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16. Abstract

The adoption of battery electric trucks (BETs) as a replacement for diesel trucks has potential to significantly reduce greenhouse gas (GHG) emissions from the freight transportation sector. However, BETs have shorter driving range and lower payload capacity, which need to be taken into account when dispatching them. This paper addresses the energy-efficient dispatching of BET fleets, considering backhauls and time windows. To optimize vehicle utilization, customers are categorized into two groups: linehaul customers requiring deliveries and backhaul customers requiring pickups, where the deliveries need to be made following the last-in-first-out principle. The objective is to determine a set of energy-efficient routes that integrate both linehaul and backhaul customers, while considering factors such as limited driving range, payload capacity of BETs and the possibility of en route recharging. The problem is formulated as a mixed-integer linear programming (MILP) model and propose an adaptive large neighborhood search (ALNS) metaheuristic algorithm to solve it. The effectiveness of the proposed strategy is demonstrated through extensive experiments using a real-world case study from a logistics company in Southern California. The results indicate that the proposed strategy leads to a significant reduction in total energy consumption compared to the baseline strategy, ranging from 7% to 40%, while maintaining reasonable computational time. This research contributes to the development of sustainable transportation solutions in the freight sector by providing a practical and more efficient approach for dispatching BET fleets. The findings emphasize the potential of BETs in achieving energy savings and advancing the goal of green logistics.

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EXECUTIVE SUMMARY

The past decade has seen a surge in efforts to combat greenhouse gas emissions and promote cleaner transportation solutions. This project focuses on the heavy-duty freight transportation sector, particularly battery electric trucks (BETs) which offer a promising solution due to their zero emissions during operation.

Motivated by a real-world logistics company's challenge in Southern California, this study aims to develop an energy-efficient routing strategy for a BET fleet, considering practical constraints such as cargo load, battery capacity, backhauls, partial recharging, and time windows. In addition, the proposed strategy incorporates a partial recharging policy, allowing BETs to recharge en route, ensuring timely deliveries.

By classifying this challenge into an extended vehicle routing problem (VRP) using a complete directed graph, this study formulates the problem into a mixed-integer linear programming (MILP). It adopts a "last-in, first-out" approach for deliveries and backhauls, optimizing vehicle utilization and reducing empty runs. Furthermore, the study operates under several key assumptions, e.g., linehaul customers are served prior to backhaul customers, and BETs begin and end their routes at the depot, starting with a full charge. The methodology is based on an adaptive large neighborhood search (ALNS) metaheuristic, addressing the complex optimization problem effectively. The proposed approach is further evaluated using real-world dispatching data.

Further investigation reveals the following key findings:

- The proposed MILP model offers an effective dispatching strategy for BET fleets, accommodating customer demand, time windows, and delivery type while minimizing energy consumption.
- A realistic energy consumption model, considering vehicle characteristics and cargo load, enhances the accuracy of energy consumption estimation compared to merely minimizing travel distance.
- The ALNS metaheuristic algorithm efficiently solves the proposed problem, showcasing its effectiveness and moderate computational time, especially in comparison to baseline strategies.
- The experimentation using real-world freight operation data from a logistics company in Southern California validates the practical applicability of the proposed dispatching strategy. Compared to the existing baseline strategy, the new approach achieves a notable decrease in the fleet-wise energy usage, with reductions between 7% and 40%.

Based on the findings, the study suggests the following recommendations:

- Future work should explore problem variants suited to real-world applications. For example, considering uncertain parameters like time windows, service time, and traffic conditions could lead to the development of more robust routing strategies.
- Incorporating non-linear recharging functions can enhance the model's accuracy and reflect realistic charging dynamics. This can lead to more precise estimates of charging duration and rates during routes.
- Considering scenarios with uncertain customer information could contribute to a more adaptable routing strategy. Incorporating uncertainty models could lead to better strategies that account for unexpected changes in customer demands or conditions.

The study's findings underscore the significance of energy-efficient BET dispatching in modern logistics. By providing an accurate and efficient dispatching strategy while considering real-world challenges, this research contributes to the advancement of sustainable and cost-effective freight operations.

1. Introduction

Over the last decade, there has been an increase in new incentives and regulations aimed at reducing greenhouse gas (GHG) emissions and promoting alternative fuel choices in the transportation sector. The transportation system is the leading contributor to GHG emissions, primarily coming from burning fossil fuels for the vehicular transportation and goods movement [1]. For instance, in the US, it accounted for 28% of total GHG emission in 2021 [2]. Specifically, the heavy-duty freight transport contribute approximately 23% of total GHG emissions in the transportation sector [3], which also has negative in the form of local pollutants, such as particular matter and noise. For these reasons, one way to mitigate the negative effect of environmental in the freight transportation sector is by using the clean heavy-duty vehicles, e.g., battery electric trucks (BET), in the near future [4].

The aforementioned reasons have led to increasing attention toward the utilization of battery electric trucks (BETs), which is one of the promising approaches to achieve green logistics since there is zero emission when operating [5]. The application of electric vehicles (EVs) or BETs has attracted more interest from various logistics companies as part of their operational fleets for conducting last-mile deliveries, e.g., Amazon, DHL, and UPS [6], [7], [8]. Although there are several benefits of the BETs, however, it is not trivial to substitute conventional heavy-duty diesel trucks (HDDTs) with BETs due to several limitations, e.g., high purchase prices and battery replacement costs, limited driving range, potentially long recharging time, and the scarcity of public recharging stations. Therefore, a well-planned dispatching strategy is necessary to better utilize the BET fleets and conduct the last-mile delivery by logistics companies.

In many realistic logistics systems, one of the major activities is dispatching commercial goods by visiting a set of customers with a set of trucks that start and end at the depot and minimizing their travel cost, which is known as the vehicle/truck routing problem (VRP) [9]. Other than the traditional internal combustion conventional vehicles, designing an efficient fleet dispatching strategy for a BET fleet is also crucial, which has been a rise in the related research field during the past decades. Due to several realistic constraints of the electric fleet, such studies (e.g., [10], [11], [12]) address the electric fleet dispatching problem considering their limited driving range, and the possibility of recharging at assigned charging stations, where the goal is minimizing the total travel energy or distance cost. Additionally, some other real-life factors have been considered when making a dispatching strategy for the electric fleet, such as cargo capacity, delivery time windows [11], partial recharging policy [13], and multiple charging rates [14]. Those studies show the effects of improving freight transportation efficiencies from economic applications and energy efficiency perspectives.

This study is motivated by a real-world dispatching problem of a large pallet logistics company in Southern California, CA. The goal aims to reduce the total energy consumption through an energy-efficient routing strategy for the BET fleet, together with the electric recharging plan. The green vehicle routing problem (G-VRP) [10] and classic electric vehicle routing problem (E-VRP) [11] is extended, where the energy consumption is proportional to travel distance. A more realistic BET energy consumption model is implemented in this study, considering varying cargo payload and speed. In the context of the BET fleet, a macroscopic energy consumption model can estimate the electricity cost for the routes but also provides energy-related information for the dispatcher to decide a near-optimal recharging visit. Other than a fully recharging restriction, a partial en route policy is considered in this study, which is more realistic and efficient in the real-world scenario. The BET fleet can be partially recharged during the route, reducing the potential recharging time, and satisfying the customer's time window.

The BET dispatching strategy investigated here incorporates the backhauling strategy [15]. Specifically, a "last-in, first-out" approach is adopted for deliveries. The fleet departs from the depot with fully or partially loaded trailers and first serves linehaul customers who request delivery orders. After emptying the trailer, the fleet then serves backhaul customers who request pickups and finally terminate at the depot. Implementing the backhauling strategy offers several practical advantages. From a sustainable perspective, it reduces the empty running of vehicles and increase the degree of vehicle utilization [16]. Additionally, from an economic perspective, this strategy helps minimize loading and unloading time. Since the trailers are often rear loaded, an appropriate dispatching plan ensures well-organized delivery orders when the BET fleet departs from the depot. This eliminates the need for extensive rearranging of large pallets or goods at each customer location [15].

Therefore, the major contributions of this research are summarized as follows:

- In this study, an energy-efficient BET dispatching problem is proposed, considering limited cargo load and battery capacity, backhauls strategy, partial recharging policy, and time windows.
- To address this problem, this problem is mathematically formulated as an optimization problem by devising a directed acyclic graph (DAG), which considers the linked level BET energy consumption model. The problem is formulated as a single objective problem where the goal is to find an energy-efficient dispatching strategy for the BET fleet. An effective adaptive large neighborhood search (ALNS) based metaheuristic approach is developed to solve the proposed BET dispatching problem.
- The proposed dispatching strategy is evaluated on a real-world BET fleet dispatching data, including orders, itineraries, and routes. Extensive experiments demonstrate the efficiency of the proposed dispatching strategy can reduce total energy consumption significantly when compared to a baseline strategy.

The remainder of this research is organized as follows. In Section 2, a brief review of related literature is presented. Section 3 introduces the BET energy consumption model and presents a mixed integer programming (MILP) model for the proposed BET dispatching problem. In Section 4, the proposed ALNS-based metaheuristic algorithm is presented in detail. To assess the performance of the proposed solution approach, Section 5 presents computational case studies involving the description of real-world dispatching data and the analysis of the solution performance. Finally, Section 6 concludes the key findings and points to future research.

2. Literature Review

The literature review focuses on algorithms related to: 1) general fleet dispatching (e.g., generic vehicle routing problems), 2) electrification of commercial fleet, and 3) BET fleet dispatching and green vehicle routing problem (G-VRP).

The past two decades have witnessed research interest in green logistics, aiming to improve the sustainability of producing and distributing goods and services in the transport sector [17]. To achieve the goal of green logistics, such efforts have been made to reduce negative environmental impacts based on operation research and mathematical programming techniques, which provide an efficient management strategy for the truck fleet. In this section, first, the solution methods are briefly reviewed to solve the generic vehicle routing problem (VRP). Second, the related work is discussed, focusing on the green vehicle routing problem (G-VRP) in city logistics. Finally, considering a dispatching with pick-up service in the logistics systems, the VRP with backhauls and its applications are reviewed.

2.1 Fleet Dispatching

As one of the major aspects of fleet management systems, the VRP is one of the most important problems during the operational decision stage. The problem assumes that a homogeneous vehicle fleet with limited capacity needs to serve customers' demand in a single visit, and each route should start and end at the same depot. The goal is to minimize the total travel cost (usually in terms of total travel distance). Due to the NP-hardness of VRP (i.e., the complexity of the problem increases exponentially when the problem size increases) [9], large numbers of heuristics and metaheuristics approaches have widely applied to solve the VRP and its variants. As the methods may include large neighborhood search (LNS) [18], the adaptive large neighborhood search (ALNS) [19], variable neighborhood search [11], etc.

In [18], Shaw proposed a large neighborhood search (LNS) heuristic algorithm to solve the VRP by defining a move as the removal and reinsertion of a set of customer visits. For the removal process, a group of *related* customers is chosen and stored in a removal list. While during the reinsertion process, those customers are inserted into the trip iteratively, following the predetermined constraints. Therefore, a set of new solutions will be obtained. Extending the LNS heuristic approach, Ropke and Pisinger [19] introduced an adaptive large neighborhood search (ALNS) metaheuristic approach involving an "adaptive" mechanism in the removal and reinsertion process. The authors implemented the ALNS on vehicle routing problems with pickup and delivery problems. This method is composed of several sub-heuristics that are used with a frequency based on their performance. The ALNS approach shows the advantages of the solution performance, which improves the best-known solutions for more than 50% of the problems from more than 350 benchmark instances [19]. Considering the energy consumption during the dispatching process, Demir et al. [20] studied the pollution-routing problem (PRP), an extension of the traditional VRP with time windows. They presented an ALNS-based solution framework to find energy-efficient routes considering fuel consumption and greenhouse gases emissions.

2.2 Battery Electric Truck Routing

As one of the promising alternatives to reduce GHG emissions in the transportation sector, developing a dispatching strategy for the electric fleet in city logistics has gained greater interest. In [10], Erdoğan and Miller-Hooks proposed a green vehicle routing problem model, where the goal is to find an efficient dispatching strategy for a homogenous alternative fuel vehicle fleet (including EVs), considering refueling stations and limited driving range. The authors developed a saving heuristic and a density-based clustering algorithm to solve the proposed problem. Extended [10], Schneider et al. [11] introduced an electric vehicle routing problem with time windows and recharging stations (EVRP-TW). The authors implemented a metaheuristics algorithm, the variable neighborhood search algorithm hybrid with tabu search strategies (VNS/TS). This study used a simulated annealing (SA) heuristic strategy as an acceptance criterion to improve the solution quality. Based on the previous studies, Keskin and Çatay [13] introduced an electric vehicle routing problem with time windows and a partial recharging policy (EVRPTW-PR). An ALNS metaheuristic algorithm was proposed to solve the proposed problem. The authors demonstrated the proposed model and solution approach improve the best-known solutions in [11]. Dönmez et al. [21] introduced a mixed fleet VRP with time windows and partial recharging with multiple chargers (MFVRP-MC). Motivated by the progression transition to electric vehicles, they investigated multiple charging configuration types for the charging stations when designing the routing strategy for the mixed fleet. To solve the proposed problem, they developed an ALNS heuristic algorithm to address the problem.

The models in the aforementioned literature assume that the energy consumption of the EV fleet is proportional to the travel distance. To further investigate a more energy-efficient dispatching strategy, Lin et al. [22] developed an energy consumption model for an EV fleet, where the goal aims to minimize the total energy consumption during routing and dispatching. In [12], Goeke and Schneider addressed the electric vehicle routing problem with time windows and a mixed fleet (EVRPMFTW), considering a realistic energy consumption model of an EV and fuel consumption of an internal combustion vehicle (ICV). The authors proposed an ALNS-based metaheuristics approach to solve the EVRPMFTW and validated it on a real-world instance. Zhang et al. [23] introduced an EVRPTW for minimizing energy consumption and developed the corresponding mathematical formulation. The authors developed an ant colony (AC) based metaheuristics algorithm and compared it with the performance of the ALNS approach [12]. Recently, Yu et al. [24] introduced a green mixed fleet dispatching problem with realistic energy consumption, aiming to minimize the total GHG consumption of an ICV fleet and the energy consumption of an EV fleet. Amiri et al. [25] presented a bi-objective GVRP with a mixed fleet of conventional trucks and BETs. An ALNS-based metaheuristic algorithm is used to solve the proposed model. A set of real-world instances was used in [25] to evaluate the performance of the dispatching strategy.

Considering a pickup and delivery strategy for EVs, in [26], Yang et al. proposed an electric vehicle routing problem with mixed backhauls, time windows, and recharging stations, where the goals it to minimize the total travel cost. The authors constructed a multi-dimensional representation network to reduce the types of variables and simplify the model structure. The augmented Lagrangian relaxation (ALR) model was proposed to solve the proposed problem.

Additionally, Yang et al. [27] investigated an integrated electric logistics vehicle recharging station location and routing problem with backhauls. The problem aimed to determine the selection of a recharging station considering the electric vehicle routing plan and other realistic constraints, such as limited battery capacity, recharging capacity, facility construction budget, mixed pickup and delivery requests, and time windows. Peng et al. [28] developed a bi-level dispatching strategy for the BET fleet and implemented it in a real-world case study. Due to the NP-hardness of the GVRP, the upper level uses the k-means clustering approach to decouple the customers into different dispatching zones. Then, the author applied the variable neighborhood search and AC optimization algorithms to find the near-optimal dispatching strategy for the electric truck fleet at the lower level.

2.3 Vehicle Routing Problem with Backhauls

In city logistics systems, the vehicle routing problem with backhauls (VRPB) aims to find a cost-efficient routing plan that meets customer demand. In VRPB, the customers are divided into two groups: linehaul customers who require deliveries and backhaul customers who require pickups. The linehaul customers are first served, followed by the backhaul customers. In [15], Toth and Vigo presented a mixed integer programming model for a general VRPB and developed an exact branch-and-bound algorithm to address the VRPB. Extending the classic VRPB, Ropke and Pisinger [29] developed a heuristic solver to address variants of VRPB, including classic VRPB, VRPB with time windows, mixed VRPB, multiple depot VRPB, etc. The authors proposed an improved LNS algorithm as a solver to address those types of VRPB.

Researchers have also investigated many realistic models to accommodate practical constraints. For example, Nagy and Salhi [30] proposed a MILP model for the single and multiple depot vehicle routing problem with pickups and deliveries, where the goal is to find a cost-efficient dispatching strategy for a set of linehaul and backhaul customers. An integrated heuristic method was proposed in this study to solve VRPB. To investigate a large size dispatching problem in a logistics company, Salhi et al. [31] considered a more realistic routing and distribution problem, the fleet size and multi-depot VRPB. This problem aims to determine the composition of the vehicle fleet and optimize their dispatching strategy, which minimizes the total travel cost. In [32], Chávez et al. presented a multi-depot vehicle routing problem with backhauls, where the vehicle fleet is collecting after the delivering process. The authors proposed a multi-optimization approach based on a Pareto ant colony optimization (PACO) approach to solve the proposed problem with respect to three objectives of travel distance, travel time and total energy consumption.

3. Overview of BET Fleet Dispatching System

3.1 System Architecture

The proposed BET fleet dispatching problem aims to find an energy-efficient dispatching strategy for a set of linehaul and backhaul customers. The effect on energy consumption of combining two separate flows can be described as follows: the forward flows from the dispatching center to the delivery orders, and the backward flows from the pickup orders to the dispatching center. In this section, the problem is formulated by devising a mixed integer mixed programming model on a directed acyclic graph.

Figure 1 illustrates an example of the proposed dispatching problem, involving seven linehaul customers (D1-D7) who request deliveries, four backhaul customers (P1-P4) who request pickups, two charging stations (CS1 and CS2), and a dispatching center (depot) where the BET fleet fully charged when starting the daily operation. A homogenous fleet of BETs is fully recharged when departing the depot, and the commercial goods are loaded in the trailer according to the dispatching sequences assigned by the proposed strategy. The percentage value in each arc/flow shows the battery SOC when the BET arrivals at each vertex or departs at the CS. It should be noted that the BET can visit the CS at most once and the maximum SOC after recharging is 80%.

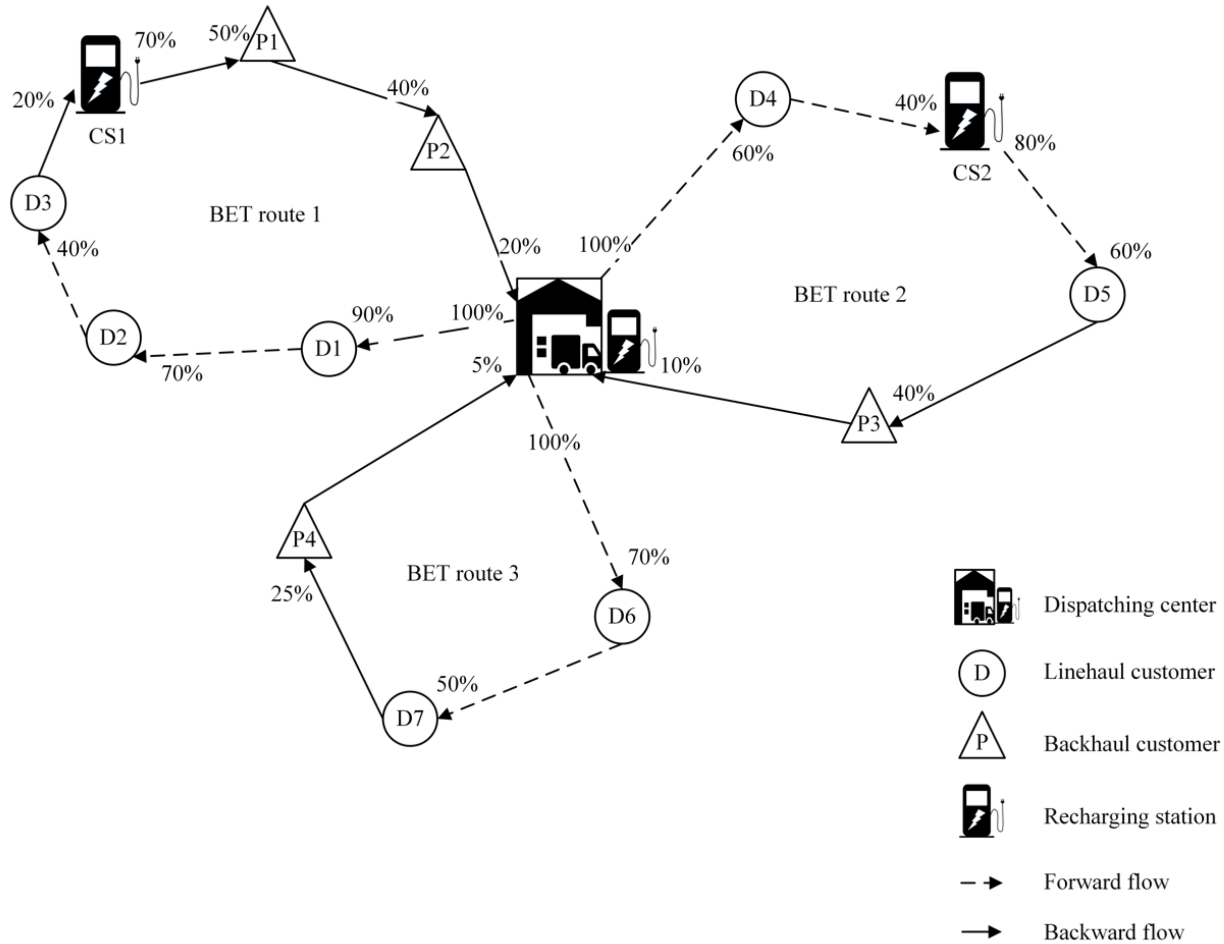

Figure 1. A toy instance for the BET dispatching problem with backhauling.

3.2 BET Fleet Dispatching with Backhauls and Time Window Constraints

The BET dispatching problem with backhauls and time windows concerns a set of clustered customers with known delivery types, demand, address, appointment time windows, and service times. The dispatching center receives the customers' information, then makes a precedence dispatching strategy for a homogeneous fleet of BETs with limited cargo payload capacity and battery capacity. The goal is to create the most energy-efficient routes that simultaneously satisfy the demand of linehaul customers and collect goods from the backhaul customers. The assumptions in the BET dispatching problem are presented in the following:

- Each BET serves exactly one route.
- Each customer (either linehaul or backhaul) is visited exactly once.
- For each route, all linehaul customers should be visited before backhaul customers.
- The BET fleet is fully recharged before departure at the depot, which partial/full loaded the requested delivery orders for the linehaul customers. The destination is at the same depot.

- The operation time for the BET fleet is restricted to 8 hours.
- The total demand of both linehaul customers and backhaul customers are considered separately and cannot exceed the truck cargo payload capacity.
- The BET fleet has limited battery capacity and is fully recharged when departing from the depot. It can be partially recharged at the recharging station at most once if needed.
- The energy consumption of the BET fleet is monitored which is a non-linear function with the travel distance. The truck load, speed, and gradient of the terrain are considered within the energy consumption model.

3.3 Problem Formulation

3.3.1 Assumptions

The BET dispatching problem can be defined as a complete directed graph $\mathcal{G} = (\mathcal{N}'_{O,D} \cup \mathcal{R}, \mathcal{A})$, where $\mathcal{N}'_{O,D}$ denotes the vertices including all customers' nodes $\mathcal{N}$ and depot (O, D), and $\mathcal{R}$ represents recharging stations. A set of customers $\mathcal{N}$ can be partitioned into two groups $\{L, B\}$, where the set $L = (1, 2, \dots, n)$ represents the linehaul customers, and the set $B = (n+1, n+2, \dots, n+m)$ denotes the backhaul customers. Each customer $i \in \mathcal{N}$ has an assigned delivery type with demand q_i (positive if pick-up, negative if delivery), service time s_i and time window $[e_i, l_i]$, where e_i and l_i denotes the earliest and latest service starting times, respectively. All BETs should departure from the depot O and returns at D, with a maximum load capacity C and a battery capacity Q.

Extending the integer linear programming formulation and notation of [15], the set of arc $\mathcal{A} = A_1 \cup A_2 \cup A_3$ is defined. Specifically, let $A_1 = \{(i,j) \in A: i \in L \cup O, j \in L \cup \mathcal{R}\}$ denote all forward flows (i.e., from the depot to the linehaul vertices), $A_2 = \{(i,j) \in A: i \in B \cup \mathcal{R}, j \in B \cup D\}$ represent the backward flows include all backhauling vertices, and the interface arc $A_3 = \{(i,j) \in A: i \in L \cup \mathcal{R}, j \in B \cup D\}$. Each arc (i,j) is associated with a travel distance d_{ij} and travel time t_{ij}. Define $\Delta_i^+ = \{j: (i,j) \in \mathcal{A}, i \in \bar{V}\}$ which denotes the forward of i, and $\Delta_i^- = \{j: (j,i) \in \mathcal{A}, i \in \bar{V}\}$ which denotes the backward of i.

3.3.2 Energy Consumption Model

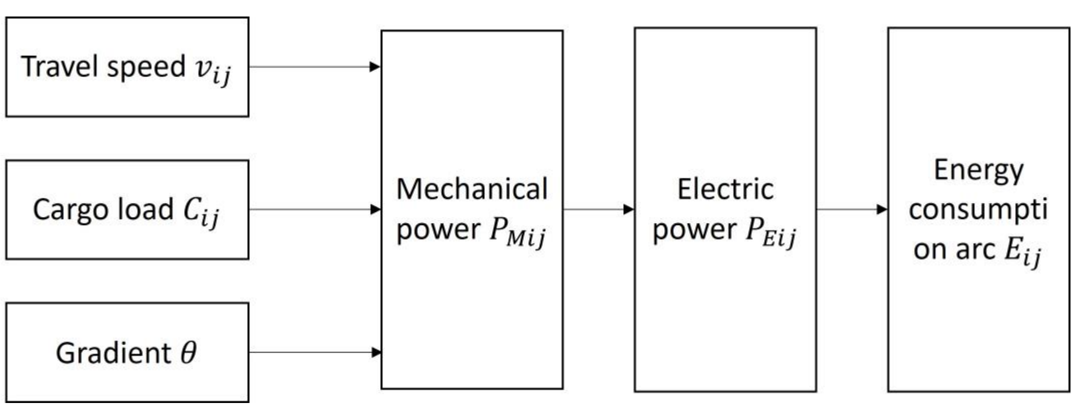

Figure 2. Calculation of required energy on arc.

Figure 2 shows the calculation of required energy consumption of a BET. First, the mechanical power P_M is determined using the model presented in [33]. In mechanical power, it determines the energy consumption based on factors such as travel distance, vehicle weight, speed, acceleration, etc. Second, the mechanical power P_M is translated into the electric power P_E that the electric motor needs to provide the required amount of mechanical power. Third, the electric energy needed by the electric motor is converted to the amount of power that has be taken from the battery P_B based on the battery discharge efficiency [23].

The mechanical power P_M of a BET is needed to overcome rolling, drag and wind resistance, and gravitational force as well as to enable the acceleration (a). With the rolling resistance factor c_{r} , the total vehicle mass M and the gravitational constant g, and the gradient angle θ, the rolling resistance F_r can be determined as

$$F_{\mathrm{r}} = c_{\mathrm{r}} \cdot M \cdot g \cdot \cos{(\theta)}. \tag{1}$$

The aerodynamic resistance F_{a} is a function of the speed v, the aerodynamic drag coefficienct c_{d}, ρ_{a} the air density and the frontal area A. Then, the aerodynamic resistance can be calculated by

$$F_{\mathrm{a}} = \frac{1}{2} \cdot \rho_{\mathrm{a}} \cdot A \cdot c_{\mathrm{d}} \cdot v^2. \tag{2}$$

Therefore, the total mechanical power P_M is:

$$P_{\mathrm{M}} = \left(M \cdot a + \frac{1}{2} \cdot c_{\mathrm{d}} \cdot \rho \cdot A \cdot v^2 + M \cdot g \cdot \sin(\theta) + c_{\mathrm{r}} \cdot M \cdot g \cdot \cos{(\theta)}\right) \cdot v. \tag{3}$$

To calculate the mechanical power requirement P_E of the BET on the linked level arc (i, j), the model presented in [22] and [23] is used, which is a linear function of vehicle weight and a quadratic form of vehicle speed. To simplify the problem, the total weight is assumed to be $M = w + C_{ij}$ where w and C_{ij} represent the curb weight and load carried by the BET, respectively, the distance for the arc (i, j) is represents as d_{ij}. Therer, the mechanical energy required by the BET is shown as follows:

$$P_{E\,ij} \approx P_M\left(d_{ij}/v_{ij}\right) = \frac{P_M d_{ij}}{v_{ij}} = \alpha_{ij}\left(w + C_{ij}\right)d_{ij} + \beta v_{ij}^2 d_{ij}. \tag{4}$$

where, $\alpha_{ij} = a + g\sin\ \theta_{ij} + gC_r\cos\ \theta_{ij}$ is an arc specific constance, and $\beta = 0.5C_d A\rho$ is a vehicle specific constant. In this problem, the vehicle speed is assumed to be constant, and the result is represented by kilowatt hour (kWh).

Hence, to compute the battery power demand on a graph, the motor efficiency (eff_m) and battery discharging efficiency (eff_d) of a BET are taken into consideration in the model. The electric energy consumption E_{ij} for traveling this arc can be calculated by:

$$E_{ij} = eff_d \cdot eff_m \cdot P_{E\,ij} = eff_d \cdot eff_m \cdot \left[\alpha_{ij}\left(w + C_{ij}\right)d_{ij} + \beta v_{ij}^2 d_{ij}\right]. \tag{5}$$

3.3.3 Objective Function

The BET dispatching problem extend the classic EVRPTW [11], and the goal is to minimize the total energy consumption to serve a set of customers, considering precedence constraint (first-out, last-in), cargo load capacity, battery capacity, and partial en route recharging policy. The variables and parameters used in this study are summarized in Table 1.

Table 1. Variable definitions

Variable	**Description**
m_B	Set of BETs available at the depot
$\mathcal{N}$	Sets of customer vertices
L	Sets of linehaul customer vertices
B	Sets of backhaul customer vertices
K	A total number of BETs in operation
$\mathcal{R}$	Recharging station(s)
r	Recharging rate
d_{ij}	Distance between vertices *i* to *j*
t_{ij}	Travel time between vertices *i* to *j*
E_{ij}	Energy consumption between vertices *i* to *j*
T_O	Earliest departure time
T_D	Latest return time
C	Cargo payload capacity
Q	BET maximum battery capacity
q_i	Demand at vertex (positive if pick-up, negative if drop-off)
e_i	Earliest start of service time at vertex *i*
l_i	Latest start of service time at vertex *i*
s_i	Service time at vertex *i*
τ_i	Decision variable specifying the time of arrival at vertex *i*
k_i	Decision variable specifying the visit to recharging station vertex *i*. 0 if customer, 1 if charging station.
u_i	Decision variable specifying the remain cargo on arrival at vertex *i*
y_i	Current SOC for BET v_B when arrive at vertex *i*
Y_i	Finish charging SOC for BET v_B at vertex *i*
x_{ij}	Binary decision variable. 0 if the route from *i* to *j* is not visited by BET v_B, 1 otherwise

Thus, the BET dispatching problem can be formulated as a mixed-integer programming as follows:

$$min \sum_{i\in\mathcal{N}'_O\cup\mathcal{R}, j\in\mathcal{N}'_D\cup\mathcal{R}, i\neq j} eff_d \cdot eff_m \cdot \left[\alpha_{ij}\left(w + C_{ij}\right)d_{ij} + \beta v_{ij}^2 d_{ij}\right] \cdot x_{ij} \tag{6}$$

Subject to:

(Demand and flow balance constraints)

$$\sum_{i\in\Delta_j^-} x_{ij} = 1,\ j \in \mathcal{N} \cup \mathcal{R} \tag{7}$$

$$\sum_{j\in\Delta_i^+} x_{ij} = 1,\ \ i \in \mathcal{N} \cup \mathcal{R} \tag{8}$$

$$\sum_{j\in \mathcal{N}'_D\cup\mathcal{R}, \mathrm{i}\neq j} x_{ij} - x_{ji} = 0, \forall i \in \mathcal{N}'_O \cup \mathcal{R} \tag{9}$$

$$\sum_{i\in\Delta_O^-} x_{ij} = K \tag{10}$$

$$\sum_{i\in\Delta_D^-} x_{ij} = K \tag{11}$$

(Vehicle constraints)

$$y_O = Q,\ \forall j \in\ \mathcal{N} \cup \mathcal{R} \tag{12}$$

$$\sum_{j\in \mathcal{N}\cup\mathcal{R}} x_{Oj} \leq m_B \tag{13}$$

(Recharging visit constraints)

$$\sum_{j\in(D\cup\mathcal{N}\cup\mathcal{R})} x_{ij} \leq 1, \forall i \in \mathcal{R} \tag{14}$$

(Recharging time with time window)

$$T_O \leq \left(t_{ij} + (1-k_i)s_i + k_i \cdot \frac{Y_i - y_i}{r}\right)x_{ij} \leq T_D,$$
$$\forall i \in O \cup \mathcal{N} \cup \mathcal{R}, j \in (D \cup \mathcal{N} \cup \mathcal{R}), i \neq j \tag{15}$$

$$Y_i = Min\{3600 \cdot r, (Q - y_i)\}, \forall i \in \mathcal{R} \tag{16}$$

(Time window constraints)

$$\begin{gathered}\tau_i + \left(s_i + t_{ij}\right)x_{ij} - l_0\left(1 - x_{ij}\right) \leq \tau_j \\ \forall i \in O \cup \mathcal{N} \cup \mathcal{R}, \forall j \in j \in (D \cup \mathcal{N} \cup \mathcal{R}), i \neq j\end{gathered} \tag{17}$$

$$e_i \leq \tau_i \leq l_i,\ \forall i \in \mathcal{N}'_{O,D} \tag{18}$$

(Demand constraints)

$$0 \leq u_o \leq C \tag{19}$$

$$\begin{gathered}0 \leq u_j \leq u_i - q_i x_{ij} + C\left(1 - x_{ij}\right) \\ \forall i \in O \cup \mathcal{N} \cup \mathcal{R}, \forall j \in D \cup \mathcal{N} \cup \mathcal{R}, i \neq j\end{gathered} \tag{20}$$

(Battery recharging constraints)

$$0 \leq \Big((1-k_i)\cdot y_i + k_i \cdot Y_i - h \cdot E_{ij}\Big) x_{ij} \leq Q, \forall i \in \mathcal{N}'_O \cup \mathcal{R}, j \in \mathcal{N}'_D \cup \mathcal{R},\ i \neq j \tag{21}$$

(Binary decision variable)

$$x_{ij} \in \{0,1\},\ \forall i,j \in \mathcal{N}'_{O,D}, i \neq j \tag{22}$$

The objective function of minimizing the total energy consumption is defined in (6). Constraints (7), (10) and (8), (11) impose the indegree and outdegree constraints for the customers nodes and the charging stations. Constraints (9) define the flow conservation constraints. Constraint (12) ensures the BET is fully charged when departure at the depot. Constraint (13) ensures that the operating BETs do not exceed the maximum number of BETs available at the depot. Constraints (14)-(16) define the en route recharging policy, each BET is allowed to recharge at most once, considering one-hour maximum recharging time as full charge may slowly. Constraints (17) and (18) define the arrival time at each vertex should satisfy the time windows. Constraints (19) and (20) represent the capacity of each BET does not exceed the maximum cargo payload when visiting each vertex, for both inbound and outbound trips. Constraint (21) restricts the battery SOC is non-negative when dispatching. Finally, condition (22) defines the binary decision variables.

4. BET Fleet Dispatching Algorithm Development

4.1 State-machine Diagram of BET Fleet Dispatching Strategy

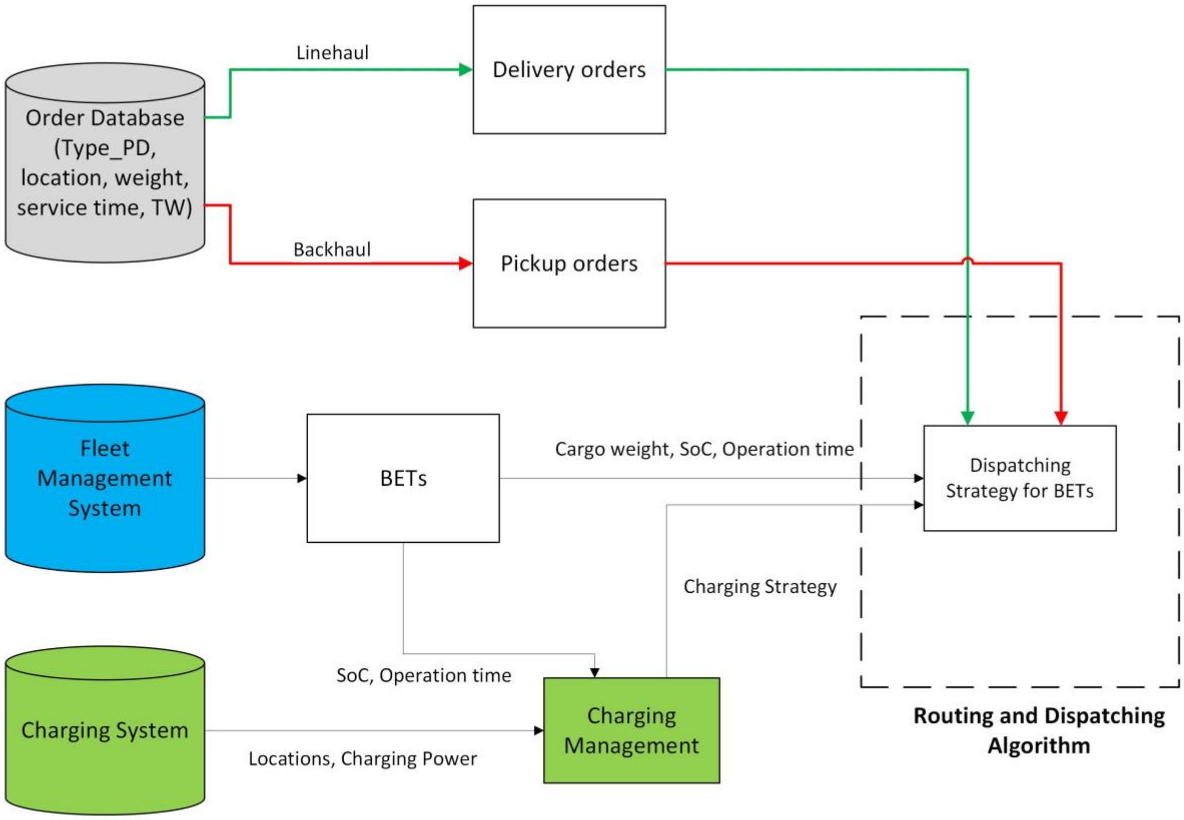

Figure 3. A state-machine diagram of BET fleet dispatching strategy.

The state-machine diagram of the proposed BET fleet dispatching strategy is shown in Figure 3, involving the order database, the fleet management system, charging management system, and the dispatching algorithm module. The fleet management system collects the dispatching information of the customers and generates the road network information (detailed in Section 5.1) as the inputs of the dispatching algorithm. In the fleet management system, it monitors the battery level, cargo weight, and driving time of the BET fleet, which helps making dispatching decisions. The charging system provides charging guidance, including the address, and charging power for the available recharging stations. The dispatching algorithm generates an energy-efficient dispatching and recharging scheme based on that information.

4.2 Proposed ALNS-based Metaheuristic Algorithm

In this section, the adaptive large neighborhood search (ALNS) framework is introduced to solve the proposed BET dispatching problem. The ALNS first introduced by [19], which extended the large neighborhood search (LNS) [18], has been demonstrated as a succussed approach capable of solving the standard vehicle routing problem with pickup and delivery [29], the electric vehicle routing problem with backhaul and time windows [13], pollution routing problem [33], mixed fleet vehicle routing problem [12], etc.

4.2.1 Algorithm Flow

The entire framework of the ALNS algorithm is described in **Algorithm 1**. The algorithm is initialized with an energy-feasible solution generated by a constructive heuristic (see **Algorithm 2**). In line 2, at the beginning of the main loop of ALNS improvement process, the initial feasible solution S^c is regarded as the current best solution S^b. Additionally, the weight vectors (ω^- and ω^+) is initialized for the destroy and repair operators, denoted by Γ^- and Γ^+, respectively. The main loop of the ALNS improvement (lines 3-16) is then started and search for a near-optimal solution S^b until the stop criterion is met, where the near-optimal solution S^b is not improved over a predefined iteration (i.e., a non-improved number of iterations η). To iteratively improve the best solution, a set of destroy operators Γ^- and repair operators Γ^+ are used to modify the initial current solution S^c and obtain a new current solution $S^{c\prime}$. An accept rule is applied to determine whether the new current solution $S^{c\prime}$ should be accepted for the next iteration.

Algorithm 1. Overview of the ALNS framework

Input: An initial feasible solution S generated by initialization phase;

Output: a set of near-optimal solution S^b

$S^c \leftarrow$ $generate\_inital\_solution(\ )$

$S^b = S^c$; $\omega^- = (1, \dots, 1)$; $\omega^+ = (1, \dots, 1)$

while a non-improved number of iterations η is not reached **do**

  {select a destroy operator $\zeta^- \in \Gamma^-$ by $P(\omega_i^-)$}

  destroy current solution S^c with destroy operator ζ^-

  $S^{c\prime} \leftarrow$ DestroyedOperator (S^c)

  {select a repair operator $\zeta^+ \in \Gamma^+$ by $P(\omega_i^+)$}}

  $S^{c\prime} \leftarrow$ RepairOperator ($S^{c\prime}$)

    if accept_SA($S^{c\prime}$, S^b) **then**

      $S^c \leftarrow S^{c\prime}$

      if $S^{c\prime}$ is better than S^b **then**

        $S^b \leftarrow S^{c\prime}$

      end if

    end if

  Update: the weight of destroy operators ω^- and repair operators ω^+

end while

return S^b

4.2.2 Key Components

A general ALNS procedure hybrid with a simulated annealing (SA) process is employed as a search engine to construct a set of energy-efficient routes for the BET fleet. To develop the ALNS-based metaheuristic algorithm, there are four key components: 1) construction of an initial energy feasible solution for the BET fleet, 2) destroy operators, 3) repair operators, 4) acceptance and termination criteria, and 5) adaptive mechanism. In the following, the main components of the ALNS-based solution approach is elaborated.

1) Construct initial solution

The initial solution for ALNS is generated by a greedy constructive heuristic (as shown in **Algorithm 2**), which is similar to the method implemented by [34]. Unvisited customers $\mathcal{N}$ are first sorted in a non-decreasing order of linked-level energy consumption and iteratively inserted into the solution. Then, during each iteration, a candidate customer is inserted into an appropriate position at the current BET route, leading to the minimum increase in the total energy consumption. Once the current route is energy infeasible, a possible recharging schedule could be inserted based on a set of available charging stations $\mathcal{R}$. Therefore, the remaining unvisited customers are allowed to insert into the current route. When there are no vertices can be routed into the current BET route since the battery capacity, time windows, or cargo capacity violation, the current route terminates. Then, several new routes are repeated as the same strategy until all customers have been visited.

Algorithm 2 Construction of initial feasible solution

Input: A set of customers $\mathcal{N} = \{L, B\}$, recharging stations $\mathcal{R}$;

Output: an energy-feasible solution S^{inital}

$\mathcal{N}^{Unvisited} \leftarrow \mathcal{N}$

Current route for BET $K_i \in m_B, i \in \{1, 2, \dots, m_B\}$

while unvisited customer $\mathcal{N}^{Unvisited} \neq \emptyset$ **do**

    $p \leftarrow Sample\ a\ candidate\ customer\ from\ \mathcal{N}^{Unvisited}$

    if c can be inserted in the current solution without violation **then**

        Find best insertion position for c which generate lowest cost $f(S^{inital})$

        Update: $\mathcal{N}^{Unvisited} \leftarrow \mathcal{N}^{Unvisited} \setminus p$

    if n cannot be inserted in the current solution since energy infeasible **then**

        Find best insertion position for CS $\mathcal{R}$ which generate lowest cost $f(S^{inital})$

    else

        Update: start new route for BET K_{i+1}

end while

return S^{inital}

2) Destroy operators

The number of customers/vertices n to remove is predefined by the destroy rate ϵ, where $n = \epsilon \cdot \mathcal{N}$. The ALNS framework employs four removal operators to find a set of removal vertices based on the input n and store them in the removal pool $L^{removal}$. The removal heuristics are detailed as follows:

Random removal randomly removes some vertices from the BET routes. The procedure terminates when n customers/vertices have been removed.

Random path removal destroys an entire consecutive sub-path with n vertices.

Worst removal iteratively removes n unfavorable vertices based on their cost. This operator sorts the insertion cost of all customers in descending order by calculating $c_i = f(s) - f(s_{-i})$, where s_{-i} is the route without customer i and s is the route with customer i. During each iteration, the worst vertex contributes the largest insertion cost and will be removed to the unvisited list.

Shaw removal removes a set of n customers according to their similarity, which can be calculated by the relatedness function $\Lambda(i,j) = \phi_1 \frac{d_{ij}}{\max\limits_{i,j\in\mathcal{N}}(d_{ij})} + \phi_2 |e_i - e_j| + \phi_3 \frac{|q_i - q_j|}{\max\limits_{i\in\mathcal{N}}(q_i) - \min\limits_{i\in\mathcal{N}}(q_i)}$, where the weight vector $\phi = (\phi_1, \phi_2, \phi_3)$ is used to normalize the relatedness function, d_{ij} represents the distance between customers i and j, $|e_i - e_j|$ is the absolute difference between their arrival time, and $|q_i - q_j|$ is the absolute difference of their demand. At the beginning of using the Shaw removal algorithm, a customer $i \in \mathcal{N}$ is randomly selected as a candidate customer to be removed, calculating the most related customer $j \in \mathcal{N} \backslash i$. The customer with the highest similarity to i is the one with the smallest value of $\Lambda(i,j)$. Next, the most similarly customer is calculated and removed by evaluating relatedness with j. Finally, this operator terminates until n vertices have been removed.

3) Repair operators

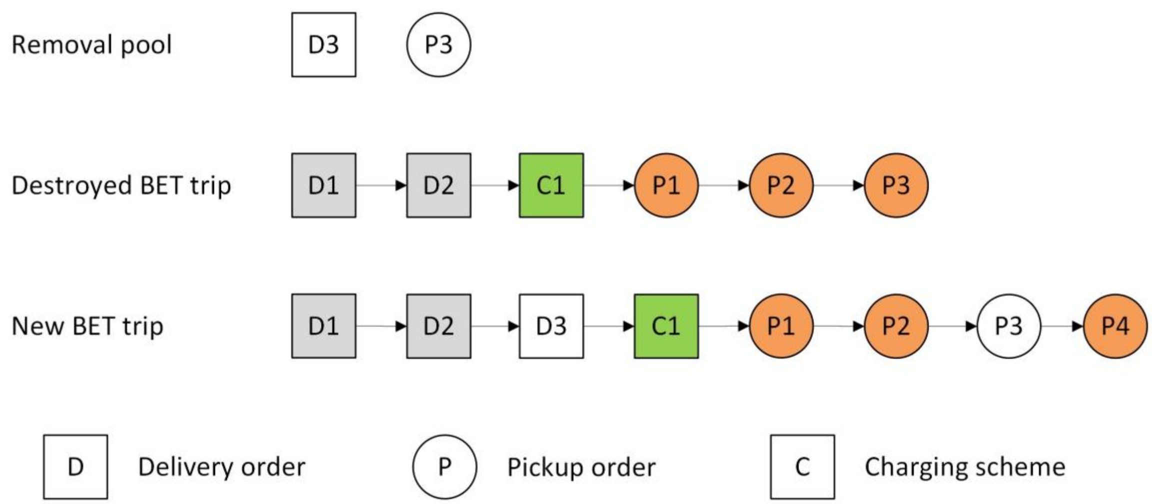

Figure 4. An example of repairing process of ALNS.

After n vertices have been removed from a solution, the repair operators are employed to reconstruct a new solution by inserting the removed n vertices into the incomplete solution. Figure 4 shows an example of the repairing process. The following repair operators are used in the ALNS framework.

Greedy insertion iteratively conducts a series of insertions by selecting the best option. At each iteration, the operator selects one unassigned customer from the removal pool $L^{removal}$. Then, it assesses the cost function to determine whether the current insertion yields the minimum cost. This insertion process continues until all unvisited customers have been chosen.

Regret insertion selects the customer with the highest difference between the cost of the first and k^{th} best insertion and inserts it into its optimal position. The regret-k value is calculated by $reg_{i,k} = \Delta f(i, pos_{i,1}) - \Delta f(i, pos_{i,k})$, where $\Delta f(i, pos_{i,1})$ represents the cost improvement generated by the best insertion, and $\Delta f(i, pos_{i,k})$ denotes the cost improvement generated by the k^{th} best insertion. At each iteration, the operator finds the k^{th} best insertion for customer i, which generates the highest regret-k value. This approach avoids the myopic behavior of the greedy insertion algorithm by not necessarily selecting the task with the lowest cost. In this study, the regret-2 insertion method is implemented.

Greedy insertion with charging stations was introduced in [35], a variation of the greedy insertion operator was introduced to handle energy constraints in BET routes that include CSs. This operator extends the general greedy insertion approach, which assumes that BETs do not visit en route CSs. Initially, the operator inserts customers until the battery SOC violation. Then, it computes a near-optimal charging scheme to minimize the deviation from the original BET route, allowing additional unvisited customers to be inserted. However, if a feasible charging scheme cannot be found in the current solution, the operator will terminate the insertion process after adding the customers.

4) Acceptance and termination criteria

In order to overcome the local optimal results, a simulated annealing (SA) approach is used to accept or reject the new solution $S^{c\prime}$ generated by the ALNS algorithm. There are three circumstances in an iteration. If a new solution $S^{c\prime}$ has been found and it is better than or equal to the global best solution S^b, the new solution $S^{c\prime}$ will be accepted as a new global best solution S^b. If the new solution worse than the global best solution, a SA heuristic algorithm will accept the worse solution with the probability $e^{-\left(f(S^{c\prime})-f(S^b)\right)/T}$, where $f(X)$ is the total energy consumption of solution *X*, and T is the current temperature of a SA heuristic. An initial temperature T_{init} is predefined, which can be decreased at every iteration by $T = \delta T_{init}$, where the deteriorate rate $\delta \in (0, 1)$. Furthermore, in the ALNS framework, the algorithm terminates when the solution does not improve over η iterations.

5) Adaptive mechanism

This section details the ALNS procedure for solving the BET dispatching problem, which includes a set of removal operators $\Gamma^- = \{\zeta_1^-, \zeta_2^-, \dots, \zeta_{ND}^-\}$ to destroy vertices (i.e., a few customers and CSs), and a set of repair operators $\Gamma^+ = \{\zeta_1^+, \zeta_2^+, \dots, \zeta_{NR}^+\}$ to reinsert unvisited customers or CSs, where *ND* and *NR* represent the number of destroy and repair operators, respectively. The feasible initial solution can be obtained in section *Construct initial solution*, which can be also defined as the current feasible solution S^c. Then, the ALNS procedure iteratively improves S^c until the termination criteria meet.

At each iteration, a removal operator $\zeta^- \in \Gamma^-$ and a reinsertion operator $\zeta^+ \in \Gamma^+$ are applied to destroy and repair the current solution S^c, respectively. Those operators are selected dynamically and adaptively based on the roulette wheel principle. To choose an operator in each iteration, two weight vectors are defined, $\omega^- = [\omega_1^-, \omega_2^-, \dots, \omega_{ND}^-]$ and $\omega^+ =$

$[\omega_1^+, \omega_2^+, \dots, \omega_{NR}^+]$, to store the weight of a set of destroy and repair operators, consecutively. Therefore, the probability of choosing an operator ζ can be calculated by $P^t(\omega) = \omega_i / \left(\sum_{j=1}^{|\Gamma|} \omega_j\right)$. After the current solution $S^{c\prime}$ is repaired, a new solution $S^{c\prime}$ is obtained.

Moreover, in the "adaptive" mechanism, the weight vectors ρ^- and ρ^+ will be updated dynamically based on the quality of new solution $S^{c\prime}$. A score variable $\psi = [\varphi_1, \varphi_2, \varphi_3, \varphi_4]$ is employed to assess the performance of the ALNS improvement. For example, a score φ_1 denotes that a new solution S^b has been found. Similarly, a score φ_2 is obtained when an improved solution is found. φ_3 indicates when a new solution has been accepted by a SA heuristic, while the score φ_4 is used when the solution is rejected. At the end of each iteration, the weight vector updates by $\omega_i = \lambda\omega_i + (1-\lambda)\psi$, where $\lambda \in (0,1)$ is a smooth variable to control the sensitivity of the weight vector.

5. Case Study

This section presents the results of the numerical experiments using a real-world case study in a full-service supply chain company. To evaluate the performance of the proposed strategy, the new results are compared with the historical dispatching data. The mathematical model in section 3.2 is implemented in Python 3.9, and all experiments are conducted on a PC with Intel Core i7 CPU 3.6 GHz processor and 16 GB RAM.

5.1 Data Collection

In this section, the numerical study is conducted and the results are analyzed, using a real-world dataset in a full-service supply chain company to evaluate the performance of the proposed strategy. Four instances are generated, ranging from 47 to 90 customers based on the real-world dataset, a typical one-day historical movements of a heavy-duty diesel truck fleet that operated in the Riverside and San Bernardino County regions of California.

For each generated instance in the case study, it contains the geographic coordinates of customer locations, as well as information on the delivery types, required demands, time windows, and service times. Five customers' locations are randomly selected, where a linear recharging station is in their parking lot. The BET has the flexibility to visit the charging stations during operation. Table 2 summarizes the characteristics of the four instances.

Table 2. Summary of dataset characteristics

Instance	# of Customers	# of Linehauls	# of Backhauls	CSs
BETVRPB1	47	33	14	5
BETVRPB2	58	26	32	5
BETVRPB3	71	39	32	5
BETVRPB4	90	54	36	5

The Direction Service Application Programming Interface (DSAPI) provided by OpenRouteService [36] is adopted to generate distance and travel duration matrices for the truck routes between node-to-node locations, which is more realistic than the Euclidian distance. Specifically, those matrices consider the real-world road network, speed limitation and restricted zones for heavy-duty trucks. However, to simplify the dispatching problem, the traffic conditions are not considered in this study.

5.1 Parameter Tuning

In the numerical study, the problem parameter settings used are presented in Table 3 based on a real-world scenario. The total operation time is limited to 8 hours, including driving, idling when recharging, and service time. In this study, a set of homogenous BETs in the fleet is set, with short-range battery capacity (i.e., 300 kWh) or long-range battery capacity (i.e., 452 kWh) to evaluate the effect of driving range. Please note that the selection of these two ranges is based on the BET models that are available on the current US market. For instance, Volvo Truck [37] provides several electric trucks with two battery sizes, 375 kWh and 565 kWh (both nominal values). To safely use the battery and extend its life, this study assumes 80% of the nominal battery capacity sizes, i.e., 300 kWh and 452 kWh.

Table 3. Summary of problem parameters

Notation	Description	Value
A	Frontal surface area of a BET $[\mathrm{m}^2]$	5
C	Maximum BET cargo capacity [37] [lbs.]	37,000
Q	Maximum BET battery capacity [kWh]	{300, 452}
eff_m	Motor efficiency [23]	1.25
eff_d	Discharging efficiency [23]	1.11
c_{r}	Unitless rolling resistance	0.01
c_d	Coefficient of rolling drag	0.7
w	Vehicle curb weight [lbs.]	8,000
g	Gravitational constant $[\mathrm{m/s}^2]$	9.81
ρ_{a}	Air density $[\mathrm{km/m}^3]$	1.2041
θ	Road angle	0°
a	Acceleration $[\mathrm{m/s}^2]$	0
v	Vehicle speed [mph]	68
s	Loading/unloading time [hour]	(0, 2]
C	Cargo capacity [lbs.]	22,000
$[T_O, T_D]$	Working hour	[8 am, 4 pm]
r	Recharging rate [kWh/min]	3.96

Instance BETVRPB2 with 58 customers is used and the ALNS heuristic algorithm is implemented with seven restarts to finetune the parameters in this study. Table 4 summarizes the parameter settings used in the case study. The bold values are the selected parameters used in the experiments.

Table 4. Summary of parameters in the experiment

Variable	Value
Score vector $\psi = [\omega_1, \omega_2, \omega_3, \omega_4]$	**[15, 9, 4, 3]**, [18, 10, 5, 2],
Decay parameter λ	**0.8**, 0.85
Destory percentage	**38%**, 35%
Number of removal vertices	$\lfloor \mathbf{0.38\mathcal{N}} \rfloor$, $\lfloor 0.35\mathcal{N} \rfloor$
Number of non-improved iterations	**750**, 500
Shaw removal weight vector $\phi = (\phi_1, \phi_2, \phi_3)$	**[0.5, 0.25, 0.25]**, [0.5, 0.30, 0.30]
SA initial temperature	**20**, 10
SA end temperature	**0.5**, 0.8
SA deterioration rate δ	**0.99991**, 0.99900

5.2 Comparative Experiment

Comparison of the results to historical movement data and discussion of the implications of the results and their impacts on the BET fleet dispatching problem.

In order to assess the performance of the BET dispatching strategy, the ALNS algorithm is applied to solve the real-world instances. The results are compared with a baseline dispatching strategy from the supply chain company. The baseline strategy was provided by a routing solver in the supply chain company, which has been implemented in real-world freight operations. To make a fair comparison between the baseline strategy and the proposed dispatching strategy, all historical movements are presumed to be served by a BET fleet and estimated the total energy consumption by the objective function (6) for the historical iterations using the same distance matrices. Table 5 summarizes the historical iterations as the baseline in the case study.

Table 5. Summary of real-world historical movements

Instances	# of BETs	Total Energy	Total_dist	Total_time
BETVRPB1	5	915	512	13.1
BETVRPB2	5	1094	490	13.7
BETVRPB3	5	1406	726	18.5
BETVRPB4	8	1062	657	22.7

Using the problem parameter settings shown in Table 3, ten runs are initiated and the best solution for each test is recorded. To assess the effect of battery capacity on total energy consumption, two case studies with two types of battery capacity are conducted: a short-range

BET fleet fitted with a 300-kWh battery and a long-range BET fleet equipped with a 452-kWh battery.

The results show that the dispatching strategy can solve the BET dispatching problem with time windows for all generated instances efficiently. The proposed strategy is compared with the baseline strategy by using the relative percentage deviation ($RPD_{a,b,c}$) with respect to a) the total energy consumption, b) total vehicle miles traveled, and c) total travel time. The formula to calculate the $RPD_{a,b,c}$ is shown as follows:

$$RPD_{a,b,c} = \frac{C_{a,b,c}(hist) - C_{a,b,c}(opt)}{C_{a,b,c}(hist)} \times 100\%,$$

where, $C_{a,b,c}(hist)$ denotes the historical cost and $C_{a,b,c}(opt)$ denotes the solutions obtained from the dispatching strategy, regarding the aforementioned aspects.

Table 6. Results for the BET dispatching problem with short-range battery

Instances	**# of BETs**	**Total Energy**	$\boldsymbol{RPD_a}$	**Total_dist**	$\boldsymbol{RPD_b}$	**Total_time**	$\boldsymbol{RPD_c}$	**t*(s)**
BETVRPB1	5	769	16	422	18	11.4	13	357
BETVRPB2	6	786	28	430	12	12.7	7	711
BETVRPB3	5	846	39	473	34	12.9	30	2036
BETVRPB4	7	988	7	606	8	21.1	7	2268
Total	23	3389	24	1931	19	58.1	15	-

Note: t* denotes the CPU time.

Table 7. Results for the BET dispatching problem with long-range battery

Instances	**# of BETs**	**Total Energy**	$\boldsymbol{RPD_a}$	**Total_dist**	$\boldsymbol{RPD_b}$	**Total_time**	$\boldsymbol{RPD_c}$	**t*(s)**
BETVRPB1	5	755	17	414	19	11.3	13	611
BETVRPB2	5	739	32	397	19	11.7	15	928
BETVRPB3	5	839	40	465	34	12.5	36	2602
BETVRPB4	7	947	11	579	12	21.0	7	3086
Total	22	3280	27	1855	22	56.5	17	-

Note: t* denotes the CPU time.

As demonstrated in Table 6 and Table 7, the proposed strategy can reduce total energy consumption, ranging from 7% to 40%, compared with the baseline strategy. The columns total_dist and total_time describe the total vehicle miles traveled and total travel time under the energy-efficient routes, respectively. When using the energy-minimizing objective function, the total energy consumption can be reduced by 24% and 27%, which is not proportional to the total vehicle miles traveled since the distribution of the cargo payload may affect the total energy consumption for the BET fleet. Additionally, it is observed that using short-range BETs may result in more BETs being deployed during operation, as seen in the BETVRPB2 instance with a short-range battery. Conversely, the long-range BET fleet can save more energy compared with short-range BET fleet, since there may be less detour trips to visit the charging stations.

The historical fleet activities of instance BETVRPB1 and the energy-efficient routes are illustrated in Figure 5, with each trip depicted in a different color. As shown in Figure 5, the historical data comprises five HDDT trucks, covering a total travel distance of 512 miles. To enable a fair energy consumption comparison with the BET fleet, it is assumed that these routes are traveled by the BET trucks and subsequently recalculate the total energy consumption using the same model (as described in Section 3.3). The historical trips require a total energy consumption of 915 kWh. Figure 5 shows energy-efficient routes dispatching strategy for problem instance BETVRPB1 with a long-range BET fleet. The total energy consumption amounts to 755 kWh, with a tour length of 414 miles.

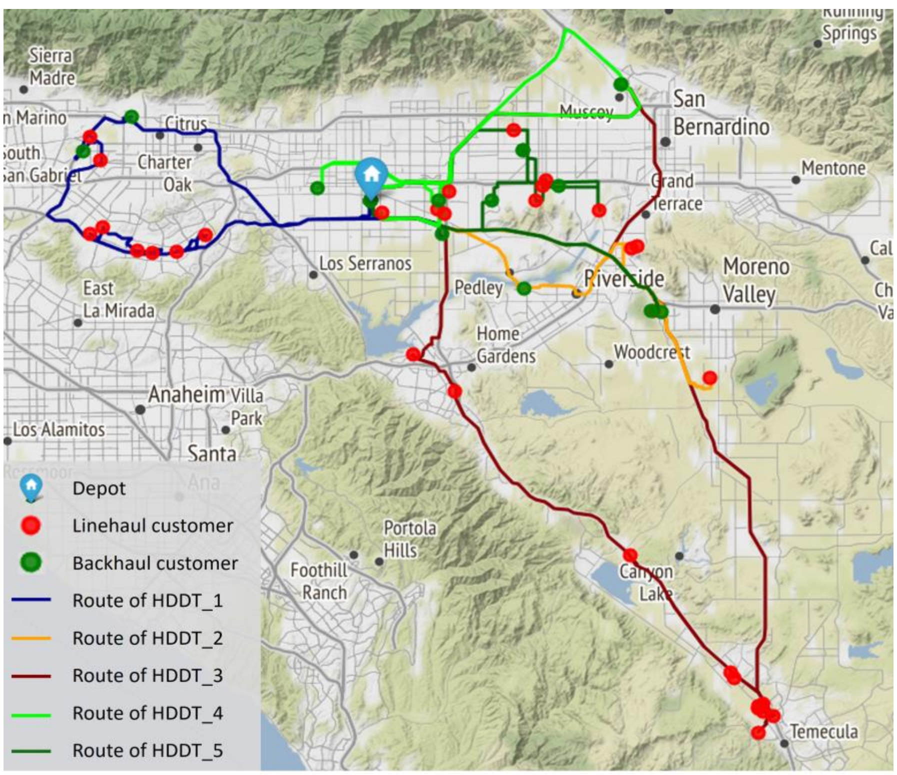

Figure 5. The historical movements of instance BETVRPB1 with a HDDT fleet.

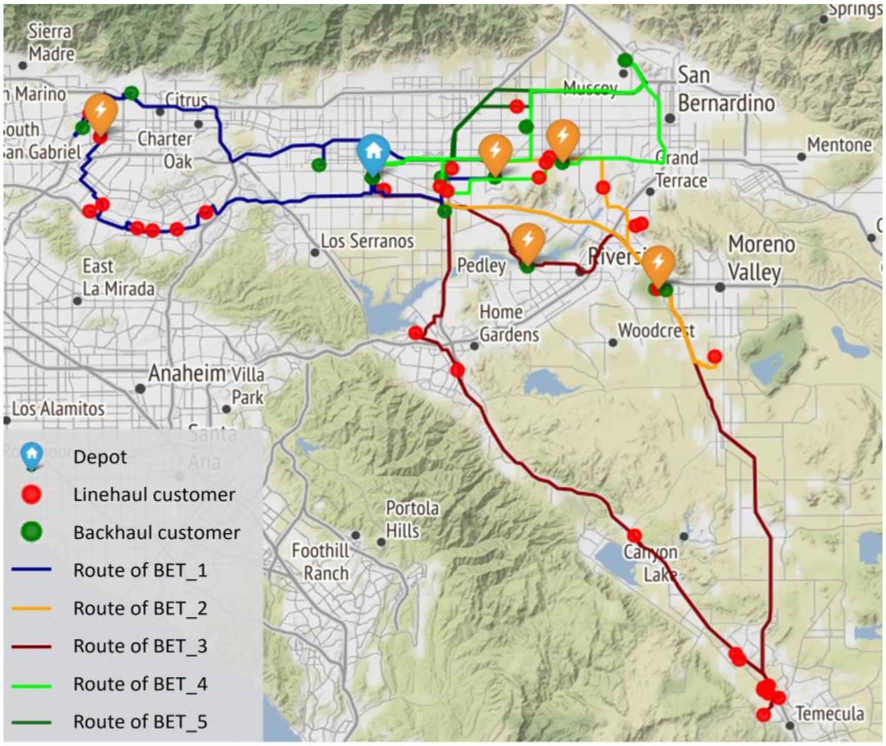

Figure 6. A near-optimal solution for instance BETVRPB1 with a long-range BET fleet.

Figure 7 and Figure 8 show the energy consumption and total travel distance versus different battery capacities, respectively. It can be observed that the cargo weight influences the BET energy consumption since the energy consumption is not proportional to the travel distance. For instance, in BETVRPB2 with 58 customers, the total energy consumption may be reduced by 28% when deploying the short-range BET fleet compared with the baseline strategy. However, the total travel distance is reduced by 12%.

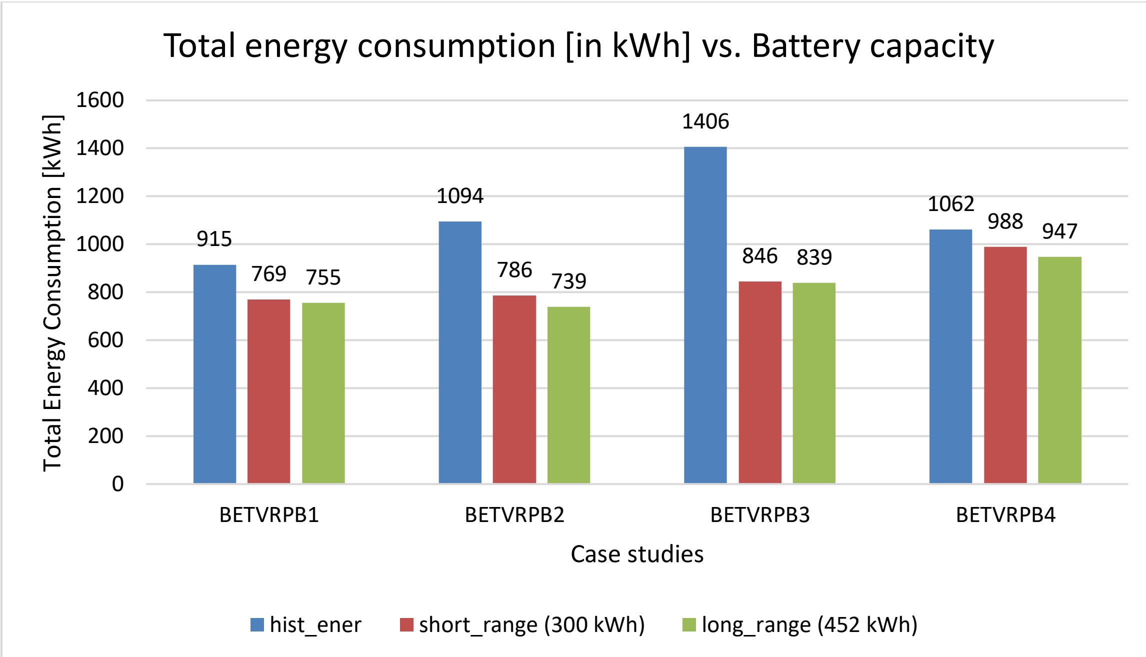

Figure 7. Total energy consumption [in kWh] vs. battery capacity.

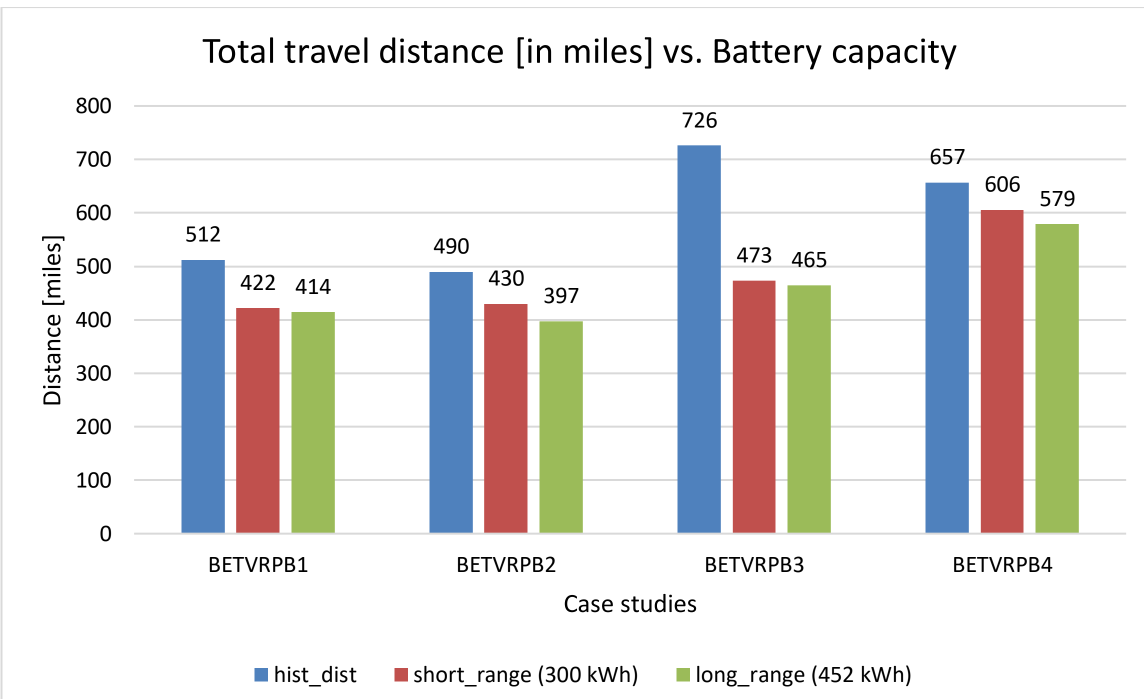

Figure 8. Total travel distance [in miles] vs. battery capacity.

6. Key Findings and Recommendation

In this project, an energy-efficient BET dispatching problem with backhauls and time windows is investigated. Extended the classic green-vehicle routing problem, this study focuses on a homogeneous BET fleet with limited cargo load and battery capacity, a precedence constraint for the set of customers composed of linehaul customers who required deliveries and backhaul customers who required pickups and their time windows. Moreover, an en route partial recharging policy for the BET fleet is incorporated, allowing partial recharging at any available charging station, based on the battery state-of-charge (SOC) upon arrival.

A mixed-integer linear programming (MILP) model is defined whose goal is to make a dispatching strategy for a BET fleet to serve all customers that satisfy their demand, time windows and delivery type, while minimizing the total energy consumption. A realistic energy consumption model of BET is incorporated into the MILP formulation. To highlight the efficiency of the proposed model, this study also shows that minimizing the total travel distance may underestimate the total energy consumption since the cargo load may affect the total energy consumption of BET.

To solve the proposed problem, a metaheuristic algorithm is developed based on adaptive large neighborhoods search (ALNS) framework. To evaluate the performance of the dispatching strategy, the model is applied to real-world freight operation data from a logistics company in Southern California. The experiment results show that the proposed strategy can solve the BET dispatching problem efficiently within a moderate computational time compared with the baseline strategy.

There are several directions in future work. Firstly, more variants of the BET dispatching problem based on real-world applications can be considered. For instance, some order information may be unknown before designing the routing strategy, such as time windows, service time, or traffic conditions. Therefore, an uncertain model can be considered an extension in future work. Secondly, a non-linear recharging function (e.g., [14]) can be incorporated into the existing model, for better estimating the charging duration and reflecting the realistic charging rate dynamics.

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Data Summary

Products of Research

In this project, the real-world dispatching data were collected in support of numerical experiments in the *Case Study* section. The list of data sets with descriptions are organized in Table 8. Each of these data products has been uploaded to the NCST Dryad repository. The URL to the data is described in the Data Access and Sharing Section.

The items in Table 8 are organized into their own subdirectory within the Dryad repository for this project. This data is necessary for the analysis of the Task 5 results in this project.

Table 8. Data products that resulted from the project.

Data description	Data Files	File Format
The dispatching data were saved in CSV files, including four cases where the customers' sizes range from 47 to 90. Additionally, real-world travel distance and time matrices were provided by OpenRouteService.	BETVRPB1.csv BETVRPB2.csv BETVRPB3.csv BETVRPB4.csv BETVRPB1_dist.csv BETVRPB2_dist.csv BETVRPB3_dist.csv BETVRPB4_dist.csv BETVRPB1_time.csv BETVRPB2_time.csv BETVRPB3_time.csv BETVRPB4_time.csv	CSV

Data Format and Content

The file types and formats are described in Table 8.

Data Access and Sharing

The data are made available publicly via the UC Riverside instance of Dryad: https://datadryad.org/stash, which is licensed under a CC0 1.0 Universal (CC0 1.0) Public Domain Dedication license. The DOI for the dataset is https://doi.org/10.6086/D11974.

Reuse and Redistribution

The data should be restricted for research use only. If the data are used, our work should be properly cited as:

> Guoyuan Wu, Dongbo Peng, Kanok Boriboonsomsin (2023), Developing an Efficient Dispatching Strategy to Support Commercial Fleet Electrification, Project Funded by NCST 2022-2023, UC Riverside, Dataset, https://doi.org/10.6086/D11974