	2	4	8	0	6	7	9	0
Destination (*j*)	10	0	5	0	1	0	8	2	4	9	0	3	6
Truck (*k*)	1	1	1	2	2	4	4	4	4	5	5	5	5
Mode (*m*)	1	2	3	2	3	2	2	2	3	2	2	2	3
Value	1	1	1	1	1	1	1	1	1	1	1	1	1

Table A.7. The value of the variable u_i^+ and u_i^-

Node	1	2	3	4	5	6	7	8	9	10
U+	40	20	20	0	40	0	40	0	20	0
U-	0	40	40	20	40	20	40	40	20	40

Table A.8. The value of the variable I_i

Node	1	2	3	4	5	6	7	8	9	10
$\mathbf{l_i}$	16.8	7.95	0	16.8	11.23	16.8	9.01	11.42	1.84	0

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