

Multi-period truck scheduling with queueing for post-disaster debris removal: A case study of the 2025 Los Angeles wildfires

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Abstract—Disasters such as wildfires, earthquakes, hurricanes, and floods have long posed severe threats to communities worldwide, generating massive amounts of debris. Existing truck scheduling models often minimize time cost or maximize profit, failing to accommodate updating demand and chaotic environment after major disasters, as well as the impact of secondary hazards. This study proposes the *Multi-Period Truck Scheduling problem for Debris Removal after major disasters with explicit queue modeling (MPTS-DR)*. The model minimizes the remaining debris periodically to minimize secondary hazards and accommodate updating demand due to ongoing cleaning and sorting. Queues at disposal sites are explicitly modeled to absorb demand surges and smooth operational uncertainty. A solution heuristic is proposed and applied to the removal of 2025 LA wildfire debris in Palisades and Eaton. Optimal fleet size and sufficient queue length are identified. Results show that it takes more than 700 days to remove all debris with workday opening hours, and around 260 days to remove with 24-hour operations.

Keywords—truck scheduling, disaster relief, debris removal, LA wildfire

I. INTRODUCTION

Disasters such as wildfires, earthquakes, hurricanes, and floods have long posed threats to communities. They generate massive amounts of debris that might cause secondary hazards and hinder recovery. Hurricane Katrina in 2005 produced over 100 million cubic yards of debris in New Orleans metropolitan area alone [1], leading to a cleanup process of more than five years [2]. The 2011 Tōhoku earthquake and tsunami generated 18.73 million tons of debris in Miyagi prefecture, requiring up to two years to remove [3]. In early 2025, the Eaton and Palisades wildfires in Los Angeles County generated an estimated 4 million tons of debris [4], which could take up to 18 months to remove according to the US Corps of Engineers (USACE) [5].

Transporting debris is an important task that requires large manpower and resources. Post-disaster truck scheduling to transport debris to disposal sites is an important task with many factors to be considered: fleet size, operations at disaster sites and disposal sites, and high uncertainties in post-disaster scenarios. Such debris transport problem differs significantly from conventional truck scheduling in operational context and

objectives. Traditional truck scheduling operates under stable conditions, typically assume predictable demand, reliable infrastructure and dispatch control [6]. In contrast, post-disaster operations face significant uncertainty in chaotic environments where urgent needs, unknown demand, scarce resources, and lack of coordination are the norm [7,8].

An important objective of post-disaster logistics is a fast response [8]. However, at the planning stage, there is often insufficient time and personnel to accurately assess the volume and types of debris. This forces decision-makers to operate with demand that keeps updating. Full Truckload Vehicle Routing Problems (FTVRPs) are commonly used to model post-disaster debris transportation, as such debris is typically homogeneous and generated in massive volumes. However, conventional FTVRP typically minimizes time cost or maximizes profit [9-11]. Existing debris removal studies also focus on minimizing total removal duration, travel costs, or queueing costs [12,13]. However, with such updating demand, comprehensive planning with early-stage information is less reliable. Maximizing the amount of debris transported on a periodic basis is a more practical and adaptive objective, as the estimated amount, type, and distribution of debris change throughout the cleaning and sorting process.

Another key distinction between conventional and post-disaster truck scheduling is the need to minimize the impact of secondary hazards caused by unremoved debris. Disaster debris often contains a wide range of hazardous materials and dangerous items, such as explosive gas canisters and batteries. Toxic materials like asbestos, heavy metals, and polycyclic aromatic hydrocarbons (PAHs) remain in fire ash [14]. Wind can spread fine particles [15], and rainwater can carry contaminants into soil and groundwater [16]. Such impacts can be controlled by minimizing remaining debris throughout the removal process, which can be done through maximizing debris transported periodically.

Queues are often avoided or minimized in truck scheduling problems [6,12,13]. However, post-disaster debris transport operates under extreme uncertainty, fragmented authority, and limited processing capacity. In such cases, mechanisms to absorb demand surges and smooth operational uncertainties are necessary for robustness, since the supporting systems are weak

and response actions can be chaotic at early stages [7]. As a result, buffering and the ability to allow temporary delays are not inefficiencies, but operational necessities in highly disrupted environments [17]. Creating truck queueing areas provides a physical buffer that absorbs surges and uncertainty. Truck queueing without enough queueing space could lead to traffic disturbances and management chaos. In existing debris removal studies, Brooks and Mendonça [12] used a queueing theory approach to model truck queueing at temporary debris staging sites, while it is unreliable to assume any arrival distribution for trucks during debris removal after major disasters. Explicit queue modeling at disposal sites would be more accurate, facilitating the analysis of the impact of queue length on system performance, supporting the design and sizing of truck queueing areas.

To address the unique challenges of post-disaster debris transport, this study proposes a *Multi-Period Truck Scheduling problem for Debris Removal after major disasters with explicit queue modeling* (MPTS-DR), considering multiple disaster sites, multiple disposal sites with multiple entrances, and multiple debris types. The model accounts for characteristics of debris removal after major disasters: full-truckload operations with massive debris volumes. Multiple debris types require transporting to specific disposal sites (e.g. landfill, recycling). Instead of minimizing removal time and costs [13], we prioritize the reduction of secondary hazards through minimizing remaining debris amount at any time step. Such a goal is achieved through maximizing debris removed periodically, which also accommodates the updating demand at early stage when debris knowledge is updating as cleaning and sorting goes on. The model explicitly captures truck queueing behavior at disposal site without adopting any queueing models, enabling analysis and design of truck queueing space. MPTS-DR is formulated into a many-objective mixed integer problem which is NP-hard. A solution heuristic is proposed.

The algorithm is applied to the 2025 LA wildfire debris at Palisades and Eaton, with a workday as a period. The impact of truck fleet size and maximum queue length is analyzed. It is observed that daily tonnage increases with fleet size when fleet size is insufficient. When fleet size increases to a certain value, daily tonnage would stop increasing, indicating the existence of an *optimal fleet size*. Daily tonnage decreases when longer queues are allowed, while stops decreasing when maximum queue length reach certain values since more queueing spaces are not used. This indicates the existence of a *sufficient queue length*, which facilitates the design of truck queueing space. Cases with different scheduling strategy (greedy vs. weighted sampling) is compared, showing that greedy means higher efficiency but more queueing. A 24-hour operation case (finish in 263 days) is compared with a case with workday hours (finish in 742 days) with the same fleet size. A completely greedy case is compared with a weighted probability sampling case, showing shorter total time but more queueing.

MPTS-DR aims to support both strategic planning and operational design. It outputs executable, multi-period truck schedules constrained by factors including fleet size, maximum queue length, loading and unloading time. It also helps assess

how these factors affect the debris clearance procedure and informs planning-level decision-making.

The rest of the paper is organized as follows. Part II presents MPTS-DR and the solution heuristic. Part III shows the 2025 LA wildfire case study results and analysis. Part IV concludes the paper.

II. METHODOLOGY

A. Problem formulation

There is a set of disaster sites $i \in I$ where there are different debris types $p \in P$. The amount of debris at disaster site i of type p is \mathbb{D}_{ip} . There is a set of debris disposal sites $j \in J$. Each disposal site j accepts one type of debris, with one or more entrances $n \in N_j$. Entrances at the same disposal site are capable of parallel unloading. Each entrance n of disposal site j allows a maximum queue length of $L_{max}[j, n]$ trucks, where L_{max} is a matrix of maximum queue lengths for all entrances at all disposal sites. Each disposal site has a maximum acceptable debris amount C_j in a period (e.g. a day), with an opening time window $[T_j^O, T_j^C]$. The set of disposal sites that accepts debris type p is denoted as J_p .

There is a truck fleet V that transport debris from disaster sites I to debris sites J . Each truck has a capacity of a tons for a single trip. All trucks are at disaster sites at the start of a period. The time when truck v is ready for the first loading at any disaster site in a period is T_v^0 (e.g. 6 AM). Loading time and unloading time are denoted as t_L and t_U , respectively. The goal is to design a multi-period truck schedule which (1) minimizes the total remaining debris at any time point in the removal process, and (2) minimizes the total removal duration. The first objective has higher priority over the second. In the context of major disasters, the amount of debris is very large, which cannot be removed within one typical repeatable time period such as a day or a week, while the disposal sites usually operate periodically with daily opening hours, and daily capacities. Hence, we do a multi-period truck scheduling to output a schedule that can be separated into typical operation cycles such as days.

To formulate the problem, first we define a task $(i, j, n, i', k, v, s, p, u)$ as follows: truck v depart from disaster site i transporting type p debris to entrance n of disposal site j on the truck's k th trip in period u , as the s th truck that arrives at site j in period u , and then go to the next disaster site i' . Binary variables $y_{ijn'kvsp}^u, \forall i, i' \in I, j \in J_p, n \in N_j, k \in K, v \in V, s \in S, p \in P$ are defined to indicate whether the task happens. A set of continuous time variables are defined to track the time points of the task, including $T_{ijn'kvsp}^{DI,u}$ as the time when truck v departs from disaster site i , $T_{ijn'kvsp}^{AJ,u}$ as the arrival time at entrance n of disposal site j , $T_{ijn'kvsp}^{UJ,u}$ as the unloading start time at disposal site j , $T_{ijn'kvsp}^{DJ,u}$ as the departure time from disposal site j , $T_{ijn'kvsp}^{AI,u}$ as the arrival time at the next disaster site i' . To model queueing at entrances, queueing time of each task is defined as

a continuous variable $q_{ijni'kvsp}^u$. Whether a truck v waited in queue for a task is modeled with binary variable $x_{ijni'kvsp}^u$.

Tasks are modeled in such a way to avoid having a timestep dimension similar to [13]. With a timestep dimension τ , a trip-based formulation can be written with (i, j, n, v, p, u, τ) denoting a truck trip. However, having detailed timesteps for long-time debris removal after major disasters would lead to very large problem size. With limited number of disaster sites i' , truck arrivals s , and truck tasks k , the problem dimension would be smaller. Truck arrival sequence s at the disposal site entrance is for explicit queue modeling.

We define the problem as the Multi-Period Truck Scheduling Problem for Debris Removal (MPTS-DR), which solves for the truck schedules within multiple periods $u \in \{1, 2, \dots, U\}$, minimizing the total remaining amount of debris at the end of each period as well as minimizing the number of periods. Eq.(1) is the set of objectives O_u maximizing the total amount of debris removed in periods $u \in \{1, 2, \dots, U\}$. Eq.(2) is the objective minimizing the total number of periods. Since minimizing the remaining debris at the end of any period is the objective with highest priority, we set the objective order shown as (3). Maximization of debris removal in earlier periods is prioritized over later periods to minimize remaining debris.

$$O_u = \max \sum_{i \in I} \sum_{p \in P} \Phi_{pi}^u, \forall u \in \{1, 2, \dots, U\} \quad (1)$$

$$O_{U+1} = \min U \quad (2)$$

$$O_1 > O_2 > \dots > O_U > O_{U+1} \quad (3)$$

Constraint (4) computes the amount of type p debris removed from disaster site $i \in I$ in each period u . Constraint (5) ensures that the overall total amount of debris does not exceed the demand by disaster site and type.

$$\Phi_{pi}^u = \sum_{j \in J_p} \sum_{n \in N_j} \sum_{i' \in I} \sum_{k \in K} \sum_{v \in V} \sum_{s \in S} a y_{ijni'kvspu}^u, \forall i \in I, p \in P, u \in \{1, 2, \dots, U\} \quad (4)$$

$$\sum_{u=1}^U \Phi_{pi}^u \geq \mathbb{D}_{ip}, \forall i \in I, p \in P \quad (5)$$

All the selected tasks need to arrive at disposal sites during opening time window, which is formulated as (6). M is significantly larger in magnitude than all the other parameters and variables, ensuring that (6) only applies to the existing tasks ($y_{ijni'kvsp}^u = 1$).

$$T_j^0 - M(1 - y_{ijni'kvsp}^u) \leq T_{ijni'kvspu}^{AJ} \leq T_j^c + M(1 - y_{ijni'kvsp}^u), \quad (6)$$

$$\forall i, i' \in I, n \in N_j, j \in J_p, k \in K, v \in V, s \in S, p \in P, u \in \{1, 2, \dots, U\}$$

Constraints (7-11) defines the time sequences of tasks. Constraint (7) ensures that the loading start time at disaster site is no earlier than the time that the truck is ready. Constraint (8) defines the relationship between departure time from disaster site i and arrival time at entrance n of disposal site j . Constraint (9) defines the relationship between arrival time and unloading start time at entrance n of disposal site j . Constraint (10) defines the relationship between unloading start time and departure time from disposal site j . Constraint (11) defines the relationship

between departure time from disposal site j and arrival at the next disaster site i' . All time sequence constraints contain the $M(1 - y_{ijni'kvsp}^u)$ term to make sure that the relationships only apply to the selected tasks with $y_{ijni'kvsp}^u = 1$.

$$T_v^0 - M(1 - y_{ijni'kvsp}^u) \leq T_{ijni'kvsp}^{DJ,u} - t_L, \quad (7)$$

$$\forall i, i' \in I, n \in N_j, j \in J_p, v \in V, s \in S, p \in P, u \in \{1, 2, \dots, U\}$$

$$T_{ijni'kvsp}^{DJ,u} \leq T_{ijni'kvsp}^{AJ,u} - t_{ij} + M(1 - y_{ijni'kvsp}^u), \quad (8)$$

$$\forall i, i' \in I, n \in N_j, j \in J_p, k \in K, v \in V, s \in S, p \in P, u \in \{1, 2, \dots, U\}$$

$$T_{ijni'kvsp}^{AJ,u} \leq T_{ijni'kvsp}^{UJ,u} - q_{ijni'kvsp}^u + M(1 - y_{ijni'kvsp}^u), \quad (9)$$

$$\forall i, i' \in I, n \in N_j, j \in J_p, k \in K, v \in V, s \in S, p \in P, u \in \{1, 2, \dots, U\}$$

$$T_{ijni'kvsp}^{UJ,u} \leq T_{ijni'kvsp}^{DJ,u} - t_U + M(1 - y_{ijni'kvsp}^u), \quad (10)$$

$$\forall i, i' \in I, n \in N_j, j \in J_p, k \in K, v \in V, s \in S, p \in P, u \in \{1, 2, \dots, U\}$$

$$T_{ijni'kvsp}^{DJ,u} \leq T_{ijni'kvsp}^{AI',u} - t_{ji'} + M(1 - y_{ijni'kvsp}^u), \quad (11)$$

$$\forall i, i' \in I, n \in N_j, j \in J_p, k \in K, v \in V, s \in S, p \in P, u \in \{1, 2, \dots, U\}$$

Constraint (12) ensures that for truck v , if its $(k+1)$ th task in the period starts at disaster site i' , its k th task must end at disaster site i' .

$$\sum_{j' \in J_p} \sum_{i'' \in I} \sum_{s \in S} \sum_{p \in P} \sum_{n \in N_j} y_{i'j'n'i''(k+1)vsp}^u \leq \sum_{j \in J_p} \sum_{i' \in I} \sum_{s \in S} \sum_{p \in P} \sum_{n \in N_j} y_{ijni'kvsp}^u, \quad (12)$$

$$\forall i' \in I, k \in K, v \in V, u \in \{1, 2, \dots, U\}$$

Constraint (13) ensures that the capacities of disposal sites in a period are not exceeded.

$$\sum_{i \in I} \sum_{i' \in I} \sum_{k \in K} \sum_{v \in V} \sum_{s \in S} \sum_{n \in N_j} a y_{ijni'kvsp}^u \leq C_j, \forall j \in J_p, p \in P, u \in \{1, 2, \dots, U\} \quad (13)$$

Constraints (14-15) deals with task sequences for trucks. Constraint (14) ensures that the task sequence indices $k \in K$ are unique for each truck. Constraint (15) ensures that if the $(k+1)$ th task exists for truck v , the k th task must exist.

$$\sum_{i \in I} \sum_{i' \in I} \sum_{j \in J_p} \sum_{s \in S} \sum_{p \in P} \sum_{n \in N_j} y_{ijni'kvsp}^u \leq 1, \forall v \in V, k \in K, u \in \{1, 2, \dots, U\} \quad (14)$$

$$\sum_{i \in I} \sum_{i' \in I} \sum_{j \in J_p} \sum_{s \in S} \sum_{p \in P} \sum_{n \in N_j} y_{ijni'kvsp}^u \geq \sum_{i \in I} \sum_{i' \in I} \sum_{j \in J_p} \sum_{s \in S} \sum_{p \in P} \sum_{n \in N_j} y_{ijni'(k+1)vsp}^u, \quad (15)$$

$$\forall v \in V, k \in K / \{\max(K)\}, u \in \{1, 2, \dots, U\}$$

Constraints (16-17) deals with arrival sequences at entrances of disposal sites. Constraint (16) ensures that each arrival sequence index s at entrance n of disposal site j are unique. Constraint (17) ensures that if the $(s+1)$ th truck visits entrance n of disposal site j , the s th visit must exist.

$$\sum_{i \in I} \sum_{i' \in I} \sum_{k \in K} \sum_{v \in V} \sum_{p \in P} y_{ijni'kvsp}^u \leq 1, \forall j \in J_p, p \in P, s \in S, u \in \{1, 2, \dots, U\} \quad (16)$$

$$\begin{aligned}
& \sum_{i \in I} \sum_{i' \in I} \sum_{k \in K} \sum_{v \in V} y_{ijni'kvsp}^u \\
& \geq \sum_{i \in I} \sum_{i' \in I} \sum_{k \in K} \sum_{v \in V} \sum_{n \in N_j} y_{ijni'kv(s+1)p'}^u \quad (17) \\
& \forall n \in N_j, j \in J_p, p \in P, s \in S/\{\max(S)\}, u \\
& \quad \in \{1, 2, \dots, U\}
\end{aligned}$$

Constraints (18-21) model queues at disposal site entrances. Constraint (18) ensures that the queue lengths at disposal entrances are shorter than the maximum queue length of the entrance $L_{\max}[j, n]$. It ensures that the departure time of the s th truck at an entrance is no later than the arrival time of the $(s + L_{\max}[j, n] + 1)$ th truck at the same entrance. It only comes into effect when both tasks exist. Constraint (19) ensures that if the s th arrival at an entrance does not wait in queue ($x_{ijni'kvsp} = 0$), the arrival time of the s th arrival must be no earlier than the $(s - 1)$ th departure at the same entrance. On the contrary, if the s th arrival waits in queue ($x_{ijni'kvsp} = 1$), the arrival time of the s th arrival must be earlier than the $(s - 1)$ th departure. It comes into effect only when the two tasks both exist. Constraint (20-21) defines queueing time $q_{ijni'kvsp}$. When $x_{ijni'kvsp} = 1$, (20) comes into effect to compute $q_{ijni'kvsp}$ as the difference between the departure time of the $(s - 1)$ th arrival and the arrival time of the s th arrival, while (21) is disabled. When $x_{ijni'kvsp} = 0$, (20) is disabled, and (21) comes into effect to ensure that $q_{ijni'kvsp} = 0$.

$$\begin{aligned}
& T_{ijni'kvsp}^{DJ,u} - M(1 - y_{ijni'kvsp}^u) \\
& \leq T_{ijni''k'v'(s+L_{\max}[j,n]+1)p}^{AJ,u} \\
& \quad + M(1 - y_{ijni''k'v'(s+L_{\max}[j,n]+1)p}^u), \quad (18) \\
& \forall i, i', i'', i''' \in I, j \in J_p, n \in N_j, k, k' \in K, v, v' \in V, \\
& s \in S/\{\max(S) - L_{\max}[j, n] - 1, \max(S) \\
& \quad - L_{\max}[j, n], \dots, \max(S)\}, p \in P, u \\
& \quad \in \{1, 2, \dots, U\}
\end{aligned}$$

$$\begin{aligned}
& -M(2 - y_{ijni'kvsp}^u - y_{ijni''k'v'(s-1)p}^u) - Mx_{ijni'kvsp}^u \\
& \leq T_{ijni'kvsp}^{AJ,u} - T_{ijni''k'v'(s-1)p}^{DJ,u} \\
& \leq M(1 - x_{ijni'kvsp}^u) \\
& \quad + M(2 - y_{ijni'kvsp}^u) \\
& \quad - y_{ijni''k'v'(s-1)p}^u), \quad (19) \\
& \forall i, i', i'', i''' \in I, j \in J_p, n \in N_j, k, k' \in K, v, v' \in V, s \\
& \quad \in S/\{1\}, p \in P, u \in \{1, 2, \dots, U\}
\end{aligned}$$

$$\begin{aligned}
& q_{ijni'kvsp}^u \geq T_{ijni''k'v'(s-1)p}^{DJ,u} - T_{ijni'kvsp}^{AJ,u} \\
& \quad - M(1 - x_{ijni'kvsp}^u) \\
& \quad - M(2 - y_{ijni'kvsp}^u) \\
& \quad - y_{ijni''k'v'(s-1)p}^u), \quad (20) \\
& \forall i, i', i'', i''' \in I, j \in J_p, n \in N_j, k, k' \in K, v, v' \in V, s \\
& \quad \in S/\{1\}, p \in P, u \in \{1, 2, \dots, U\}
\end{aligned}$$

$$\begin{aligned}
& q_{ijni'kvsp}^u \geq -Mx_{ijni'kvsp}^u \\
& \quad - M(2 - y_{ijni'kvsp}^u) \\
& \quad - y_{ijni''k'v'(s-1)p}^u), \quad (21) \\
& \forall i, i', i'', i''' \in I, j \in J_p, n \in N_j, k, k' \in K, v, v' \in V, s \\
& \quad \in S/\{1\}, p \in P, u \in \{1, 2, \dots, U\}
\end{aligned}$$

MPTS-DR is composed of (1-21), which is a Many-objective Mixed Integer Problem. Binary and nonnegativity

constraints are omitted. The problem is NP-hard, and its dimensionality expands drastically with the increase of numbers of disaster sites, disposal sites, entrances, and trucks. A solution heuristic is specifically designed for MPTS-DR, which is discussed in the following section.

B. Solution heuristic

We propose a solution heuristic for MPTS-DR with 2 parts: the within-period truck scheduling heuristic (**Algorithm 1**) and the multi-period truck scheduling heuristic (**Algorithm 2**). In **Algorithm 1**, we define a task differently from the formulation: a truck departs from a disposal site j' (or a disaster site if it is the starting task of the period), go to a disaster site i , fully load, and go to an entrance n of disposal site j , stay in queue if there is a queue, and unload. A task is characterized by $[j', i, j, n, v, T_{j'ijv}^{DJ}, T_{j'ijv}^{AJ}, T_{j'ijv}^{DI}, T_{j'ijv}^{AJ}, T_{j'ijv}^{UJ}]$, where $T_{j'ijv}^{DJ}$ is departure time from j' , $T_{j'ijv}^{AJ}$ is arrival time at i , $T_{j'ijv}^{DI}$ is departure time from i after loading, $T_{j'ijv}^{AJ}$ is arrival time at j , $T_{j'ijv}^{UJ}$ is unloading start time after queuing.

The nature of **Algorithm 1** is myopic, since its assignment only considers the time cost of the next task for the earliest available truck in each step. Such myopic strategy serves the purpose of minimizing remaining debris during the period. In each step, we find the next available truck, compare the time of all the possible tasks for the truck. The constraints of maximum queue length, disposal site capacity, disposal site opening time window, and remaining debris are considered by assigning very large values to the tasks that violate these constraints. The latter three constraints are considered strict, meaning that when all of the potential tasks violate them, the scheduling in the period ends. The maximum queue length constraint can be violated when all the disposal site entrances reach their maximum queue lengths, while the latter three constraints are not violated.

Task selection for available trucks is based on task duration T . Shorter tasks should be assigned higher probability under distribution $\Phi(T)$, while making sure that probabilities of tasks violating constraints ((i, j, n) with $T[i, j, n] \geq M$ or (j, n) with $T[j, n] \geq M$) should be 0. Different $\Phi(T)$ introduces different level of randomness, enabling escape from local optima. For example, if probability 1 is assigned to the shortest task, **Algorithm 1** becomes a greedy algorithm. If task probabilities are inversely proportional to task durations, the algorithm would still exhibit greedy characteristics, while preserving randomness to promote solution diversity and support escape from local optima.

Algorithm 1: Within-period myopic truck scheduling heuristic.

Input: list of amount of debris left of each type at each disaster site **D**

Step 1: Initialize

- List of loading start times of all trucks at its starting disaster site i_k^0 of the period: $T_{end}^0 = [T_v^0, \text{for } v \text{ in } V]$
- List of starting disaster site of all trucks in the period. Negativity is used to distinguish between disaster site indices and disposal site indices: $A_{end} = [-i_v^0, \text{for } v \text{ in } V]$
- List of scheduled tasks: $R = []$

Step 2: Iterate

- Find the next available truck v by finding the index of $\min(T_{end})$ in T_{end} .
- Compute task time of each possible next task for truck v to form vector T .
 - If $A_{end}[v] < 0$, the task starts from disaster site $i = -A_{end}[v]$, otherwise, the task starts from disposal site $A_{end}[v]$.
 - Queue time is computed for each entrance at each disposal site. The entrance with the shortest queueing time is chosen for each disposal site.
 - When any of maximum queue length, disposal site capacity, disposal site time window, and remaining amount of debris constraint is violated, time of the task is set to M , a value significantly larger than any parameter in magnitude.
 - If all possible tasks violate the maximum queue length but not all violate the other three, remove the maximum queue length constraint and recompute task times.
- Generate a probability distribution $\Phi(T)$ that describes the probability of selecting each possible next task of truck v .
- Select next task of truck v according to $\Phi(T)$.
- Save the task to R .
- Update $T_{end}[v]$ as the unloading finish time of the saved task.
- Update $A_{end}[v]$ as the unloading disposal site of the saved task.
- Search R to find all tasks arrive at the same entrance of the same disposal site, re-compute queueing times if the newly scheduled task arrives earlier.

Step 3: Period end check

- When all possible tasks for the next available truck violate disposal site capacity, disposal site time window, or remaining amount of debris constraint, the period ends.

Output: R

Algorithm 2 does multi-period scheduling based on the within-period schedules output by Algorithm 1. While maximizing the total amount of debris removed within periods, Algorithm 1 does not ensure that the debris removed within a period is proportional to the total debris in terms of types and disaster sites. **Algorithm 2** ensures that a periodic schedule is conducted repeatedly until one type of debris at a disaster site is entirely removed and then make a new periodic schedule with the remaining debris type and site distribution. The multiple periods during which the same periodic schedule is conducted is called a phase. Such a mechanism serves the purpose of minimizing the total remaining debris at the end of each period.

Algorithm 2: Multi-period truck scheduling heuristic.

Inputs: \mathbb{D}_{ip} , for i in I , p in P ; inputs of **Algorithm 1**.

$\mathbb{R} = []$ #set of all periodic truck schedules

$\mathbb{T} = []$ #set of the number of periods for each schedule

$\mathbf{D} = [\mathbb{D}_{ip}, \text{for } i \text{ in } I, p \text{ in } P]$

While there is any debris left for any site of any type **do**

- Run **Algorithm 1** with input \mathbf{D} , which outputs R .
- Add R into \mathbb{R} .
- Compute amount of each debris type p removed from each disaster site i q_{ip} from R .
- $t = \min\left(\left\lfloor \frac{D[i,p]}{q_{ip}} \right\rfloor \text{ for } i \text{ in } I, p \text{ in } P\right)$, add t into \mathbb{T} .
- $D[i,p] = D[i,p] - tq_{ip}$, for i in I , p in P

$\mathcal{T} = \sum_{t \in \mathbb{T}} t$ #total number of periods to finish all removal

Outputs: $\mathbb{R}, \mathbb{T}, \mathcal{T}$

III. LA WILDFIRE CASE STUDY

A. Background

The 2025 LA wildfire at Palisades and Eaton is used to test the heuristic. Total amount of debris at Palisades and Eaton is estimated to be 4 million tons (60% in Eaton, 40% in Palisades). There are two types of debris: recycle and landfill. For both fire sites, landfill debris accounts for 75% of the total volume, recycling debris accounts for 25% (Source: USACE). The 16 designated disposal sites are shown in **Table 1** and **Figure 1**.

Table 1: Disposal site information (Source: USACE).

ID	Type	Workday open time	Number of entrances	Daily capacity (tons)
0	Landfill	7:00 AM-4:00 PM	1	-
1	Landfill	7:00 AM-4:00PM	2	5000
2	Landfill	7:00 AM-4:00PM	4	15000
3	Landfill	7:00 AM-5:00PM	1	-
4	Landfill	8:00 AM-5:00PM	1	-
5	Landfill	8:00 AM-5:00PM	2	4000
6	Landfill	7:30 AM-3:00PM	1	-
7	Landfill	6:00 AM-6:00PM	1	-
8	Landfill	6:00 AM-5:00PM	1	-
9	Landfill	8:00 AM-3:30PM	1	-
0	Recycle	9:00 AM-3:00PM	1	200
1	Recycle	6:00 AM-3:30PM	1	1000
2	Recycle	6:00 AM-6:00PM	1	2000
3	Recycle	7:00 AM-4:00PM	1	250
4	Recycle	8:00 AM-4:00PM	1	500
5	Recycle	6:00 AM-4:00PM	1	2000

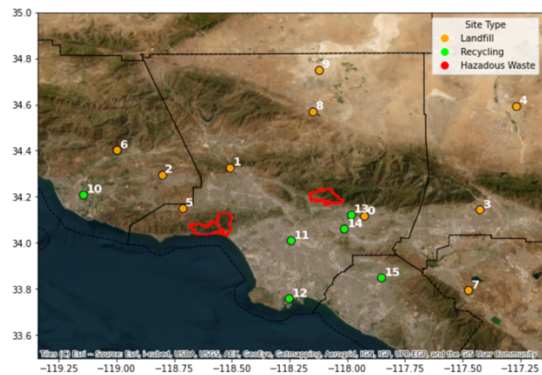


Figure 1: Fire sites and 16 disposal sites for landfill and recycling (Data source: USACE).

For the benchmark case (Case 0), we define a workday as a period and apply **Algorithm 2** to solve MPTS-DR. For $\Phi(T)$, a completely greedy method is applied: the shortest task is chosen with probability 1 for each available truck. With fleet size and maximum queue lengths undetermined, we run **Algorithm 2** with a sequence of different fleet sizes and maximum queue lengths to analyze the relationship between these 2 parameters and system performance. We will then identify fleet size and maximum queue length for Case 0. Case 0 will be compared with the following cases:

- **Case 1:** $\Phi(T)$ is changed such that task probabilities are inversely proportional to task durations.
- **Case 2:** 24-hour operation for all disposal sites.

Following is a list of assumptions:

- Loading/unloading times: $t_U = t_U = 30$ minutes (Source: USACE). No queue at fire sites (start loading whenever the truck arrived).
- At the start of the day, all trucks are at fire sites (50% fleet at Palisades, 50% at Eaton).
- If a truck arrives at a disposal site and gets in queue before its closing time, it is going to be unloaded.
- When trucks first departing fire sites in the period, we assume a 5-min interval between trucks.
- For workday scenarios (Case 0, 1), the first truck at both fire sites starts loading at 6AM. For the 24-hour case (Case 2), the first truck at both fire sites starts loading at 0AM on the first day.

Travel times are obtained from LASim, which is a Multi-Agent Transport Simulation (MATSim) testbed calibrated for Los Angeles County [18]. Incidents are integrated into LASim [19]. Shortest paths from all fire sites to all disposal sites and reverse are found. Travel times of these paths during each hour of a day are pre-generated from LASim. Travel time of a path is obtained from an hour if the departure is within that hour. A comparison between traffic status with and without debris trucks was conducted by LASim and shows only moderate impacts on highway travel times.

B. Impact of fleet size and maximum queue length

We explore the impact of maximum queue length and fleet size by running **Algorithm 1** for the first day (with all debris). We assume the same maximum queue lengths for all entrances at all disposal sites, which is denoted as ℓ_{max} . For each $\ell_{max} \in [0,1, \dots, 10]$, we run a sequence of **Algorithm 1** with fleet sizes between 50 and 300 with an interval of 10. **Figure 2** shows the relationship between daily total removed tonnage and fleet sizes with different maximum queue lengths. **Figure 3** shows the relationships between daily total removed tonnage and ℓ_{max} with different fleet sizes.

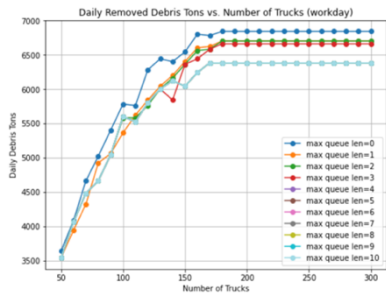


Figure 2: Relationships between daily removed debris tons, day for debris removal and fleet size.

Overall, fleet size increase leads to daily tonnage increase, but we also observe fluctuations. This is because that, when fleet size increases for a small amount, queues at disposal site entrances become longer, which decrease the number of tasks some trucks conduct in a day. When fleet size keeps increasing, the added trucks compensate the loss caused by increased queuing times. Daily tonnage keep on increasing after dropping slightly. When fleet size is increased to a point that daily tonnage stops increasing, fleet size reaches the number that is necessary. Further increase in fleet size becomes unused. We define such a fleet size as the *optimal fleet size* $f_{\ell_{max}}^*$ given ℓ_{max} in **Definition 1**. Judging from **Figure 2**, $f_{\ell_{max}}^* = 180$ for $\ell_{max} \in [0,1,2,3]$, $f_{\ell_{max}}^* = 170$ for $\ell_{max} \in [4,5, \dots, 10]$.

Definition 1 (Optimal fleet size): Optimal fleet size $f_{\ell_{max}}^*$ is a fleet size such that with any fleet size $f > f_{\ell_{max}}^*$, the amount of removed debris in a period is unchanged given a maximum queue length ℓ_{max} allowed for all entrances $n \in N_j$ of all disposal sites $j \in J$.

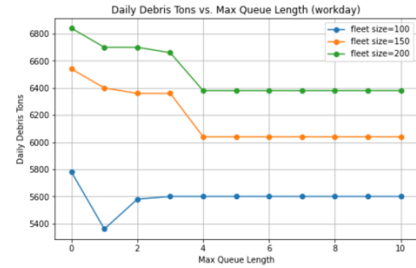


Figure 3: Relationships between daily removed debris tons, day for debris removal and maximum queue length.

Overall, when longer queues are allowed, system efficiency is decreased and daily tonnage becomes smaller. Such decrease stops when ℓ_{max} increases to a point when additional queuing spaces are no longer used. From such a trend, we can identify the sufficient queue length ℓ_f^S given a fleet size f , whose definition is shown in **Definition 2**.

Definition 2 (Sufficient queue length): Sufficient queue length ℓ_f^S is a queue length for all the entrances $n \in N_j$ of all the disposal sites $j \in J$, such that with queue length $l > \ell_f^S$, the amount of removed debris in a period is unchanged, given a fleet size f .

For system efficiency, queues should be completely avoided. However, in the post-disaster scenario where perfect control and

Table 3: Comparison of Case 0,1,2.

		Case 0	Case 1			Case 2	
			Run 1	Run 2	Run 3		
Day 1 of Phase 1	Total (tons)	Landfill	4400	4180	4080	4120	15060
		Recycle	2980	1700	1820	1700	3980
	Palisades (tons)	Landfill	2900	2100	1920	1960	9300
		Recycle	400	820	1000	680	1400
	Eaton (tons)	Landfill	1500	2080	2160	2160	5760
		Recycle	1580	880	820	1020	2580
	Average number of tasks per truck		1.88	1.73	1.74	1.71	5.60
	Average task time		4h 5min	4h 32min	4h 17min	4h 28min	4h 24min
	Average task travel time		1h 11min	1h 43min	1h 40min	1h 39min	1h 44min
	Average task queue time		1h	50min	45min	50min	1h 24min
	Time estimate (days)		742	806	779	764	263

coordination cannot be achieved, identifying ℓ_f^S would facilitate the design of truck queuing space and avoid traffic disturbance caused by unmanaged truck queueing. Judging from **Figure 3**, $\ell_{100}^S = 3$, $\ell_{150}^S = \ell_{200}^S = 4$, indicating that a queuing space for 3-4 trucks would be enough for each entrance. There also exist some cases where increasing ℓ_{max} leads to increase in daily tonnage (e.g. ℓ_{max} increases from 1 to 2 with fleets size 100). Such cases often occur when fleet size is insufficient and unable to cover enough disposal sites. In this case, longer queues allowed at close disposal sites would increase daily tonnage.

C. Case 0: Benchmark

As shown by **Figure 2**, the highest daily tonnage is achieved by $\ell_{max} = 0$ with $f_0^* = 180$. But to show the impact of queuing, we take $\ell_{max} = 5$ with $f_5^* = 170$ as the benchmark

Phase 4	Recycle	1440	1440	0	
Phase 5	Landfill	4040	0	4040	99
	Recycle	1820	1820	0	
Phase 6	Landfill	3920	0	3920	1
	Recycle	1220	1220	0	
Phase 7	Landfill	3280	0	3280	219
	Recycle	0	0	0	
Phase 7	Landfill	1020	0	1020	1
	Recycle	0	0	0	

We show the details of a day in Phase 1 in **Figure 3 (a,d)**. We see uneven task distribution over disposal sites: site 2 receives significantly more debris due to larger number of entrances. This shows that, with workday time windows, increasing the number of entrances would help increasing system efficiency, since disposal site capacities are typically not reached in this case.

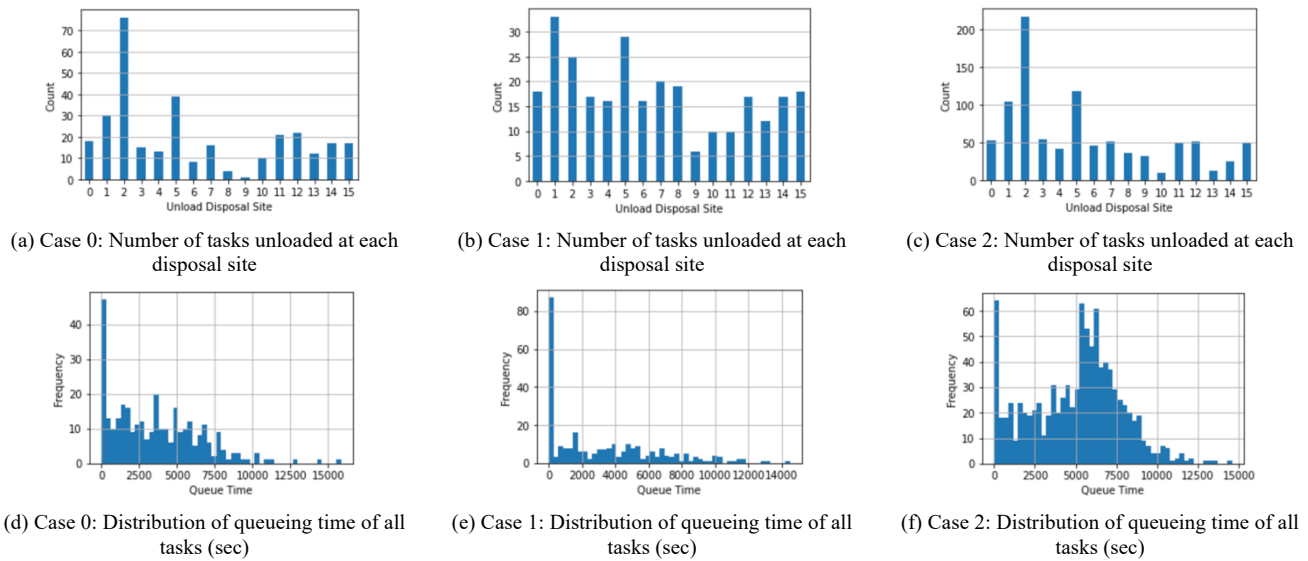


Figure 3. Phase 1 task distributions of Case 0,1,2.

Case 0 and run **Algorithm 2. Table 2** shows the results. Total number of workdays is 742. There are 7 phases with different daily schedules. Debris types and locations that are more efficient to transport are prioritized. Earlier phases prioritize removal of landfill debris at Palisades, since it is closer to landfill disposal sites 6,2,1,5, and site 2 has the most entrances (4 entrances). For Eaton, recycling debris is prioritized since it is closer to disposal sites 11,14,13. The last two phases only transport landfill debris at Eaton, since it is the least efficient to transport. Such observation aligns with the goal of minimizing total remaining debris at the end of each period.

Table 2: Multi-period removal plan of Case 0.

	Type	Daily tonnage	Palisades tonnage	Eaton tonnage	Number of days
Phase 1	Landfill	4400	2900	1500	379
	Recycle	1980	400	1580	
Phase 2	Landfill	4480	2760	1720	1
	Recycle	1960	780	1180	
Phase 3	Landfill	4880	2360	2520	41
	Recycle	1580	1580	0	
	Landfill	4620	1380	3240	

D. Case 1: Weighted sampling

We define distribution $\Phi(T)$ such that task selection probabilities are inversely proportional to task durations. Maximum queue length and fleet size are the same as Case 0. Due to randomness, we run **Algorithm 2** three times and show results in **Table 3**. In **Figure 3 (b,e)**, we show the details of a day in Phase 1 of Run 1. Average total number of workdays for the three runs is 783, which is longer than Case 0. This shows that assigning higher probabilities to shorter tasks improves system efficiency.

Comparing with Case 0, longer tasks are selected. Travel times are significantly increased, while queuing times decrease. Tonnage distribution over disposal sites is more even, and as a result, queuing is alleviated. This could reduce the need for truck queuing space and avoid potential traffic disturbances caused by truck queues, as well as alleviate management pressure for disposal sites.

E. Case 2: 24-hour operation

In the 24-hour operation case, we run **Algorithm 2** with 1 week as a period, and time windows of all disposal sites as 0 AM of the first day to 11:59:59 PM of the seventh day. We assume that the first truck is ready to be loaded at 0AM of the first day, and then the trucks work continuously until the end of the one-week period. When checking daily disposal site capacity constraint, a day check mechanism is added to set daily cumulative tonnages $Q[j, p]$ back to 0 when a new day starts. Another approach is to use **Algorithm 1** alone, regarding the entire removal process as one period. We did not do that since the periodic method discards unnecessary history schedule records and fastens computation. Maximum queue length and fleet size are the same as Case 0.

Results are compared in **Table 3**. In **Figure 3 (c,f)**, we show the details of the first day. Total number of days is 263, which is significantly shorter than workday operation with the same fleet size. Average number of trips per truck in phase 1 is around 3 times of Case 0. Task total time, travel time, and queuing time all increased. Queuing times are centered around 6000 sec (1h 40min), which corresponds to a queue length of around 3 trucks. Such centering effect is not observed in other cases since the operation time is not long enough to show pattern with stable operation.

CONCLUSION

This study investigates the truck scheduling problem for debris removal of massive amounts after major disasters, considering updating demand in early stage. MPTS-DR is proposed with a solution heuristic. The objective of minimizing remaining debris at any time step is prioritized, accounting for both updating demand and mitigation of secondary hazards. Truck queuing at disposal sites is explicitly modeled as a robustness mechanism to absorb potential disturbances in post-disaster settings. The solution heuristic is applied to the 2025 LA wildfire debris at Palisades and Eaton, identifying optimal fleet size and sufficient queue length. The case study demonstrates that MPTS-DR is helpful for both operational and strategic decision-making. For next steps, further improvement on solution quality could be done through combinatorial optimization methods like simulated annealing and Tabu search. Integrating work troop assignment could be another direction.

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