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Addressing the Robust Battery Electric Truck Dispatching Problem with Backhauls and Time Windows under Travel Time Uncertainty

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Abstract—**The emergence of battery electric trucks (BETs) in recent years has shown great promise in reducing greenhouse gas (GHG) emissions in urban freight logistics. However, designing a customer-oriented dispatching strategy for a BET fleet is more complex than traditional vehicle routing problems (VRP) due to several constraints, such as limited driving range, potential need for en route recharging, and long recharging times. Also, in practice, the uncertain travel times in urban transportation network may lead to the violation of scheduled customer time windows and impact overall energy consumption. To better utilize the BET fleet, this paper introduces a robust BET dispatching problem with backhauls and time windows under travel time uncertainty, which aims to minimize the overall fleet energy consumption while also minimizing the risk of violating customer time window. A mathematical optimization model based on novel route-related sets is developed, and an adaptive large neighborhood search (ALNS) metaheuristic algorithm is used to find robust dispatching solutions. Based on real-world data from a truck fleet in San Bernardino County, California, a simulation study is conducted to demonstrate the robustness of the solutions obtained by the proposed method. Moreover, a sensitivity analysis with respect to uncertainty parameters is performed to assess the trade-off between the overall fleet energy consumption and the robustness of the solutions.**

I. Introduction

The emergence of battery electric trucks (BETs) in recent years has shown promise in reducing greenhouse gas (GHG) emissions in the freight transportation sector [1]. Especially in urban freight transportation, there are several advantages when deploying heavy-duty (i.e., Classes 7 and 8) BETs rather than conventional heavy-duty diesel trucks, such as zero tailpipe emissions, reduced noise pollution, and reduced independence on fossil fuels. However, the major concerns of logistics companies about electrifying their fleet include range anxiety, long recharging times, and limited charging infrastructure. The decision-makers need to ensure that their BETs have enough energy to reach charging stations while satisfying the level of service requirements of customers.

In urban areas, trip travel times can be uncertain because of traffic congestion, which may increase the risk of the dispatched BETs missing one or more of the scheduled customer time windows. In addition, uncertain travel times may increase or decrease the average speed of the BETs and affect their energy consumption [2].

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This study aims to explore the impact of uncertain travel time on the BET dispatching problem. In an attempt to find a robust dispatching strategy for a BET fleet, we formulate a robust BET dispatching problem with backhauls and time windows under travel time uncertainty, a variant of the green vehicle routing problem (GVRP). The proposed problem is applied to a real-world case study, and an optimization model is developed to find a set of robust soluitons. The main contributions of this research are as follows:

- A mathematical optimization model based on novel route-dependent uncertainty sets for a BET fleet is developed. In addition, a microscopic energy consumption model is incorporated into the optimization model.
- An adaptive large neighborhood search (ALNS) metaheuristic algorithm incorporating a robust optimization method is employed to find robust solutions for the BET dispatching problem under uncertain travel times.
- The optimization model and the solution approach are applied to a real-world case study from a regional distribution fleet in San Bernardino County, California. Monte Carlo simulation is performed to verify the robustness of the solutions.

The remainder of this paper is organized as follows. The related literature on the GVRP is briefly discussed in Section II. Then, Section III introduces the mixed integer linear programming (MILP) model of the robust BET dispatching problem. Next, Section IV describes the incorporation of a robust optimization method and the ALNS metaheuristic algorithm in detail. Finally, the results and conclusions are presented in Sections V and VI, respectively.

II. Literature Review

The proposed BET dispatching problem is an extension of the traditional GVRP introduced by Erdoğan and Miller-Hooks [3]. The GVRP introduces the concept of refueling along the route where alternative fuel vehicles can refuel at specific refueling stations and continue to visit more customers. Furthermore, Schneider et al. [4] formally proposed the electric vehicle routing problem with time windows (EVRP-TW) as an extension of GVRP. The electric vehicles in the fleet can visit recharging stations to recharge their batteries while ensuring that the customers' time windows are still satisfied. Keskin and Çatay [5] introduced a partial recharging scheme when devising the dispatching solution, which was shown to be a more efficient strategy compared to the full recharging scheme. Considering a backhauling strategy [6] and a realistic BET energy

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consumption model, Peng et al. [7] studied an energy-efficient dispatching strategy for a BET fleet. For more information about the GVRP, readers can refer to [8] and [9].

Most of the existing literature on GVRP did not consider uncertain factors (e.g., [1], [3], [4], [10], [11]). In the context of GVRP, only a handful of existing papers considered uncertainties. For example, Pelletier et al. [2] studied the EVRP under energy consumption uncertainty. They proposed a robust optimization (RO) model and solved the problem with the ALNS algorithm. Shen et al. [12] introduced a robust EVRP-TW under demand uncertainty. They considered the cargo weight-dependent energy consumption of the electric vehicles through the use of a microscopic energy consumption model. Recently, Jeong et al. [13] adopted an adaptive robust RO model to solve the EVRP under energy consumption uncertainty.

In order to enhance the efficient utilization of BET fleets for last-mile delivery in urban areas, this study extends [7] and presents a robust BET dispatching problem with backhauls and time windows under heterogeneous uncertain travel times. Furthermore, we apply the ALNS metaheuristic incorporating the RO method to address the proposed MILP model. The goal is to find a robust dispatching solution that minimize the overall fleet energy consumption while satisfying the customers' time windows under travel time uncertainty within the uncertain sets.

III. Problem Formulation

Section III-A briefly describes the proposed BET dispatching problem. Section II-B presents a microscopic energy consumption model for BETs. Lastly, a robust version of the BET dispatching problem is discussed in Section II-C where a route-dependent uncertainty set is incorporated to describe the heterogenous uncertain travel times.

A. Problem Description

Figure 1 shows an example of the proposed BET dispatching problem. The dispatching follows the backhauling strategy [6] where the linehaul customers (who require deliveries) should be visited first, followed by the backhaul customers (who require pickups). A set of homogenous BETs with battery capacity Q and cargo payload capacity C are available at the depot to serve all customers. These BETs start service at T_O and return to the same depot before T_D due to operating time constraints. It should be noted that the travel time for some arcs may vary due to the uncertain traffic condition.

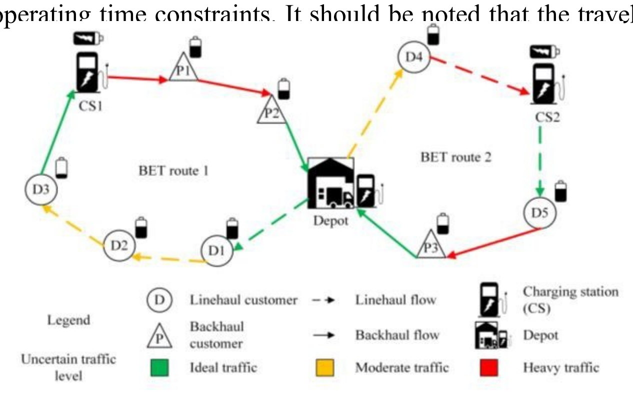

Figure 1. An example instance of the proposed BET dispatching problem with backhauls and time windows under uncertain travel time.

The proposed BET dispatching problem considers the backhauling strategy, en route partial recharging policy, and customer time windows under uncertain travel time. To formally formulate this problem, we first define it on a complete directed graph $\mathcal{G} = (\mathcal{N}'_{O,D} \cup \mathcal{R}, \mathcal{A})$, where $\mathcal{N}'_{O,D}$ is the set of nodes including customer nodes $\mathcal{N}$, a depot node O for departure (or D for destination), and $\mathcal{R}$ represents a set of recharging stations. There are two types of orders, i.e., deliveries and pickups. Then, the customers $\mathcal{N}$ can be partitioned into two sets, i.e., $N = \{L, B\}$, where the sets $L = (1, 2, \ldots, n)$ and $B = (n+1, n+2, \ldots, n+m)$ represent the linehaul customers and the backhaul customers, respectively. Each customer $i \in \mathcal{N}$ has a specific service type, a service time s_i, a time window $[e_i, l_i]$, and a demand q_i (negative if delivery and positive if pickup). The arc set $\mathcal{A}$ is defined by $\mathcal{A} = A_1 \cup A_2 \cup A_3$, where a set $A_1 = \{(i,j) \in \mathcal{A} : i \in L \cup O, j \in L \cup \mathcal{R}\}$ connects all forward flows, a set $A_2 = \{(i,j) \in \mathcal{A} : i \in B \cup \mathcal{R}, j \in B \cup D\}$ represents the backward flows, and the interface arcs are represented by $A_3 = \{(i,j) \in \mathcal{A} : i \in L \cup \mathcal{R}, j \in B \cup D\}$. Following the integer linear programming formulation of [6], we define $\Delta_i^+ = \{j : (i,j) \in \mathcal{A}, i \in \mathcal{N}'_{O,D}\}$, which denotes the forward of i, and $\Delta_i^- = \{j : (j,i) \in \mathcal{A}, i \in \mathcal{N}'_{O,D}\}$, which denotes the backward of i. Each arc $(i,j) \in \mathcal{A}$ has an associated travel distance d_{ij}, energy consumption E_{ij}, and travel time t_{ij}.

The BETs are fully recharged starting from the depot. Additionally, a possible en route partial recharging at one of the recharging stations $\mathcal{R}$ is allowed when the state-of-charge (SOC) of a BET is insufficient to complete the remaining jobs. Several constraints are considered to ensure an efficient recharging process. The recharging time is up to one hour with a constant charging speed r. Additionally, a BET receives a charge of up to 80% of battery capacity Q. This particular assumption is based on [14], which shows that the battery level increases linearly until 80% SOC and then grows at a slow rate afterward. Also, the recharging frequency is at most once for each BET route.

B. Microscopic Energy Consumption Model for BETs

A microscopic energy consumption model is used to estimate the link-level energy consumption of BETs. We extend the energy consumption models of BETs introduced in [10] and [15], considering travel distance, travel time, the weight of cargo payload, and accessory load. Specifically, similar to the model in [16], we first determine the tractive power required to meet the BET's acceleration demand and overcome the air resistance and the rolling resistance, as in (1).

$$P_T = (M \cdot a + \frac{1}{2} \cdot c_d \cdot \rho_a \cdot A \cdot v^2 + M \cdot g \cdot \sin(\theta) + c_r \cdot M \cdot g \cdot \cos(\theta)) \cdot v. \quad (1)$$

In this equation, the total weight of a BET is calculated by $M = w + C_{ij}$, where w represents the curb weight with no payload, and C_{ij} is the payload carried from node i to j. Moreover, c_d is the aerodynamic drag coefficient, while ρ_a denotes the air density and A represents the frontal area of the BET. c_r represents the rolling friction coefficient, and θ is the angle of the road. The gravitational acceleration is represented by g . In addition, considering varying travel speeds in different road segments, the average travel speed for an arc is estimated by $v_{ij} = d_{ij}/t_{ij}$. Then, the energy consumption for a BET in each arc is estimated by (2), according to the tractive power P_T and the accessory power P_{Acc} . To simplify the formulation, we define a coefficient $\alpha_{ij} = a + g\sin\theta + gC_r\cos\theta$, which is a constant value. $\beta = 0.5C_d A\rho_a$ is a vehicle-specific coefficient.

$$W_{E_{ij}} \approx (P_T + P_{acc})\frac{d_{ij}}{v_{ij}} = \alpha_{ij}(w + C_{ij})d_{ij} + \beta v_{ij}^2 d_{ij} + P_{acc}\frac{d_{ij}}{v_{ij}}. \tag{2}$$

Considering the efficiencies of the electrical components, such as motor efficiency (eff_m) and battery discharging efficiency (eff_d), the link-level electric energy consumption can be estimated by (3). Also, to simplify the dispatching problem, it should be noted that the energy regeneration during braking is not considered.

$$E_{ij} = \frac{W_{E_{ij}}}{eff_d \cdot eff_m} = \frac{(P_T \pm P_{acc}) \cdot \frac{d_{ij}}{v_{ij}}}{eff_d \cdot eff_m} = \frac{1}{eff_d \cdot eff_m} \cdot \{\alpha_{ij}[(w + C_{ij})d_{ij} + \beta v_{ij}^2 d_{ij}] + P_{acc}\frac{d_{ij}}{v_{ij}}\}. \tag{3}$$

C. A Robust BET Dispatching Problem under Travel Time Uncertainty

As the uncertain travel time is considered in this study, we introduce a robust BET dispatching problem based on the RO theory in Ben-Tal et al. [17]. For each BET k, the uncertain travel time $\tilde{t}$ for some arcs $(i,j) \in \mathcal{A}$ are varying within a predefined uncertain set U_t. Since historical travel time data may not be available to determine a specific distribution of the uncertain travel time, we define a budget uncertainty polytope to describe the uncertain travel time, which is similar to [18].

The budgeted uncertain set U_t is defined as in (4) and (5).

$$U_t = \times_{k\in K} U_t^k , \tag{4}$$

$$U_t^k = \{\tilde{t} \in R^{|A^k|} \,|\, \tilde{t}_{ij} = t_{ij} + \beta_{ij}\hat{t}_{ij}, \sum_{(i,j)\in A^k} \beta_{ij} \le \Gamma_t^k,$$
$$0 \le \beta_{ij} \le 1, \Gamma_t^k = \theta |A_t^k| , \forall (i,j) \in A^k\} \tag{5}$$

In (4), U_t is the Cartesian product of the travel time uncertainty set U_t^k for each BET $k \in K$. In (5), A^k represents the set of arcs on a route traveled by BET k. The uncertain travel time $\tilde{t}_{ij}$ of an arc $(i,j) \in A^k$ can take any value from its interval $[t_{ij}, t_{ij} + \hat{t}_{ij}]$. t_{ij} denotes the nominal value of uncertain travel time in an arc $(i,j) \in A^k$, and $\hat{t}_{ij}$ represents the maximum deviation from the nominal value t_{ij}. β_{ij} is an auxiliary variable, and Γ^k denotes the uncertain travel time route robustness as it takes into account a higher degree of travel time uncertainty.

The mathematical formulation of the proposed BET dispatching problem contains the following decision variables. First, the binary variable $x_{ijk} = 1$ indicates if an arc (i,j) is traveled by BET k ($\forall k \in K$); otherwise, it equals 0. K denotes a set of available BETs. Battery recharging decision variable g_{ik} defines whether a recharging is needed for the BET. Considering the partial recharging policy, variable Y_{ik} determines the SOC when the BET finishes the recharging. Additionally, a time decision variable τ_{ik} specifies the arrival time of the trip. The remaining cargo capacity and battery capacity variables are defined by u_{ik} and y_{ik}, respectively. Therefore, the proposed robust BET dispatching problem is expressed as follows.

$$\min \sum_{k\in K} \sum_{i\in \mathcal{N}'_O \cup \mathcal{R}, j\in \mathcal{N}'_D \cup \mathcal{R}, i\neq j} E_{ijk} x_{ijk} \tag{6}$$

Subject to:

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

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

$$\sum_{j\in \mathcal{N}'_D \cup \mathcal{R}, i\neq j} x_{ijk} - x_{jik} = 0, \forall i \in \mathcal{N}'_O \cup \mathcal{R}, k \in K \tag{9}$$

$$\sum_{i\in\Delta_O^-} x_{ijk} = K , \forall k \in K \tag{10}$$

$$\sum_{i\in\Delta_O^+} x_{ijk} = K , \forall k \in K \tag{11}$$

$$y_{Ok} = Q,\ \forall j \in \mathcal{N} \cup \mathcal{R}, k \in K \tag{12}$$

$$\sum_{j\in(D\cup\mathcal{N}\cup\mathcal{R})} x_{ijk} \le 1, \forall i \in \mathcal{R}, k \in K \tag{13}$$

$$0 \le Y_{ik} \le Min\{0.8Q, 3600r\}, \forall i \in \mathcal{R}, k \in K \tag{14}$$

$$\tau_{ik}(\tilde{t}) + (s_i + \tilde{t}_{ijk})x_{ijk} - l_0(1 - x_{ijk}) \le \tau_{jk}(\tilde{t}),$$
$$\forall i \in O \cup \mathcal{N} \cup \mathcal{R}, j \in j \in (D \cup \mathcal{N} \cup \mathcal{R}), i \neq j, k \in K \tag{15}$$

$$e_i \le \tau_{ik}(\tilde{t}) \le l_i,\ \forall i \in \mathcal{N}'_{O,D}, k \in K \tag{16}$$

$$0 \le u_{ok} \le C,\ \forall k \in K \tag{17}$$

$$0 \le u_j \le (u_i - q_i)x_{ij} + C(1 - x_{ij}) \tag{18}$$
$$\forall i \in O \cup \mathcal{N} \cup \mathcal{R}, \forall j \in D \cup \mathcal{N} \cup \mathcal{R}, i \neq j$$

$$0 \leq ((1-g_{ik}) \cdot y_{ik} + g_{ik} \cdot Y_{ik} - E_{ijk}) x_{ijk} \leq Q, \forall i \in \mathcal{N}'_O \cup \mathcal{R}, j \in \mathcal{N}'_D \cup \mathcal{R}, i \neq j, k \in K \quad (19)$$

$$x_{ijk} \in \{0,1\}, \forall i, j \in \mathcal{N}'_{O,D}, i \neq j, k \in K. \quad (20)$$

budget for a BET trip. Specifically, Γ_t^k controls the number of arcs with high travel time uncertainty, which is calculated by $\theta_t A^k$, where $\theta_t \in [0,1]$ is the travel time uncertainty budget coefficient and A^k is the number of arcs in route k. For example, if $\theta_t = 0$, then $\Gamma_t^k = 0$, which means the uncertainty degree is zero so the uncertain travel time $\tilde{t}_{ij}$ equals t_{ij} for all arcs in route k. If $\theta_t = 1$ and $\Gamma_t^k = A^k$, all the arcs in route k can take any value in the interval $[t_{ij}, t_{ij} + t_{ij}]$. Thus, the larger value of Γ_t^k provides greater

Objective (6) is to minimize the total energy consumption of all BETs. Constraints (7) through (9) guarantee the forward and backward flow conservation constraints. Constraints (10) and (11) define the degree constraints for the depot. Constraint (12) ensures that each BET is fully recharged before departing from the depot. Constraint (13) defines that the recharging frequency is at most once for a BET. Constraint (14) specifies the charging constraints. For the time window constraints, considering uncertain travel time $\tilde{t}$, constraints (15) and (16) guarantee that the arrival time at each node satisfies its time window. Constraints (17) and (18) ensure that the cargo payload is less or equal to the maximum cargo capacity for each BET. Constraint (19) enforces that the SOC of any BET cannot be less than 0. Constraint (20) defines a binary variable.

IV. SOLUTION APPROACHES

To address the proposed BET dispatching problem, we first incorporate a RO method [17] into the proposed mathematical model. Then, an ALNS metaheuristic algorithm is used to find a robust dispatching solution.

A. Incorporating Uncertainty and Reformulating the Cost Function

While the heterogenous travel time uncertainty is considered in the proposed robust BET dispatching problem, it may not always be possible to enforce the feasibility of the solution during the search. To ensure the effectiveness of the algorithm, infeasible solutions due to tight constraints, such as time windows, battery capacity, and restricted recharging time, are allowed during the search process. We use a surrogate objective function based on Equation (6) and add penalties associated with travel time violations. So, the latest possible vehicle arrival time at each vertex, as well as the potential penalty costs, can be estimated.

To calculate the potential latest arrival time for a node on a given solution S under uncertain travel times, let's start with a solution S that comprises m BET routes, represented by $S = \{\mathfrak{s}_1, \mathfrak{s}_2, \cdots, \mathfrak{s}_m\}$. A route traveled by BET k is defined as $\mathfrak{s}_k = \{p_1^k, p_2^k, \cdots, p_{\mathfrak{s}_k-1}^k, p_{\mathfrak{s}_k}^k\}$, which contains $\mathfrak{s}_k$ nodes, where $k \in K$ and $\mathfrak{s}_k \in S$. For the route s_k, the start node and the end node are represented by p_1^k and $p_{\mathfrak{s}_k}^k$, respectively. Also, the customers' nodes or a recharging station visit are included in $\{p_2^k, \cdots, p_{\mathfrak{s}_k-1}^k\}$. Considering an uncertainty degree of travel time Γ_t^k for a route traveled by BET k, we denote the latest arrival time for node i in this route as $\Lambda(i, \Gamma_t^k)$. Inspired by a calculation of $\Lambda(i, \Gamma_t^k)$ in [19] and [18], we take recharging time $h_{p_i^k}$ into account during the route. Therefore, the latest arrival time function $\Lambda(i, \Gamma_t^k)$ is formulated as follows.

$$\Lambda(i,\Gamma_t^k) = \begin{cases} 0, \text{if } i = 1 \\ \Lambda(i-1,\Gamma_t^k) + s_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}, \text{if } p_i^k \in \mathcal{R}, \text{and } \Gamma_t^k = 0 \\ \max(e_{p_i^k}, \Lambda(i-1,\Gamma_t^k) + h_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}), \text{if } p_{i-1}^k \in \mathcal{R}, \text{and } \Gamma_t^k = 0 \\ \max(e_{p_i^k}, \Lambda(i-1,\Gamma_t^k) + s_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}), \text{if } 2 \le i \le \mathfrak{s}_k, \text{and } \Gamma_t^k = 0 \\ \max(\Lambda(i-1,\Gamma_t^k - 1) + s_{p_{i-1}^k} + t_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}, \Lambda(i-1,\Gamma_t^k) + s_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}), \text{if } p_i^k \in \mathcal{R} \\ \max(e_{p_i^k}, \Lambda(i-1,\Gamma_t^k - 1) + h_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k} + t_{p_{i-1}^k p_i^k}, \Lambda(i-1,\Gamma_t^k) + h_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}), \text{if } p_{i-1}^k \in \mathcal{R} \text{ and } 1 \le \Gamma_t^k \le i-1 \\ \max(e_{p_i^k}, \Lambda(i-1,\Gamma_t^k - 1) + s_{p_{i-1}^k} + t_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}, \Lambda(i-1,\Gamma_t^k) + s_{p_{i-1}^k} + t_{p_{i-1}^k p_i^k}), \text{if } i \le \mathfrak{s}_k \text{ and } 1 \le \Gamma_t^k \le i-1 \end{cases}$$

$$Cost(S) = f(S) + \gamma_t \sum_{k \in K}^{m} \sum_{i=1}^{\mathfrak{s}_k} \max(0, \Lambda(i, \Gamma_t^k) - l_i) \tag{22}$$

B. Generation of Initial Solution

A modified greedy heuristic [7] is applied to generate an initial solution. To begin, we randomly select a candidate customer and insert them into a BET route. Subsequently, a greedy heuristic is used to iteratively determine a candidate customer with the smallest insertion cost increment on $f(S)$, and then insert it into the current route. When the current route becomes energy infeasible, a potential recharging visit is attempted to insert the current route from a set of recharging stations $\mathcal{R}$, selecting the one that generates the lowest incremental insertion cost. Therefore, more customers may be reachable. The current route is terminated when no more vertices can be scheduled due to constraint violation. In such a case, if there are still unvisited customers, a new BET route is started following the same greedy insertion process described above.

C. ALNS Algorithm

To solve the proposed BET dispatching problem, we use an enhanced version of the ALNS algorithm described in Peng et al. [7]. The ALNS algorithm is used as a search engine to find a robust dispatching solution. Here, we only briefly describe the ALNS algorithm due to limited space. For more details, we refer interested readers to [7].

The ALNS, first proposed in [20], has been successfully implemented to solve VRP with pick-up and delivery and various VRP extensions (e.g., [21], [10], [22], [23]). The developed ALNS algorithm begins with an initial solution construction process described in Section IV-B and improves the solution by applying removal and reinsertion operators. Specifically, like [24], we use five removal and three reinsertion operators in the ALNS framework. Each operator has an assigned weight, which can be adjusted dynamically according to performance. We employ the simulated annealing heuristic to decide if a new solution should be accepted or rejected, aiming to diversify the solution. It is noteworthy that we use the surrogate cost function $Cost(S)$ in equation (22) as the objective function for the ALNS algorithm. Thus, the total energy consumption and the potential delay penalty can be minimized during the search process.

V. CASE STUDY

$\Lambda(i, \Gamma^k - 1), \text{if } 2 \leq i \leq \Gamma^k$.

t t (21)

Therefore, the surrogate cost function of a given solution S can be calculated as in equation (22). In (22), $f(S)$ represents the total energy cost as discussed in Section III-C and γ_t denotes the penalty factor for time window violations.

This section presents a set of experiments to evaluate the solution approach and investigate the robustness of solutions under different uncertainty degrees. The problem instance is generated from real-world dispatching data in a full-service supply chain company. The proposed algorithm is implemented in a Python environment. All experiments are run on an online server with 32 GB RAM. The problem instance and travel information are available via GitHub[1].

A. Data Description and Experiment Design

The real-world dataset is derived from the historical travel movements of a fleet of conventional heavy-duty diesel trucks

[1] https://github.com/CurtisPeng123/Robust-BET-Dispatching-Dataset

that operated in San Bernardino County, California. We generate a dispatching instance to assess the robust dispatching strategy. The real-world test instance consists of 47 customers, including 33 linehaul customers and 14 backhaul customers. The dataset contains known dispatching information, such as customers' locations, visit type (delivery or pick-up), time window, and required demand (weight of cargo to be delivered or picked up). Ten customer locations are randomly selected as recharging stations.

Based on the customer locations, we utilize the Direction Service Application Programming Interface (DSAPI) provided by OpenRouteService [25] to generate real-world travel information for BET routes, including ideal travel time and distance matrices. These matrices take into account truck-restricted zones and speed limits within the urban transportation network.

In this study, the parameters of the uncertainty set in (5) are defined as follows. Each nominal travel time t_{ij} equals the real-world travel time obtained from the DSAPI. Additionally, we assume that the maximum deviation t_{ij} is $0.2t_j$. The uncertainty budget coefficient of travel time θ_t is set to 0.3. The penalty value γ_t in (22) is set to 20. We adopt parameters setting in ALNS metaheuristics, from our previous study [7]. In the numerical study, we use the characteristics of Class 8 BETs available in the current US market [26]. Table I summarizes the problem variables.

TABLE I. SUMMARY OF PROBLEM PARAMETERS

Notation	Description	Value
A	Frontal surface area of a BET [m^2]	10
C	BET usable battery capacity [kWh]	300
Q	BET payload capacity [lbs..]	37,000
eff_m	Motor efficiency	0.7
eff_d	Discharging efficiency	0.91
c_r	Rolling resistance coefficient	0.008
c_d	Aerodynamic drag coefficient	0.7
w	Vehicle curb weight [lbs.]	8,000
g	Gravitational constant [m/s^2]	9.81
ρ_a	Air density (km/m^3)	1.2041
θ	Road angle	0°
a	Acceleration	0
r	Recharging rate [kWh/min] [27]	3.96
$[T_O, T_D]$	Operating hour	[8 am, 4 pm]
P_{Acc}	Accessory power [kW] [16]	5.6

B. Solution Robustness Evaluation

Evaluating the robustness of the solution is necessary in the experiments. We employ a Monte Carlo simulation process to assess the robustness of the final solution derived from the ALNS algorithm. To generate a simulation scenario, we uniformly sample a random variable travel time, $\tilde{t}_{ij}$, of an arc $(i, j) \in \mathcal{A}$ within its interval $[t_{ij}, t_{ij} + t_{ij}]$. It is important to note that a solution comprises numerous arcs, and the travel times of these arcs are uniformly sampled using the same method. Consequently, we obtain one simulation scenario characterized by heterogeneous uncertainty in travel time.

TABLE II. COMPARISON ON SOLUTIONS IN DETERMINISTIC TRAVEL TIME

Instance	S^{Det}			S^{Rob}			
	m_E	*OBJ*	*Risk*	m_E	*OBJ*	*Risk*	*Dev*
BETVRPB	7	686	100.0%	7	698	0.9%	5.5%

Note: m_E, *OBJ, Risk* denote the number of BETs, the total energy consumption (in kWh), and the proportion of infeasible solutions, respectively.

TABLE III. RESULTS FOR INSTANCE WITH DIFFERENT UNCERTAIN RANGE VALUES (α^t)

Uncertainty range	BETVRPB		
	m_E	*OBJ*	*Risk*
0	7	686	100.0%
0.1	7	697	72.3%
0.2	7	698	0.9%
0.3	7	701	0.3%
0.5	7	719	0.0%

TABLE IV. RESULTS FOR INSTANCE WITH DIFFERENT UNCERTAIN BUDGET COEEFICIENT VALUES (θ_t)

Uncertainty budget coefficient	BETVRPB		
	m_E	*OBJ*	*Risk*
0	7	686	100.0%
0.1	7	697	97.5%
0.2	7	697	72.1%
0.3	7	698	0.9%
0.5	7	700	0.3%

Subsequently, a "*Risk*" value is defined to represent the proportion of infeasible scenarios within a simulation.

C. Performance of the Solution Approach

To assess the effectiveness of the ALNS, we compare the solutions of the robust BET dispatching version under uncertainty with the solution of the deterministic BET dispatching scenario. Table II shows the comparison of the experiment results. For each instance, the columns S^{Det} and

Within the simulation process, a total of 1,000 scenarios are generated to evaluate the robustness of the final solution. For each solution, the number of infeasible scenarios is recorded.

S^{Rob} denote the solutions of the deterministic version and the solutions of the robust version, respectively. m_E denotes the number of BETs, and "OBJ" indicates the total energy consumption. "*Risk*" represents the proportion of infeasible scenarios in the Monte Carlo simulation.

In Table II, we observe that the deterministic solutions are fragile under travel time uncertainty. They encounter a higher risk since they may violate one or more of the constraints. However, the proposed robust BET dispatching approach can significantly reduce the risk compared with the deterministic dispatching approach. The risk can be reduced from 100% to 0.9% while the total energy consumption increases by merely 5.5%.

D. The Effect of Uncertainty Parameters

As mentioned in Section III-C, the robustness of the solution is affected by the budgeted uncertain set of travel time. Therefore, we analyze the impact of the maximum deviation of travel time $t_{ij} = \alpha^t t_{ij}$ and the uncertainty degree Γ^k separately. When investigating the effect of maximum deviation on the solutions, we assume the uncertainty budget coefficient θ_t is fixed and set it to 0.3. We define the uncertain range coefficient α^t in set $\{0.1, 0.2, 0.3, 0.5\}$, where the larger value of α^t represents the greater deviation of t_{ij}. Similarly, to

t

analyze the effect of the uncertainty budget coefficient, we fix α^t to 0.2 and change the travel time uncertainty budget coefficient θ_t in set $\{0.1, 0.2, 0.3, 0.5\}$. The larger value of coefficient θ_t may cause a larger number of arcs under travel time uncertainty. The experiment results are reported in Table III and Table IV.

As shown in Table III, when the uncertainty range α^t of travel time increases from 0 to 0.5, the total energy consumption rises from 686 to 719, or approximately 4.8%. More energy cost is required to ensure a lower risk of violating the time window constraints. In Table IV, as the degree of uncertainty increases, the solution cost increases by 2.0%. By comparing the results between these two tables, we notice that the uncertainty range of travel time has a higher impact on the robust solution. Based on the observations in this study, the proposed dispatching strategy can provide dispatching solutions under different risk levels so the decision-maker can choose a preferred robust solution.

VI. Conclusions and Future Work

This paper introduces a robust BET dispatching problem with backhauls and time windows under heterogenous travel time uncertainty. A microscopic energy consumption model is used to estimate the SOC of BETs during dispatching. We apply the ALNS metaheuristic algorithm incorporating RO method to find a robust dispatching solution. A real-world dispatching case study is used to assess the performance of our solution approach and examine the effect of the different uncertainty parameters on the solutions. For the case study examined in this paper, the solution risk can be reduced from 100% to 0.9% while the total energy consumption increases by only 5.5%. Additionally, a Monte Carlo simulation process is used to demonstrate the robustness of the solutions that were obtained. The experiment results indicate a trade-off between the total energy cost of the solution and its robustness under different levels of uncertain travel times.

There are several directions for enhancing and expanding this work in the future. For example, other uncertainties, such as uncertain loading/unloading time at customer location or waiting time at recharging stations, can be considered. Also, learning-based algorithms can be utilized to solve BET dispatching problems in a more efficient manner.

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