

Home Healthcare Routing and Scheduling with a Mixed Fleet of Electric and Conventional Vehicles

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Abstract

Home healthcare (HHC) services require caregivers to travel from healthcare centers to patients' homes, making routing and scheduling a critical operational problem. Rising fuel costs and sustainability targets are pushing providers to adopt electric vehicles (EVs), yet most HHC studies assume homogeneous fleets and ignore battery dynamics, charging decisions, and mandatory caregiver breaks. This paper studies an HHC routing and scheduling problem with a mixed fleet of electric and conventional vehicles under patient time windows, mandatory lunch breaks, battery consumption and charging, daily working and distance limits, and workload fairness among caregivers. A mixed-integer linear programming (MILP) model is proposed to minimize total travel distance while penalizing workload imbalance. Because the problem is NP-hard, a three-stage solution framework is developed: an exact MILP solved with Gurobi for small instances, an Adaptive Large Neighborhood Search (ALNS) with elimination strategies for larger instances, and two enhancements—a tabu memory mechanism and a machine-learning module that guides operator selection dynamically. Computational experiments on instances with 40, 50, and 60 service nodes and varying EV/conventional ratios show that the learning-guided variant (ALNS+Tabu+ML) improves average solution quality by about 7.5% over the exact model within a fraction of its computing time and converges in fewer iterations. The results confirm that integrating learning into ALNS yields faster, higher-quality solutions for sustainable home healthcare routing.

Keywords

Home healthcare routing, Electric vehicles, Mixed fleet, Adaptive large neighborhood search, and Machine learning.

1. Introduction

Home healthcare (HHC) has become an essential component of modern health systems because of population aging, the growing prevalence of chronic diseases, and the pressure to reduce hospital congestion and costs. In HHC systems, caregivers depart from healthcare centers and travel to patients' homes to deliver medical services, so routing and scheduling decisions directly determine cost, timeliness, and patient satisfaction. Inefficient planning increases travel distance, delays service, and reduces both patient and caregiver well-being, which makes effective optimization tools highly valuable for providers.

HHC routing is inherently complex due to strict patient time windows, deterministic service durations, caregiver working-time regulations, and the need for daily breaks. At the same time, sustainability concerns and rising fuel prices encourage providers to introduce electric vehicles (EVs) alongside conventional regular vehicles (RVs). EVs reduce emissions and operating costs but add limited battery capacity, minimum charge thresholds, and recharging decisions, which substantially increase routing difficulty. In practice, providers operate mixed fleets during a transition period, yet the literature rarely models EVs and RVs together within an HHC setting, and operational features such as mandatory lunch breaks, battery threshold policies, and integrated charging decisions are frequently neglected or oversimplified.

This paper addresses these gaps by formulating the HHC routing and scheduling problem with a mixed fleet of electric and conventional vehicles as a mixed-integer linear program and by developing a hybrid, learning-guided metaheuristic to solve realistic instances. The model integrates patient time windows, lunch-break planning, battery consumption and charging for EVs, daily working-time and distance limits, and a workload-fairness term. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature; Section 3 presents the methods, including the problem description, the mathematical model, and the solution approach; Section 4 describes data collection; Section 5 reports numerical and graphical results, proposed improvements, and validation; and Section 6 concludes.

1.1 Objectives

The objectives of this research are: (i) to formulate a MILP model for the HHC routing and scheduling problem that simultaneously captures a mixed electric/conventional fleet, patient time windows, mandatory lunch breaks, battery dynamics and charging, daily working-time and distance limits, and workload fairness; (ii) to design a three-stage solution framework that combines exact optimization with an ALNS metaheuristic enhanced by tabu memory and a machine-learning operator-selection mechanism; and (iii) to evaluate the framework on instances of varying size and fleet composition, quantifying gains in solution quality and computational efficiency. The unique contribution is the integration of a learning-guided ALNS for an HHC problem with an explicitly mixed EV/RV fleet and break constraints, a combination largely absent from prior work.

2. Literature Review

The HHC routing and scheduling problem (HHCRSP) has been studied extensively because of its practical relevance and computational difficulty. The literature can be organized by modeling framework, solution methodology, treatment of uncertainty, and, more recently, the inclusion of energy and sustainability considerations. This section reviews these streams and positions the present study within them.

Early and exact formulations integrate nurse assignment, routing, and scheduling. Trautsumwieser and Hirsch (2011) proposed daily scheduling models for home care, while Lanzarone and Matta (2014) addressed robust nurse-to-patient assignment under continuity of care. Restrepo et al. (2020) integrated staffing and scheduling decisions, and Naderi et al. (2023) developed an efficient exact technique for integrated staffing, assignment, routing, and scheduling under uncertainty. These works confirm that exact methods provide valuable optimal benchmarks but scale poorly as instance size grows, motivating heuristic approaches for realistic problems.

To overcome these limitations, many studies adopt heuristics and metaheuristics. Shi et al. (2017) designed a hybrid genetic algorithm for HHC routing with time windows and fuzzy demand, and Euchí et al. (2020) combined construction and improvement heuristics for routing with synchronized visits. Xiang et al. (2021) jointly optimized cost and participants' preference satisfaction. Within this stream, Large Neighborhood Search has become prominent: Ropke and Pisinger (2006) introduced the Adaptive Large Neighborhood Search (ALNS) framework that underlies many subsequent healthcare and routing applications, demonstrating robustness across instance characteristics.

Uncertainty and dynamic features have also received attention. Shi et al. (2019) proposed robust optimization for uncertain travel and service times, Nikzad et al. (2021) developed a matheuristic for stochastic HHC planning, and Carello et al. (2020) analyzed trade-offs among stakeholders in nurse-to-patient assignment. More recently, Zhao et al. (2024) and Nabavizadeh et al. (2024) formulated bi-objective and quarantine-based HHC scheduling under uncertainty, and Shiri et al. (2023) and Abbasi et al. (2023) addressed network design and supply-chain resilience during health crises. Rest and Hirsch (2015) further supported urban home healthcare planning in both routine operations and disaster situations through a tabu search heuristic that accommodates public-transport modes. These studies, however, typically assume homogeneous fleets and rarely model vehicle energy constraints explicitly.

Electric and green vehicle routing forms a parallel and rapidly growing stream. Schneider et al. (2014) introduced the electric vehicle routing problem with time windows and recharging stations, and Goeke and Schneider (2015) studied routing a mixed fleet of electric and conventional vehicles with realistic energy consumption. Keskin and Çatay (2016) added partial-recharge strategies, while Desaulniers et al. (2016) developed exact branch-price-and-cut algorithms. Adaptive and learning-oriented heuristics for energy-constrained routing were proposed by Kancharla and Ramadurai (2018), Zhu et al. (2020), Yang et al. (2015), and Wen et al. (2022) for green and multi-depot variants. Only a few works bring EVs into HHC: Cebeci et al. (2024) studied heterogeneous EVs with synchronization, and Erdem and

Koç (2023) routed EVs for home care and dialysis with private and public charging. In addition, machine learning has begun to support HHC operations, for example in estimating service length (Menteş et al., 2023) and in strategic long-term-care decision models (Yang et al., 2023).

In summary, exact HHC models offer benchmarks but limited scalability; metaheuristics, especially ALNS, deliver high-quality solutions for larger instances; and electric vehicle routing is well developed in transportation contexts but rarely embedded in HHC. The explicit combination of a mixed EV/RV fleet, battery thresholds and charging, mandatory lunch breaks, daily working and distance limits, and workload fairness—solved by an ALNS that is enhanced with tabu memory and a machine-learning operator-selection mechanism—remains largely unaddressed. The present study targets exactly this gap.

3. Methods

3.1 Problem Description and Assumptions

The problem is defined over a finite planning horizon in which caregivers depart from healthcare centers (hospitals) to serve patients at their homes. The system comprises a set of patients, a heterogeneous fleet of caregivers operating either regular vehicles (RVs) or electric vehicles (EVs), a set of hospitals, and a set of charging stations available exclusively to EVs. Each vehicle is permanently assigned to one hospital, departs from it at the start of the day, and returns to a corresponding artificial destination node at the end of the day. Each patient must be visited exactly once; patients requiring a second daily visit are modeled as distinct nodes, each with an earliest and a latest service start time and a deterministic treatment duration.

Routing and scheduling must respect daily working-time limits, including travel, service, charging (for EVs), and a mandatory lunch break of fixed duration whose start lies within a predefined interval and which may only be taken after visiting a patient, never at the hospital. RVs are subject only to distance and working-time limits; EVs additionally face a battery capacity, a consumption rate proportional to distance, a minimum charge threshold, and full recharging when visiting a station. An EV may traverse an arc only if its charge suffices. The objective minimizes total travel distance over the horizon while penalizing workload imbalance, subject to all operational, regulatory, and energy constraints. The main modeling assumptions are: deterministic parameters; fixed vehicle–hospital assignment; a single caregiver per vehicle; exact one-visit service per node; hard time windows (early arrival waits, late service forbidden); one mandatory lunch break per day; full recharging only (no partial charging); charging-station access restricted to EVs; battery-feasibility enforcement; maximum daily travel distance for both fleets; and independent single-day planning.

3.2 Mathematical Model

Sets. P patients; W patients requiring a second daily visit; V vehicles, with V^{ev} and V^{rv} the electric and regular subsets; C charging stations; H hospitals; $N = P \cup W \cup C \cup H$ all nodes; D days.

Parameters. d_{ij} distance and $time_{ij}$ travel time between i and j ; B^{ev} , Y^{ev} , r^{ev} battery capacity, consumption rate, and recharging rate of EVs; dur_i treatment duration; a_i , b_i earliest and latest start times; T^{max} maximum daily working time; L lunch duration with window $[st^1_L, st^2_L]$; D^{ev}_{max} and D^{rv}_{max} maximum daily distances; thr the minimum battery threshold; M a large constant; and γ^{fair} the fairness weight.

Decision variables. $x^v_{ijd} = 1$ if vehicle v travels from i to j on day d ; $l_{ivd} = 1$ if the lunch break is taken before visiting i ; t_{ivd} arrival time; s^l_{ivd} lunch start time; b_{ivd} battery level of EV v at i ; y_{vd} number of patients served; and m^{max}_d , m^{min}_d the maximum and minimum workload on day d .

$$\min \sum_{d \in D} \sum_{v \in V} \sum_{i \in N} \sum_{j \in N, j \neq i} d_{ij} x^v_{ijd} + \gamma^{fair} \sum_{d \in D} (m^{max}_d - m^{min}_d) \quad (1)$$

$$y_{vd} = \sum_{i \in P \cup W} \sum_{j \in N, j \neq i} x^v_{jid} \quad \forall v \in V, d \in D \quad (2)$$

$$m^{max}_d \geq y_{vd} \quad \forall v \in V, d \in D \quad (3)$$

$$m^{min}_d \leq y_{vd} \quad \forall v \in V, d \in D \quad (4)$$

$$\sum_{v \in V} \sum_{j \in N, j \neq i} \sum_{d \in D} x^v_{ijd} = 1 \quad \forall i \in P \cup W \quad (5)$$

$$x^v_{iia} = 0 \quad \forall i \in N, v \in V, d \in D \quad (6)$$

$$x^v_{jia} = 0 \quad \forall i \in N, j \in C, v \in V^{rv}, d \in D \quad (7)$$

$$\sum_{j \in N, j \neq i} x^v_{ijd} = \sum_{j \in N, j \neq i} x^v_{jid} \quad \forall i \in N \setminus H, v \in V, d \in D \quad (8)$$

$$\sum_{j \in P \cup W \cup C} x^v_{hjd} = 1 \quad \forall v \in V^{ev}, h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, d \in D \quad (9)$$

$$\sum_{i \in P \cup W \cup C} x^v_{ih,d} = 1 \quad \forall v \in V^{ev}, h_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, d \in D \quad (10)$$

$$\sum_{j \in PUW} x_{hjd}^v = 1 \quad \forall v \in V^r, h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, d \in D \quad (11)$$

$$\sum_{i \in PUW} x_{ihd}^v = 1 \quad \forall v \in V^r, h_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, d \in D \quad (12)$$

$$\sum_{i \in PUW} l_{ivd} = 1 \quad \forall v \in V, d \in D \quad (13)$$

$$l_{ivd} \leq \sum_{j \in N, i \neq j} x_{ijd}^v \quad \forall i \in N, v \in V, d \in D \quad (14)$$

$$l_{h,vd} = 0 \quad \forall h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, v \in V, d \in D \quad (15)$$

$$t_{h,vd} \leq T^{\max} \quad \forall v \in V, h_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, d \in D \quad (16)$$

$$t_{ivd} + (time_{ij} x_{ijd}^v + (B^{ev} - b_{ivd}) r^{ev} + L l_{jvd} \leq t_{jvd} + (1 - x_{ijd}^v) M, \quad \forall i \in C, j \in PUW, v \in V^{ev}, d \in D \quad (17)$$

$$t_{ivd} + (time_{ij} + dur_i) x_{ijd}^v + L l_{jvd} \leq t_{jvd} + (1 - x_{ijd}^v) M, \quad \forall i \in PUW, j \in C, v \in V^{ev}, d \in D \quad (18)$$

$$t_{jvd} \leq t_{ivd} + (time_{ij} + dur_i) x_{ijd}^v + L l_{jvd} + (1 - x_{ijd}^v) M, \quad \forall i \in PUW, j \in C, v \in V^{ev}, d \in D \quad (19)$$

$$t_{ivd} + (time_{ij} + dur_i) x_{ijd}^v + L l_{jvd} \leq t_{jvd} + (1 - x_{ijd}^v) M, \quad \forall i \in PUW, j \in PUW, i \neq j, v \in V, d \in D \quad (20)$$

$$t_{jvd} \leq t_{ivd} + (time_{ij} + dur_i) x_{ijd}^v + L l_{jvd} + (1 - x_{ijd}^v) M, \quad \forall i \in PUW, j \in PUW, i \neq j, v \in V, d \in D \quad (21)$$

$$t_{h,vd} = 0 \quad \forall v \in V, h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, d \in D \quad (22)$$

$$t_{h,vd} + time_{hj} x_{hjd}^v + L l_{jvd} \leq t_{jvd} + (1 - x_{hjd}^v) M, \quad \forall j \in PUW, h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, v \in V^r, d \in D \quad (23)$$

$$t_{h,vd} + time_{hj} x_{hjd}^v + L l_{jvd} \leq t_{jvd} + (1 - x_{hjd}^v) M, \quad \forall j \in PUWUC, h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, v \in V^{ev}, d \in D \quad (24)$$

$$t_{h,vd} \geq t_{ivd} + (time_{ih_v} + dur_i) x_{ih_vd}^v + L l_{h_vd} - (1 - x_{ih_vd}^v) M, \quad \forall i \in PUW, h_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, v \in V^r, d \in D \quad (25)$$

$$t_{h,vd} \leq t_{ivd} + (time_{ih_v} + dur_i) x_{ih_vd}^v + L l_{h_vd} + (1 - x_{ih_vd}^v) M, \quad \forall i \in PUW, h_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, v \in V^r, d \in D \quad (26)$$

$$t_{h,vd} \geq t_{ivd} + (time_{ih_v} + dur_i) x_{ih_vd}^v + L l_{h_vd} - (1 - x_{ih_vd}^v) M, \quad \forall i \in PUWUC, h_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, v \in V^{ev}, d \in D \quad (27)$$

$$t_{h,vd} \leq t_{ivd} + (time_{ih_v} + dur_i) x_{ih_vd}^v + L l_{h_vd} + (1 - x_{ih_vd}^v) M, \quad \forall i \in PUWUC, h_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, v \in V^{ev}, d \in D \quad (28)$$

$$x_{h_v, \bar{h}_v, d} = 0, \quad \forall h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, \bar{h}_v \in \{\bar{p} + \bar{w} + \bar{c} + \bar{v} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + 2\bar{v}\}, v \in V, d \in D \quad (29)$$

$$x_{ih_v, d} = 0, \quad \forall i \in N, h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, v \in V, d \in D \quad (30)$$

$$b_{ivd} \leq B^{ev}, \quad \forall i \in N, v \in V^{ev}, d \in D \quad (31)$$

$$b_{jvd} \leq b_{ivd} - Y^{ev} x_{ijd}^v d_{ij} + M(1 - x_{ijd}^v), \quad \forall i \in N, j \in N \setminus C, j \neq i, v \in V^{ev}, d \in D \quad (32)$$

$$b_{jvd} \geq b_{ivd} - Y^{ev} x_{ijd}^v d_{ij} - M(1 - x_{ijd}^v), \quad \forall i \in N, j \in N \setminus C, j \neq i, v \in V^{ev}, d \in D \quad (33)$$

$$b_{jvd} = B^{ev} \sum_{i \in N, i \neq j} x_{ijd}^v \quad \forall j \in C, v \in V^{ev}, d \in D \quad (34)$$

$$b_{h_vd} = B^{ev}, \quad \forall h_v \in \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, v \in V^{ev}, d \in D \quad (35)$$

$$b_{ivd} \geq thr \sum_{j \in N, i \neq j} x_{ijd}^v, \quad \forall i \in N \setminus \{\bar{p} + \bar{w} + \bar{c} + 1, \dots, \bar{p} + \bar{w} + \bar{c} + \bar{v}\}, v \in V^{ev}, d \in D \quad (36)$$

$$b_{ivd} \geq Y^{ev} x_{ijd}^v d_{ij} \quad \forall i, j \in N, i \neq j, v \in V^{ev}, d \in D \quad (37)$$

$$a_i \sum_{j \in N, i \neq j} x_{ijd}^v \leq t_{ivd} \leq b_i \sum_{j \in N, i \neq j} x_{ijd}^v \quad \forall i \in N, v \in V, d \in D \quad (38)$$

$$st^1_L \leq s^1_{vd} \leq st^2_L \quad \forall v \in V, d \in D \quad (39)$$

$$\sum_{i \in N} \sum_{j \in N, i \neq j} d_{ij} x_{ijd}^v \leq D^{ev}_{\max} \quad \forall v \in V^{ev}, d \in D \quad (40)$$

$$\sum_{i \in N} \sum_{j \in N, i \neq j} d_{ij} x_{ijd}^v \leq D^r_{\max} \quad \forall v \in V^r, d \in D \quad (41)$$

$$x_{ijd}^v \in \{0, 1\} \quad \forall i, j \in N, v \in V, d \in D \quad (42)$$

$$l_{ivd} \in \{0, 1\} \quad \forall i \in PUW, v \in V, d \in D \quad (43)$$

$$t_{ivd} \geq 0 \quad \forall i \in N, v \in V, d \in D \quad (44)$$

$$s^1_{vd} \geq 0 \quad \forall v \in V, d \in D \quad (45)$$

$$b_{ivd} \geq 0 \quad \forall i \in N, v \in V^{ev}, d \in D \quad (46)$$

$$y_{vd} \in \mathbb{Z}^+ \quad \forall v \in V, d \in D \quad (47)$$

$$m^{max}_d \geq 0 \quad \forall d \in D \quad (48)$$

$$m^{min}_d \geq 0 \quad \forall d \in D \quad (49)$$

Equation (1) is the objective function, which minimizes the total travel distance while penalizing workload imbalance through the fairness term. Equation (2) defines the number of patients served by vehicle v on day d , and Equations (3) and (4) define the maximum and minimum workloads, respectively. Constraint (5) ensures that each patient, including those requiring a second visit during the day, is served exactly once by one vehicle over the entire planning horizon. Constraint (6) eliminates self-loops by preventing any vehicle from traveling from a node to itself. Constraint (7) restricts regular vehicles from visiting charging stations, ensuring that only electric vehicles are allowed to use these facilities. Constraint (8) enforces flow conservation at each non-hospital node, guaranteeing route continuity by equating the number of arcs entering and leaving each node for every vehicle and day. Constraints (9) and (10) ensure that each electric vehicle starts its route from its assigned hospital and returns to the corresponding ending hospital at the end of the day. Similarly, Constraints (11) and (12) impose the same start-and-end requirements for regular vehicles. Constraint (13) enforces that each caregiver takes exactly one lunch break per day. Constraint (14) links the

lunch-break decision variable to the routing decisions, allowing a lunch break only if the corresponding patient is visited by the vehicle. Constraint (15) prevents lunch breaks from being taken at the starting hospital. Constraint (16) ensures that the total working time of each vehicle does not exceed the maximum allowable working hours per day. Constraints (17)–(21) model the temporal relationships between consecutive visits, incorporating travel times, service durations, charging times for electric vehicles, and lunch breaks; these constraints ensure correct time propagation along vehicle routes. Constraint (22) initializes the departure time of each vehicle at the beginning of the working day. Constraints (23) and (24) define arrival times at the first visited node after departing from the hospital for regular and electric vehicles, respectively. Constraints (25)–(28) ensure consistency of arrival times when vehicles return to their ending hospitals after completing their routes. Constraint (29) prohibits direct travel from a starting hospital to an ending hospital without visiting any patient. Constraint (30) prevents vehicles from returning to the starting hospital after leaving it. Constraint (31) imposes an upper bound on the battery level of electric vehicles, ensuring it does not exceed the maximum battery capacity. Constraints (32) and (33) model battery consumption during travel for electric vehicles, reducing the battery level proportionally to the distance traveled. Constraint (34) ensures that the battery of an electric vehicle is fully recharged upon visiting a charging station. Constraint (35) initializes the battery level of each electric vehicle at full capacity at the starting hospital. Constraint (36) enforces a minimum battery threshold for electric vehicles at each visited node. Constraint (37) guarantees that an electric vehicle can travel between two nodes only if it has sufficient battery to cover the required distance. Constraint (38) enforces patient time windows by ensuring that service at a patient location starts within the allowable interval, provided the patient is visited. Constraint (39) restricts the lunch-break start time to lie within the predefined allowable interval. Constraints (40) and (41) impose maximum daily travel-distance limits for electric and regular vehicles, respectively. Finally, Constraints (42)–(49) define the domains and types of the decision variables.

3.3 Solution Approach

Because the problem generalizes the vehicle routing problem with time windows and adds energy and break constraints, it is NP-hard. A three-stage hybrid framework is therefore developed. First, the MILP is solved with the Gurobi optimizer to obtain optimal or near-optimal solutions for small instances and to generate high-quality initial solutions for the metaheuristic. Second, an Adaptive Large Neighborhood Search (ALNS) addresses medium and large instances by iteratively destroying and repairing parts of a solution while strictly enforcing time windows, battery limits, working hours, and flow conservation.

Destroy operators include random removal, worst removal (highest marginal distance), route-based removal, related (proximity) removal, and an EV-critical removal that targets arcs causing battery infeasibility or excessive charging; the number of removed elements is controlled adaptively. Repair operators include greedy insertion, time-feasible insertion, battery-aware insertion accounting for charging opportunities, and a fairness-oriented insertion that rebalances workload; regret-2 and regret-3 insertions are also used. Each insertion checks lunch-break placement, working-time limits, and battery thresholds. Operator selection follows an adaptive scoring scheme that rewards destroy–repair pairs producing improving or accepted solutions.

Two enhancements are added. A tabu memory stores recently executed moves—patient-to-route assignments, removed–inserted arc pairs, and specific route modifications—and temporarily forbids them unless an aspiration criterion (improving the incumbent best) is met, which curbs cycling and premature convergence. A machine-learning module then extracts features from the search—cost improvements, operator success rates, acceptance probabilities, route-feasibility indicators, and convergence trends—and dynamically adjusts operator-selection probabilities, destroy sizes, and acceptance thresholds, anticipating which operators are most effective at each search stage. A simulated-annealing acceptance criterion permits controlled acceptance of non-improving solutions early in the search, and the algorithm terminates at a maximum iteration count, a no-improvement limit, or a time limit.

4. Data Collection

The computational study uses the publicly available benchmark dataset of Yücel et al. (2023), published on Mendeley Data (DOI: 10.17632/4dxm7vmc9.1) under a CC BY 4.0 licence, which accompanies the heterogeneous-fleet electric home healthcare study of Cebeci et al. (2024). The dataset combines synthetic data drawn from the literature with real-world data for the city of Ankara, Türkiye. In every instance, caregiver working hours run from 8:00 a.m. to 5:00 p.m. Patient locations are generated from the Address-Based Population Registration System of TÜİK using two strategies: random selection (rs), in which neighborhoods are drawn uniformly, and weighted random selection (wrs), in which neighborhoods are drawn in proportion to their population. Each vehicle’s depot is set to a randomly chosen

public hospital, and the coordinates of the charging stations are obtained from the Google Maps API. Pairwise distances are computed with the Haversine formula, and travel times assume an electric-vehicle speed of 55 km/h.

The electric fleet comprises three vehicle types (a, b, and c) that differ in battery capacity and energy consumption: battery capacities of 26.8, 32.3, and 52 kWh and consumption rates of 0.158, 0.158, and 0.165 kWh/km, respectively. The dataset provides small-, medium-, and large-size instances containing 10, 20 or 30, and 40, 50 or 60 jobs; ten rs and ten wrs instances are generated for each size up to 30 jobs. The large-size instances are organized into seven groups (G1–G7) that vary the location-selection method (rs or wrs), the charger type (fast or super-fast), the presence of a competency requirement, the share of synchronized jobs (0% or 10%), and the job-duration range (random in [20, 60] or in [10, 90] minutes), enabling a systematic analysis of the problem parameters.

For the present study, the large-size instances with 40, 50, and 60 service nodes are used as the basis of the experiments and are adapted to the mixed-fleet setting by combining electric vehicles with conventional regular vehicles in the proportions indicated by the instance labels (for example, 8r8e denotes eight regular and eight electric vehicles, while 16e and 16r denote all-electric and all-conventional fleets). The mixed-fleet parameters required by the model—lunch-break duration and window, daily working-time and distance limits, the minimum battery threshold, and the fairness weight—are added on top of the dataset's locations, time windows, treatment durations, distances, and energy parameters. The exact MILP was solved with Gurobi under an 1800-second time limit, and all heuristic variants were run on identical instances under the same feasibility rules and the shared objective of Equation (1), with results averaged over the instances in each size group.

5. Results and Discussion

5.1 Numerical Results

Table 1 reports the average solution gap of each heuristic relative to the exact model; negative values indicate that the heuristic obtained a better objective than the exact model within the time limit, since the exact model frequently failed to close the gap for medium and large instances. Across all groups, adding tabu memory and then machine learning consistently improves quality: ALNS+Tabu+ML attains the best average gap of -7.5% , compared with -6.4% for ALNS+Tabu and -5.7% for ALNS. Improvements are largest for the 60-node group, where the all-electric configuration (20e) reaches -17.0% , reflecting the value of learning-guided, battery-aware operators when energy constraints dominate.

Table 1. Average solution gap compared with the exact model

Instance	ALNS	ALNS+Tabu	ALNS+Tabu+ML
40	-0.027	-0.033	-0.042
10r3e	-0.021	-0.028	-0.038
13e	-0.032	-0.042	-0.051
13r	-0.031	-0.038	-0.049
3r10e	-0.024	-0.031	-0.040
7r6e	-0.024	-0.024	-0.030
50	-0.027	-0.034	-0.048
12r4e	-0.015	-0.018	-0.029
16e	-0.043	-0.053	-0.074
16r	-0.052	-0.059	-0.071
4r12e	-0.020	-0.032	-0.041
8r8e	-0.006	-0.010	-0.026
60	-0.117	-0.124	-0.136
10r10e	-0.142	-0.152	-0.161
15r5e	-0.114	-0.121	-0.133
20e	-0.145	-0.156	-0.170

Instance	ALNS	ALNS+Tabu	ALNS+Tabu+ML
20r	-0.030	-0.044	-0.059
5r15e	-0.151	-0.147	-0.159
Average	-0.057	-0.064	-0.075

Table 2 reports average computational time. The exact model reaches the 1800-second limit on essentially all medium and large instances, whereas the heuristics return high-quality solutions far faster—averaging 481, 471, and 554 seconds for ALNS, ALNS+Tabu, and ALNS+Tabu+ML, respectively. The learning variant spends modestly more time per run because of feature extraction and adaptive control, but this overhead is small relative to the exact model and is rewarded by better solutions. Expressed as a time gap relative to the exact model, all three heuristics reduce computing time by roughly 69–74% on average, confirming their scalability for realistic instance sizes.

Table 2. Average computational time (seconds)

Instance	Exact	ALNS	ALNS+Tabu	ALNS+Tabu+ML
40	1800	229.67	221.66	271.41
10r3e	1800	186.70	166.90	194.56
13e	1800	308.35	305.66	412.87
13r	1800	127.36	129.32	138.50
3r10e	1800	298.53	295.44	348.02
7r6e	1800	227.40	211.00	263.10
50	1800	365.17	418.97	477.80
12r4e	1800	265.69	344.39	362.57
16e	1800	606.59	514.20	760.52
16r	1800	214.72	262.06	276.07
4r12e	1800	406.08	539.91	548.44
8r8e	1800	332.76	434.32	441.42
60	1800	848.50	771.50	913.06
10r10e	1800	905.81	791.08	926.56
15r5e	1800	620.45	598.63	769.19
20e	1800	1134.44	1045.83	1126.34
20r	1800	482.39	428.05	537.74
5r15e	1800	1099.41	993.92	1205.47
Average	1800	481.11	470.71	554.09

Table 3 examines convergence by reporting the average iteration at which the best solution is found. The learning module accelerates convergence markedly: ALNS+Tabu+ML locates its best solution at iteration 1391 on average, against 1657 for ALNS+Tabu and 1728 for ALNS. Several EV-heavy instances (for example 10r10e and 16r) converge before iteration 1000, indicating that learned operator selection quickly identifies effective destroy–repair moves for energy-constrained routes.

Table 3. Average iteration at which the best solution is obtained

Instance	ALNS	ALNS+Tabu	ALNS+Tabu+ML
40	1709	1692	1364
10r3e	1720	1563	991
13e	1842	1855	1167

Instance	ALNS	ALNS+Tabu	ALNS+Tabu+ML
13r	1798	1613	1803
3r10e	1595	1792	1516
7r6e	1590	1639	1345
50	1703	1703	1399
12r4e	1819	1658	1583
16e	1599	1688	1727
16r	1769	1605	999
4r12e	1573	1892	1370
8r8e	1754	1674	1317
60	1773	1575	1408
10r10e	1859	1593	988
15r5e	1467	1591	1461
20e	1833	1657	1512
20r	1807	1550	1390
5r15e	1900	1486	1691
Average	1728	1657	1391

5.2 Graphical Results

Figure 1 summarizes the average improvement over the exact model for each instance group. The advantage of ALNS+Tabu+ML grows with instance size and is most pronounced for 60-node instances, where richer combinatorial structure gives the learning module more opportunity to specialize operator selection. Figure 2 contrasts convergence speed: the learning variant reaches its best solution in substantially fewer iterations, which explains how it achieves higher quality without a disproportionate increase in run time.

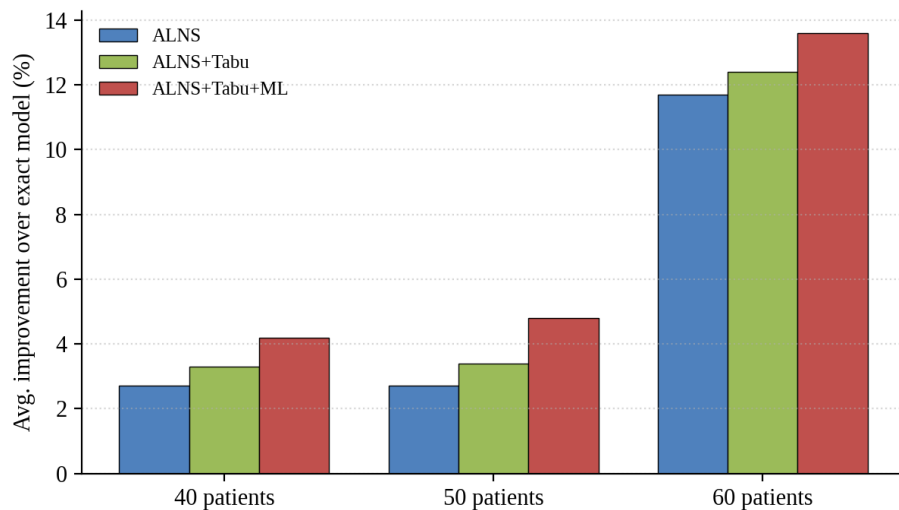


Figure 1. Average improvement over the exact model by instance group

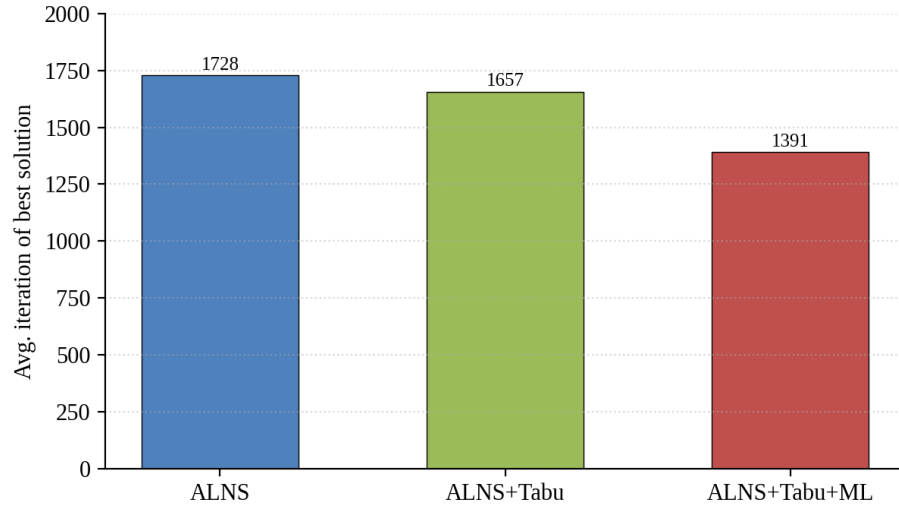


Figure 2. Average iteration at which the best solution is found

5.3 Proposed Improvements

The proposed improvements—tabu memory and machine-learning operator control—reshape how the search uses its operators. Table 4 and Table 5 report destroy- and repair-operator usage frequencies. Plain ALNS and ALNS+Tabu distribute usage almost uniformly across operators, whereas ALNS+Tabu+ML shifts decisively toward the most productive ones: among destroy operators it favors route-based (528) and worst removal (483) over random removal (267), and among repair operators it concentrates on greedy (579), regret-2 (602), and regret-3 (698) insertions while sharply reducing random (75) and rebuild (37) operations. This learned specialization is the mechanism behind the faster convergence and better gaps observed above.

Table 4. Average usage frequency of destroy operators

Method	Random	Worst	Related	Route	Proximity
ALNS	399	399	398	401	402
ALNS+Tabu	395	398	396	396	398
ALNS+Tabu+ML	267	483	417	528	297

Table 5. Average usage frequency of repair operators

Method	Greedy	Regret-2	Regret-3	Random	Best Rebuild
ALNS	336	332	668	332	333
ALNS+Tabu	330	330	658	332	333
ALNS+Tabu+ML	579	602	698	75	37

Table 6 lists the destroy–repair combinations that produced the best solutions. Route-based destruction paired with regret-2 (12) and regret-3 (11) insertions is the most effective combination, followed by related removal with regret-3 (9). These pairings exploit structural moves—removing whole route segments and reinserting them with look-ahead regret—which are particularly valuable when battery feasibility and time windows interact, and they are precisely the pairs the learning module learns to prioritize.

Table 6. Destroy–repair combinations producing best solutions

Destroy Operator	Repair Operator	Count
Proximity	Greedy	6
Proximity	Regret-2	5
Proximity	Regret-3	4
Random	Greedy	5
Random	Regret-2	1
Random	Regret-3	1
Related	Greedy	5
Related	Regret-2	6
Related	Regret-3	9
Route	Greedy	2
Route	Regret-2	12
Route	Regret-3	11
Worst	Greedy	3
Worst	Regret-2	2
Worst	Regret-3	3
Total		75

5.4 Validation

To validate the approach beyond the exact benchmark, the heuristics were compared with an Adaptive Variable Neighborhood Search (AVNS) benchmark, using the all-electric instance of each size group (13e, 16e, and 20e) as the representative validation case (Table 7). The proposed methods outperform the benchmark across all three size groups, with average improvements of 8.1%, 9.0%, and 10.4% for ALNS, ALNS+Tabu, and ALNS+Tabu+ML, respectively. The consistent ordering of the three variants—mirroring the gaps against the exact model in Table 1—confirms that the gains are attributable to the tabu and learning enhancements rather than to instance-specific effects, and that the improvement is consistent across instance sizes.

Table 7. Average solution gap between the AVNS benchmark and the proposed methods

Instance	ALNS	ALNS+Tabu	ALNS+Tabu+ML
40 (13e)	-0.027	-0.035	-0.044
50 (16e)	-0.099	-0.110	-0.129
60 (20e)	-0.117	-0.125	-0.139
Average	-0.081	-0.090	-0.104

6. Conclusion

This paper addressed a home healthcare routing and scheduling problem with a mixed fleet of electric and conventional vehicles, integrating patient time windows, mandatory lunch breaks, battery consumption and charging, daily working-time and distance limits, and workload fairness within a single MILP. To solve realistic instances, a three-stage framework combined exact optimization with an ALNS metaheuristic enhanced by tabu memory and a machine-learning operator-selection module. All three research objectives were met: the model was formulated and solved exactly for small instances; the hybrid framework was designed and implemented; and it was evaluated across instance sizes and fleet compositions.

The experiments show that the learning-guided variant (ALNS+Tabu+ML) is the strongest configuration, improving average solution quality by about 7.5% over the exact model and by 10.4% over an AVNS benchmark, while converging in fewer iterations and reducing computing time by roughly 69–74% relative to the exact model. The

unique contribution is the integration of learning-driven operator control into an ALNS for an explicitly mixed EV/RV home healthcare setting with break and energy constraints—a combination largely absent from prior work. Future research will incorporate uncertainty in travel and service times, partial-charging strategies, explicit modeling of recharging duration, multi-day continuity of care, and richer learning models for operator and parameter control.

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