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Resource Constraint Evacuation Route Planning: A Capacity-Aware Charge-Encoded State-Space Approach

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Abstract

Electric-vehicle evacuation planning requires evacuation routes that are both road-capacity feasible and driving-range feasible. Existing evacuation routing methods typically account for road capacity but do not explicitly enforce electric-vehicle range constraints, whereas electric-vehicle routing models usually focus on individual vehicle routing and do not address large-scale evacuation scheduling under shared road-capacity limits. This paper studies the Resource Constraint Evacuation Route Planning (RC-ERP) problem, in which evacuees must be routed from source locations to safe destinations while satisfying road-capacity constraints and a maximum travel-distance constraint between consecutive charging-station visits. We propose the Time-Expanded Charge-Encoded Routing Algorithm (TE-CERA), a scalable constructive heuristic that combines charge-encoded route generation with time-expanded capacity-aware scheduling. The proposed Node-Encoded Shortest Path (NESP) procedure computes charging-feasible spatial routes by tracking the accumulated travel distance since the most recent charging-station visit, while the scheduling stage assigns feasible departure times using a time-indexed edge-occupancy table. Under the stated modeling assumptions, the framework guarantees charging-feasible and capacity-feasible evacuation schedules. Experiments on real-world transportation networks show that TE-CERA eliminates charging-constraint violations while maintaining comparable evacuation times to a capacity-constrained evacuation routing baseline. The results demonstrate the feasibility and scalability of integrating electric-vehicle range constraints into evacuation routing, while also highlighting future extensions involving charging duration, charger capacity, and station-level queueing.

Keywords: evacuation scheduling; time-expanded networks; capacity-constrained routing; electric-vehicle evacuation; charging constraint; disaster transportation modeling

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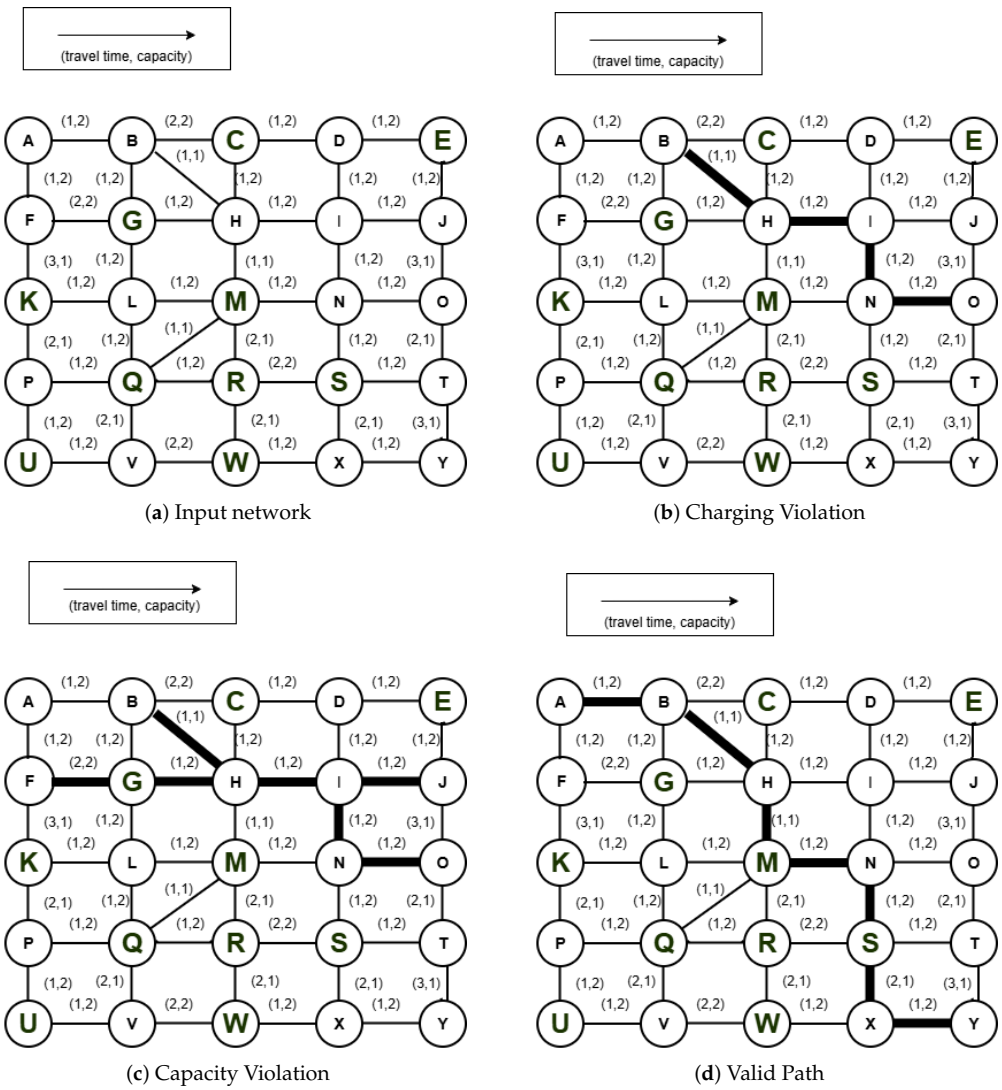
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1. Introduction

Evacuation route planning is a critical component of emergency transportation management during hurricanes, floods, wildfires, hazardous chemical spills, and other large-scale disasters. The objective is to move evacuees from threatened areas to safe destinations while respecting the operational constraints of the transportation network. Classical evacuation routing models commonly focus on road-capacity constraints and evacuation completion time. However, the increasing adoption of electric vehicles introduces an additional operational requirement: vehicles must be able to reach charging stations before exceeding their available driving range.

This paper studies the Resource Constraint Evacuation Route Planning (RC-ERP) problem for electric-vehicle evacuation under both road-capacity and driving-range constraints. Given a transportation network with edge travel times, edge capacities, source locations, destination locations, charging stations, and a maximum travel distance F between consecutive charging-station visits, the goal is to construct evacuation routes and schedules that move evacuees to destinations while avoiding both capacity violations and charging-constraint violations. A charging-constraint violation occurs when a vehicle travels more than F without visiting a charging station. A capacity violation occurs when the number of vehicles assigned to a road segment during a time interval exceeds the road-capacity limit.

Figure 1 illustrates the RC-ERP setting. Figure 1a shows an input transportation network with source nodes, destination nodes, road-capacity constraints, travel times, and charging stations. Nodes with larger labels represent charging stations. Let F denote the maximum travel distance allowed between consecutive charging-station visits. In this example, $F = 3$. Figure 1b shows a charging-constraint violation, where the distance traveled between consecutive charging-station visits exceeds F. Figure 1c shows a capacity violation, where the assigned traffic flow exceeds the capacity of a road segment. Figure 1d shows a feasible evacuation route that satisfies both the charging constraint and the road-capacity constraint.



(**a**) Input network (**b**) Charging Violation

(**c**) Capacity Violation (**d**) Valid Path

Figure 1. Example input and outputs of evacuation route planning. Nodes with larger labels represent charging stations, and highlighted edges indicate the selected route, charging violation, capacity violation, or valid path shown in each panel.

The RC-ERP problem is challenging because evacuation planning involves large transportation networks, many evacuees, limited road capacities, and electric-vehicle range restrictions. Existing capacity-constrained evacuation methods can schedule vehicles over road networks but generally do not enforce electric-vehicle charging feasibility. Conversely, many electric-vehicle routing and resource-constrained shortest-path methods model energy or range constraints but are not designed for large-scale evacuation scheduling with shared time-dependent road capacities. Therefore, an integrated approach is needed to construct evacuation schedules that are feasible with respect to both driving range and road capacity.

To address this need, we propose the Time-Expanded Charge-Encoded Routing Algorithm (TE-CERA). TE-CERA is a constructive heuristic framework that first computes charging-feasible spatial routes and then schedules evacuee departures using time-expanded capacity management. The routing stage uses a Node-Encoded Shortest Path (NESP) procedure, which augments each node state with the accumulated travel distance since the most recent charging-station visit. The scheduling stage uses a time-indexed edge-occupancy table to delay departures when necessary so that road-capacity constraints are not violated. This decoupled design avoids constructing a full node–time–charge expanded network, improving scalability for large road networks while preserving feasibility under the stated modeling assumptions.

1.1. Application Domain

RC-ERP is motivated by emergency transportation planning for communities that include electric vehicles in the evacuation fleet. During large-scale disasters such as hurricanes, floods, wildfires, or hazardous chemical incidents, evacuees must travel from threatened zones to safe destinations under limited road capacity. For electric vehicles, route feasibility also depends on whether a vehicle can reach charging stations before exceeding its available driving range. Therefore, evacuation planning for electric vehicles requires both capacity-aware scheduling and driving-range-feasible routing.

During Hurricane Irma, which affected Florida in 2017, evacuation route computation became a critical element of emergency preparedness [1]. One major issue during the storm was mass evacuation, where many travelers relied on predefined evacuation corridors while traffic demand exceeded available road capacity. Figure 2 shows severe traffic backup on a Florida highway during the evacuation, illustrating how congestion can reduce evacuation efficiency and increase travel time. Extended travel times can further increase operational risk for electric vehicles if routes are planned without considering driving-range limits.

Figure 3 shows an electric vehicle charging at a station [2]. In this paper, charging stations are modeled as range-reset locations: when a vehicle reaches a charging-station node, the accumulated travel distance since the previous charging visit is reset. This abstraction allows the proposed model to enforce driving-range feasibility during evacuation routing. However, the model does not explicitly represent charging duration, charger availability, station-level service capacity, or queueing delay. These charging-service dynamics are important in real evacuation operations and are identified as future extensions of the present work.

The importance of the charging constraint is particularly evident in large-scale evacuation planning, where assigning an electric vehicle to a route that exceeds its feasible driving range may lead to vehicle stalling, emergency assistance needs, or unplanned rerouting. RC-ERP addresses this issue by requiring each evacuation route to satisfy a maximum travel-distance bound between consecutive charging-station visits while also respecting road-capacity constraints. Thus, the proposed framework focuses on generating

evacuation schedules that are feasible with respect to both road capacity and electric-vehicle driving range.

In addition, an algorithm for RC-ERP should be scalable enough to support repeated planning under changing disaster conditions. During emergencies, road closures, traffic incidents, destination availability, and charging-station accessibility may change over time. A computationally efficient method can be rerun when such conditions change, allowing planners to update evacuation schedules as new information becomes available.



Figure 2. Traffic backup during Hurricane Irma illustrating massive vehicle accumulation on a Florida highway (September 2017). Courtesy USA Today [1].



Figure 3. An electric vehicle charging at a station [2].

1.2. Problem Definition

In the RC-ERP problem, the transportation network is represented as a directed graph $G = (N, E)$, where N is the set of nodes and E is the set of directed edges. Each node represents a spatial location such as a road intersection, evacuation source, destination, or charging-station location. Each edge $e \in E$ represents a road segment with travel time T_e, distance or energy-consumption value W_e, and capacity C_e. Let $S \subseteq N$ denote the set of source nodes, $D \subseteq N$ denote the set of destination nodes, and $CS \subseteq N$ denote the set of charging-station nodes. Let K denote the set of evacuees, and let F denote the maximum travel distance allowed between consecutive charging-station visits.

The objective of RC-ERP is to construct evacuation routes and schedules that move all evacuees from source nodes to destination nodes while satisfying both road-capacity and driving-range constraints. The exact optimization objective is to minimize the evacuation

completion time, also called the evacuation makespan. Since solving the fully integrated node–time–charge problem can be computationally expensive for large-scale networks, the proposed TE-CERA framework is designed as a scalable constructive heuristic that seeks to reduce evacuation completion time while guaranteeing feasible schedules under the stated assumptions. Algorithm 1 summarizes the input, output, and constraints of the RC-ERP problem.

Algorithm 1: Resource Constraint Evacuation Route Planning (RC-ERP) problem statement

Input:

- a directed transportation network $G = (N, E)$;
- edge capacities C_e, travel times T_e, and distances W_e for all $e \in E$;
- a set of evacuees K and their source locations in S;
- a set of evacuation destinations D;
- a set of charging stations CS; and
- a maximum travel distance F between consecutive charging-station visits.

Output: An evacuation plan consisting of a route and a departure schedule for each evacuee.

Constraints:

- The accumulated travel distance between consecutive charging-station visits must not exceed F.
- The number of vehicles assigned to each edge at each time step must not exceed the edge capacity.
- Edge travel times preserve the First-In-First-Out (FIFO) property.

Definition 1. ***Charging constraint:*** *A charging violation occurs when a vehicle travels a distance greater than F without visiting a charging-station node $cs \in CS$. In this paper, charging stations are modeled as range-reset nodes. Therefore, the model enforces driving-range feasibility, but it does not explicitly model charging duration, charger capacity, or station-level queues.*

Definition 2. ***First-In First-Out (FIFO):*** *The FIFO principle assumes that a vehicle cannot overtake another vehicle traveling in the same direction on the same road segment. Under fixed positive travel times, a later departure along the same edge cannot arrive earlier than an earlier departure.*

Definition 3. ***Capacity constraint:*** *A capacity violation occurs when the number of vehicles assigned to an edge during a time interval exceeds the edge-capacity limit C_e.*

1.3. Mathematical Formulation of RC-ERP

This subsection presents a simple mathematical formulation of RC-ERP. The purpose of the formulation is to clearly define the decision variables, objective, and constraints of the problem. The TE-CERA algorithm proposed later is a scalable heuristic for solving this problem on large transportation networks.

Let K be the set of evacuees, E be the set of road segments, N be the set of nodes, and $\mathcal{T} = \{0, 1, \ldots, T_{\max}\}$ be the set of discrete time steps. For each evacuee $k \in K$, let $s(k)$ be the source node of the evacuee. We define the following decision variables:

- $x_{k,e,t} = 1$ if evacuee k starts using road segment e at time t; otherwise, $x_{k,e,t} = 0$.
- $y_{k,i,t} = 1$ if evacuee k is located at node i at time t; otherwise, $y_{k,i,t} = 0$.
- $r_{k,t}$ is the accumulated travel distance of evacuee k since the most recent charging-station visit at time t.
- a_k is the arrival time of evacuee k at a destination.

- Z is the evacuation completion time, i.e., the time when the last evacuee reaches a destination.

The objective is to minimize the evacuation completion time:

$$\min Z. \tag{1}$$

Each evacuee must start from its assigned source node:

$$y_{k,s(k),0} = 1, \qquad \forall k \in K. \tag{2}$$

Each evacuee must reach at least one destination node:

$$\sum_{d \in D} \sum_{t \in \mathcal{T}} y_{k,d,t} \geq 1, \qquad \forall k \in K. \tag{3}$$

The evacuation completion time must be at least as large as the arrival time of each evacuee:

$$a_k \leq Z, \qquad \forall k \in K. \tag{4}$$

The number of evacuees occupying a road segment at the same time must not exceed its capacity. If evacuee k starts traversing edge e at time θ, the evacuee occupies that edge until time $\theta + T_e$. Therefore, the capacity constraint is as follows:

$$\sum_{k \in K} \sum_{\theta:\, \theta \leq t < \theta + T_e} x_{k,e,\theta} \leq C_e, \qquad \forall e \in E,\ \forall t \in \mathcal{T}. \tag{5}$$

The accumulated travel distance since the most recent charging-station visit must not exceed the maximum driving range F:

$$r_{k,t} \leq F, \qquad \forall k \in K,\ \forall t \in \mathcal{T}. \tag{6}$$

When an evacuee reaches a charging station, the accumulated distance is reset to zero. Otherwise, the accumulated distance increases by the distance of the road segment traveled:

$$r_{k,t+1} = \begin{cases} 0, & \text{if evacuee } k \text{ reaches a charging station at time } t+1, \\ r_{k,t} + W_e, & \text{if evacuee } k \text{ travels on edge } e \text{ without charging.} \end{cases} \tag{7}$$

Finally, the movement and location variables are binary:

$$x_{k,e,t} \in \{0,1\}, \qquad \forall k \in K,\ e \in E,\ t \in \mathcal{T}, \tag{8}$$

$$y_{k,i,t} \in \{0,1\}, \qquad \forall k \in K,\ i \in N,\ t \in \mathcal{T}. \tag{9}$$

This formulation shows that RC-ERP combines three main requirements: moving all evacuees from sources to destinations, respecting road-capacity limits, and ensuring that electric vehicles do not exceed their driving range between charging-station visits. A direct solution requires reasoning over node, time, and charge states. This motivates the TE-CERA framework, which separates charging-feasible route generation from time-expanded capacity scheduling to obtain feasible evacuation plans more efficiently.

1.4. Contributions

The main contribution of this work is not the use of a charge or resource state alone, since state-augmentation ideas are well established in resource-constrained shortest-path and electric-vehicle routing problems. Rather, the contribution lies in adapting and inte-

grating charge-encoded route generation with time-expanded capacity-aware evacuation scheduling for large-scale electric-vehicle evacuation planning. Specifically, this paper makes the following contributions:

- We formulate the Resource Constraint Evacuation Route Planning (RC-ERP) problem, which combines evacuation routing, road-capacity constraints, and electric-vehicle driving-range feasibility.
- We propose the Time-Expanded Charge-Encoded Routing Algorithm (TE-CERA), a scalable constructive heuristic that integrates charging-feasible route computation with time-expanded capacity-aware evacuation scheduling.
- We develop the Node-Encoded Shortest Path (NESP) procedure to generate charging-feasible evacuation routes by tracking the accumulated travel distance since the most recent charging-station visit.
- We introduce a decoupled charge-space and time-scheduling structure that avoids full node–time–charge expansion and reduces memory requirements compared with a naive three-dimensional state-space representation.
- We prove that the proposed framework terminates and produces evacuation schedules that satisfy the charging constraint, road-capacity constraint, and FIFO assumption under the stated model.
- We evaluate the proposed approach on real-world transportation networks and analyze the trade-off between computational efficiency, driving-range feasibility, and evacuation performance.

1.5. Related Work

There has been considerable research on evacuation route planning (ERP) in recent years. Existing ERP studies can be broadly grouped into three categories: network-flow optimization methods, simulation-based methods, and heuristic methods. Network-flow optimization methods use spatiotemporal or time-expanded network models to identify evacuation schedules under road-capacity constraints [3–7]. These methods provide a strong theoretical foundation for evacuation planning, but they typically assume conventional vehicles and do not explicitly enforce electric-vehicle driving-range constraints. Recent work has also addressed shelter location and population allocation under multi-hazard scenarios [8], transit accessibility to shelters in conflict zones [9], and predict-then-optimize frameworks for hurricane shelter placement [10], highlighting the breadth of the emergency planning problem beyond route scheduling alone. Simulation-based methods model traveler behavior and traffic dynamics in greater detail [11,12]. However, detailed simulation can be computationally expensive for large-scale evacuation planning and does not directly provide route schedules with hard feasibility guarantees. Heuristic methods, such as the Capacity-Constrained Route Planner (CCRP), improve scalability by constructing capacity-feasible evacuation routes with reduced computational cost [13,14]. However, CCRP and related capacity-constrained evacuation methods do not directly model charging-station visits or electric-vehicle range feasibility.

The charging-feasibility component of RC-ERP is closely related to the resource-constrained shortest-path problem, where a path must satisfy one or more resource limits while minimizing travel cost [15–17]. State-space expansion and labeling methods are commonly used to track resources such as time, energy, or accumulated distance along candidate routes [18,19]. Electric-vehicle routing studies extend these ideas by considering battery capacity, charging stations, energy consumption, charging decisions, or charging-time functions [20–29]. These studies provide important tools for computing energy-feasible or charging-feasible routes. However, many EV routing models focus on individual vehicles, logistics operations, or fleet routing, and they typically do not address large-scale

evacuation scheduling in which many evacuees share road segments with time-dependent capacity limits.

Conflict-aware and capacity-aware evacuation planning has also been investigated to avoid movement conflicts and improve safety in evacuation networks [30,31]. These approaches are relevant because evacuation routes must be feasible not only spatially but also temporally. Nevertheless, they do not explicitly model electric-vehicle driving-range constraints. In contrast, the proposed RC-ERP formulation combines both requirements: each route must satisfy the driving-range constraint between consecutive charging-station visits, and the final schedule must respect road-capacity constraints.

Recent studies have also explored deep learning and reinforcement learning for transportation prediction and vehicle routing problems. Learning-based approaches can generate fast approximate decisions after training and have been applied to several routing and transportation-network tasks, including capacitated routing, time-window routing, and spatiotemporal demand or throughput prediction [32,33]. These methods are promising for large-scale transportation applications, but they usually require problem-specific training data and additional mechanisms to guarantee hard operational constraints. Therefore, learning-based methods are complementary to the present work and may be useful for future adaptive or real-time extensions of RC-ERP.

Overall, prior work provides important building blocks for RC-ERP, including time-expanded evacuation scheduling, capacity-constrained routing, resource-state shortest paths, and electric-vehicle routing. The proposed TE-CERA framework builds on these ideas by integrating charge-encoded route generation with time-expanded capacity-aware scheduling. Thus, the contribution is not the use of a resource state alone, but the adaptation and integration of driving-range-feasible routing with capacity-aware evacuation scheduling for large-scale electric-vehicle evacuation planning.

1.6. Scope and Outline

This paper focuses on the spatiotemporal network optimization problem based on the charging constraint. We model the transportation network using fixed travel times and maximum road capacities [24]. The capacity constraints and charging constraints are restricted to a spatiotemporal network (STN) [4–6]. We consider that the transportation network exhibits the FIFO (First-In-First-Out) property. The simulation of individual driver behaviors and complex battery discharge dynamics is beyond the scope of the present research.

The rest of this paper is organized as follows: Section 2 describes our proposed approaches to RC-ERP. Section 3 presents the feasibility and complexity analysis of the proposed framework. Section 4 describes the experiment design and presents the experimental observations and results. Finally, Section 5 concludes this paper.

2. Proposed Algorithms for RC-ERP

This section presents the proposed Time-Expanded Charge-Encoded Routing Algorithm (TE-CERA) for the RC-ERP problem. TE-CERA is designed as a scalable constructive heuristic that produces evacuation routes and schedules satisfying two operational constraints: electric vehicles must remain within their driving-range limit, and assigned vehicle movements must respect road-capacity constraints.

Traditional evacuation routing methods typically emphasize road-capacity constraints, whereas electric-vehicle routing methods typically emphasize battery or charging constraints. RC-ERP requires both. TE-CERA addresses this requirement through a two-stage framework. First, a charging-feasible spatial route is computed using the Node-Encoded Shortest Path (NESP) procedure. NESP tracks the accumulated travel distance since the

most recent charging-station visit and removes route candidates that exceed the maximum travel-distance bound F. Second, the route is scheduled using a time-expanded capacity-management procedure. This stage checks road availability over time and delays departures when necessary to avoid capacity violations.

The overall TE-CERA workflow is summarized as follows:

(1) Input preparation: Construct the directed transportation network with edge travel times, edge distances, edge capacities, source nodes, destination nodes, charging stations, and the range bound F.
(2) Charging-feasible route generation: For each evacuee or source group, apply NESP to compute a route that satisfies the driving-range constraint.
(3) Capacity-aware scheduling: Use a time-indexed occupancy table to check whether each edge on the selected route has available capacity during the intended traversal interval.
(4) Departure-time adjustment: If a capacity conflict is detected, delay the departure time until all edges on the route can be reserved without exceeding capacity.
(5) Output generation: Return an evacuation plan consisting of a route and departure time for each evacuee.

This design decouples charge-state route generation from time-expanded capacity scheduling. As a result, TE-CERA avoids constructing a full node–time–charge state space while still producing schedules that satisfy the charging and road-capacity constraints under the stated model assumptions.

2.1. Basic Concept

Consider the evacuation network shown in Figure 4. The network consists of multiple intersections connected by road segments. Each edge is labeled with a pair (τ, cap), where τ denotes the travel time and cap denotes the capacity of the road segment. For this example, we assume a maximum allowable travel distance of $F = 3$ between consecutive charging stations. The edge between nodes A and B has travel time 1 and capacity 2. A possible evacuation route from node A to node Y passes through nodes B, H, M, N, S, and X. This route will be used later to illustrate the charging constraint and the scheduling mechanism of the proposed framework.

In evacuation scenarios involving electric vehicles, routing decisions must also consider battery limitations. Electric vehicles cannot travel arbitrarily long distances without recharging. Therefore, evacuation routes must ensure that vehicles encounter charging stations before exceeding their allowable driving range. In the example network, charging stations are represented by nodes with larger size. When a vehicle reaches one of these nodes, its battery can be recharged and the travel distance counter is reset.

To enforce road-capacity constraints, TE-CERA models vehicle movements using a time-expanded representation of the network. In this representation, each spatial node is replicated across discrete time steps, producing temporal nodes such as $A(0)$, $A(1)$, $A(2)$, and $A(3)$ that represent the same intersection at different time points. If a spatial edge (u, v) has travel time τ and capacity cap, it is represented in the time-expanded network as a temporal edge $(u, t) \rightarrow (v, t + \tau)$ labeled (τ, cap). For example, if a vehicle departs from node A at time 0 along an edge with label $(1, 2)$, the corresponding temporal movement is $A(0) \rightarrow B(1)$. Vehicles may also remain at the same intersection, which is represented by waiting edges such as $A(0) \rightarrow A(1)$. Figure 5 shows the resulting time-expanded network, where solid edges represent vehicle movements and dashed edges represent waiting operations. Using this framework, evacuation routing can be separated into two tasks: computing routes that satisfy the charging constraint and scheduling these routes over time so that road-capacity constraints are respected.

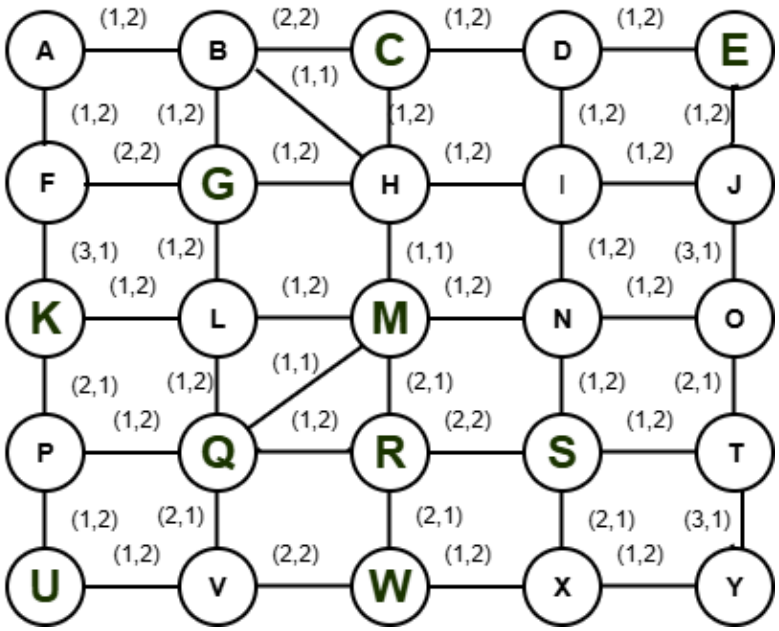


Figure 4. Illustrative evacuation network used to explain the proposed framework. Each edge is labeled with (τ, cap) representing travel time and capacity.

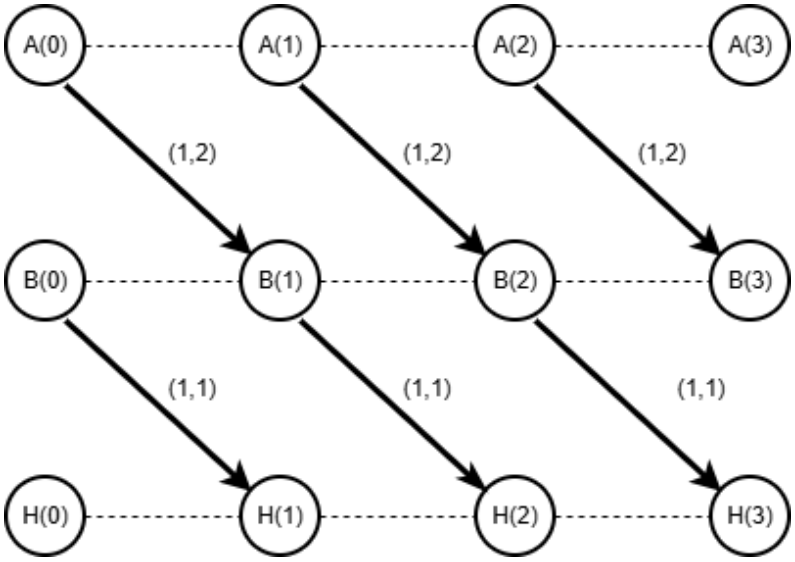


Figure 5. Time-expanded network representation. Solid edges denote vehicle movements (τ, cap) and dashed edges denote waiting operations.

2.2. Node-Encoded Shortest Path

The first component of TE-CERA is the computation of spatial routes that satisfy the electric-vehicle driving-range constraint. We refer to this procedure as the Node-Encoded Shortest Path (NESP) method. NESP follows the general idea of resource-state shortest-path search: each search state stores both the current node and the accumulated resource consumption. In this paper, the resource is the travel distance accumulated since the most recent charging-station visit.

The purpose of NESP is not to replace general resource-constrained shortest-path methods. Instead, NESP provides a charge-encoded route-generation component that can be integrated with the time-expanded capacity-scheduling stage of TE-CERA. This design allows the proposed framework to enforce electric-vehicle driving-range feasibility before assigning departure times and checking road-capacity availability.

The key idea is to augment each node in the transportation network with the accumulated distance traveled since the most recent charging-station visit. Instead of representing a search state only by the current node, NESP represents it as a pair (v, d), where v is the current node and d is the accumulated travel distance since the most recent charging-station visit. This representation allows the routing procedure to determine whether a vehicle can continue along a road segment without exceeding the maximum distance bound F.

Figure 6 illustrates an example network used to demonstrate the NESP procedure and its charging-feasible route.

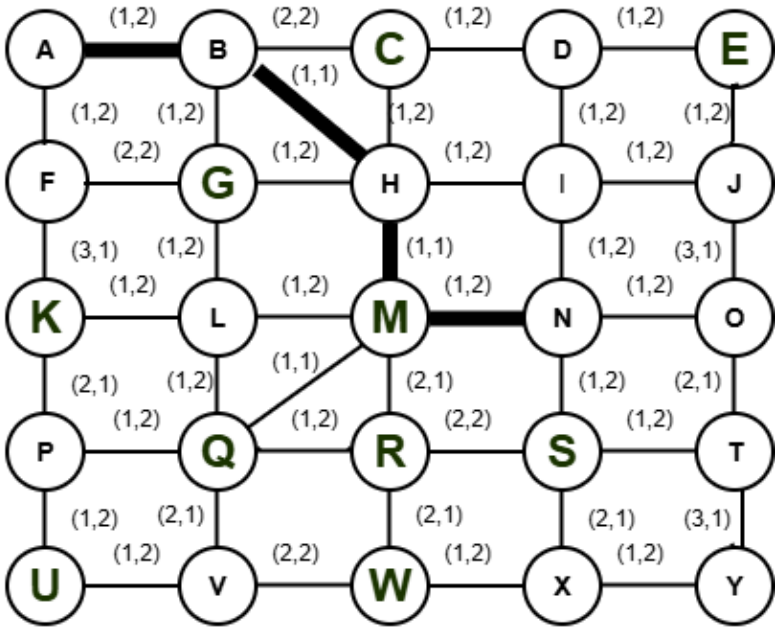


Figure 6. Example network for illustrating the Node-Encoded Shortest Path (NESP). The highlighted path shows a charging-feasible route.

Consider again the evacuation network shown in Figure 4. Suppose a vehicle travels along the route $A \rightarrow B \rightarrow H \rightarrow M \rightarrow N$. As the vehicle moves from one node to the next, NESP tracks the accumulated distance since the most recent charging-station visit. If the vehicle reaches a charging station such as node M, the accumulated distance is reset to zero. If the vehicle attempts to traverse a sequence of road segments whose total distance exceeds F before reaching another charging station, the corresponding state is discarded as infeasible.

Figure 7 shows such a situation. Although the highlighted route exists in the transportation network, the distance between charging-station visits exceeds the allowable driving range. As a result, the route cannot be used by an electric vehicle under the RC-ERP model. NESP prevents this situation by pruning states that violate the driving-range constraint during the search process.

Using this node-encoded representation, a shortest-path search is performed while tracking the accumulated travel distance. Whenever the vehicle reaches a charging station, the distance counter is reset. States that exceed the allowable distance limit are removed from the search. Therefore, NESP guarantees that each route it returns satisfies the driving-range constraint. The global evacuation schedule is then handled by the time-expanded scheduling stage described later.

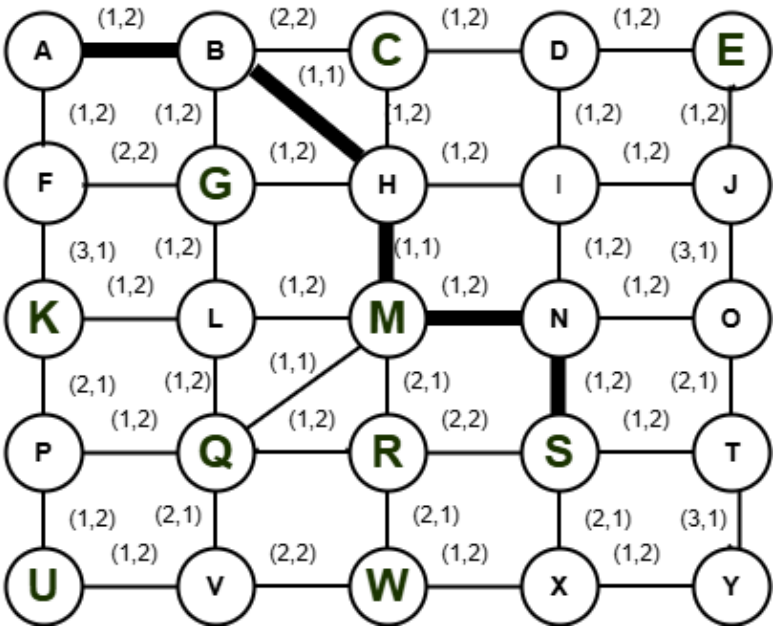


Figure 7. Example of a charging-constraint violation. The highlighted route contains a segment whose length exceeds the maximum allowable distance between charging visits.

Pruning and Efficiency

The proposed NESP procedure computes charging-feasible routes through an iterative search process that expands charge-encoded states while eliminating infeasible or dominated candidates. A state is infeasible if its accumulated distance since the most recent charging-station visit exceeds F. A state is dominated if another state reaches the same physical node with no greater travel cost and no greater accumulated distance since the most recent charging-station visit.

Iteration 1 (Initialization). The algorithm begins by inserting the source node A into the priority queue as the initial charge-encoded state $(A, 0, 0)$, representing zero distance traveled since the most recent charging-station visit and zero cumulative travel cost. All immediate neighbors of A are evaluated, and feasible successor states are generated subject to the driving-range constraint. Figure 8 shows this initialization stage. In Figure 8, blue-labeled nodes denote closed states, while gray-labeled nodes represent open candidate states. Table 1 lists the open and closed charge-encoded node sets for this initialization stage.

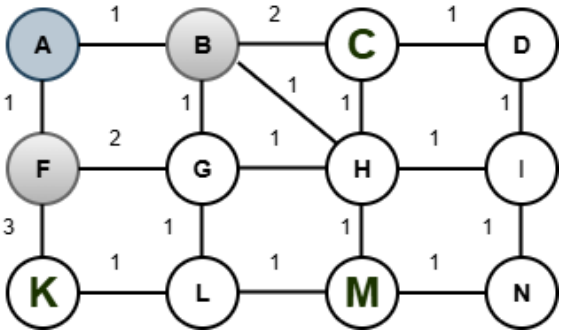


Figure 8. Iteration 1: initialization of the NESP search. The source node A is inserted into the priority queue as the initial charge-encoded state $(A, 0, 0)$. Blue-labeled nodes denote closed states, while gray-labeled nodes represent open candidate states.

Table 1. Open and closed charge-encoded node sets during Iteration 1 of the search.

Open Charge-Encoded Nodes			Closed Charge-Encoded Nodes		
Node	**Dist**	**Pred**	**Node**	**Dist**	**Pred**
B(1)	1	A(0)–B(1)	A(0)	0	–
F(1)	1	A(0)–F(1)			

Iterations 2–3 (Early/Intermediate Expansion). The charge-encoded state with the smallest cumulative distance is extracted and expanded. Feasible charge-encoded successors are generated for neighboring nodes, including multiple representations of the same physical node with different accumulated distances since the most recent charging-station visit. As the frontier advances, states whose shortest feasible distances are finalized are moved to the closed set. Figure 9 shows a representative expansion stage. Table 2 shows the open and closed charge-encoded node sets during Iteration 3.

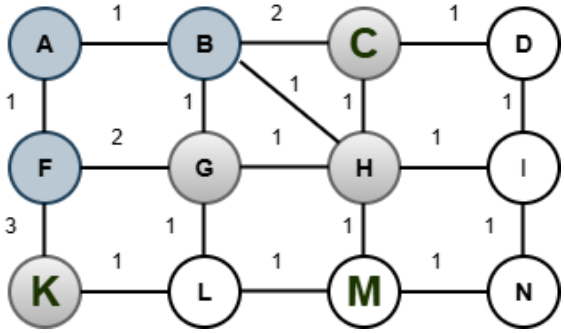


Figure 9. Iteration 3: intermediate expansion of the search frontier. Feasible charge-encoded states are expanded while finalized nodes are moved to the closed set. Blue-labeled nodes denote closed states, while gray-labeled nodes represent open candidate states.

Table 2. Open and closed charge-encoded node sets during Iteration 3 of the search.

Open Charge-Encoded Nodes			Closed Charge-Encoded Nodes		
Node	**Dist**	**Pred**	**Node**	**Dist**	**Pred**
C(0)	3	A(0)–B(1)	A(0)	0	–
G(2)	2	A(0)–B(1)	B(1)	1	A(0)
H(2)	2	A(0)–B(1)	F(1)	1	A(0)
K(0)	4	A(0)–F(1)			

Iterations 4–6. During these iterations, the algorithm continues expanding feasible states in increasing order of cumulative distance. Dominance-based pruning removes states that are inferior in both cumulative distance and accumulated distance since the most recent charging-station visit, thereby reducing redundant exploration.

Iteration 7 (Constraint Enforcement). As the search progresses deeper into the network, driving-range feasibility becomes increasingly restrictive. States that exceed the maximum allowable distance between consecutive charging-station visits are immediately removed. Figure 10 shows this enforcement stage. Table 3 provides a representative snapshot of the open and closed charge-encoded node sets during the search process. The open set contains candidate states yet to be expanded, while the closed set records finalized states.

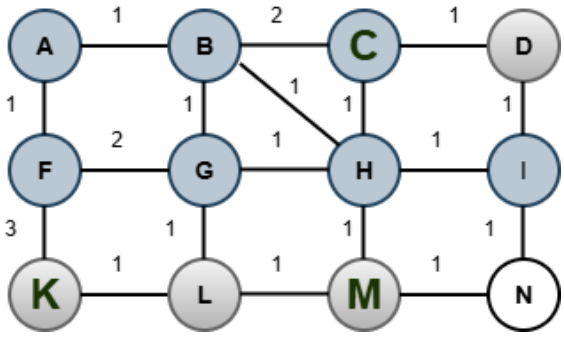


Figure 10. Iteration 7: Constraint enforcement during the search. Charge-encoded states that exceed the maximum allowable distance between charging stations are removed.

Table 3. Open and closed charge-encoded node sets during Iteration 7 of the search.

Open Charge-Encoded Nodes			Closed Charge-Encoded Nodes		
Node	**Dist**	**Pred**	**Node**	**Dist**	**Pred**
K(0)	4	A(0)–F(1)	A(0)	0	–
L(3)	3	A(0)–B(1)–G(0)	B(1)	1	A(0)
M(3)	3	A(0)–B(1)–H(2)	F(1)	1	A(0)
D(1)	4	A(0)–B(1)–C(0)	G(0)	2	A(0)–B(1)
			H(2)	2	A(0)–B(1)
			C(0)	3	A(0)–B(1)
			I(3)	3	A(0)–B(1)–H(2)

Iterations 8–11 (Contraction and Termination). After constraint enforcement, the search space contracts significantly, leaving only feasible and non-dominated states in the priority queue. During these iterations, dominated states are pruned whenever multiple states reach the same node but one has a larger cumulative cost and a larger accumulated distance since the most recent charging-station visit. Such inferior states are discarded to avoid unnecessary exploration. Figure 11 illustrates a representative example at node N, where alternative states arriving at N are compared and dominated ones are pruned. This process reduces the number of candidate states and guides the search toward feasible paths.

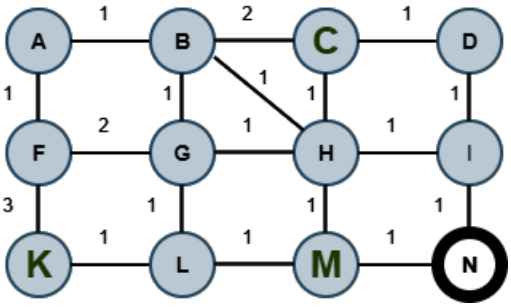


Figure 11. Example of pruning during routing. States violating the charging constraint ($d > F$) or dominated by better states are discarded.

Table 4 summarizes the iterative evaluation of charge-encoded states during the NESP search process. At each iteration, the state with the smallest cumulative distance is expanded while alternative candidates are explored and dominated states are pruned. This process ultimately yields the feasible route $A \rightarrow B \rightarrow H \rightarrow M \rightarrow N$, where node M represents a charging station that resets the accumulated-distance state.

Table 4. Iterative evaluation process highlighting the main feasible path to node N.

Iter	Node	Dist	Action
1	A	0	Initialize source state
2	B	1	Expand from A (main path)
3	F	1	Expand alternative state from A
4	G	2	Expand alternative state from B
5	H	2	Expand from B (main path)
6	C	3	Expand alternative state from B
7	I	3	Expand alternative state from H
8	L	3	Expand alternative state from G
9	M	3	Expand from H; charging reset ($M \in CS$)
10	D	4	Expand alternative state from C
11	N	4	Reach feasible state from M; dominated states pruned

Algorithm 2 presents the pseudo-code for the Node-Encoded Shortest Path (NESP) procedure used to compute charging-feasible routes. The input to the algorithm is a transportation network, a source node, a destination node, a set of charging stations, and the maximum travel distance F. The output is a charging-feasible route. NESP initializes the state $(o, 0)$ and inserts it into a priority queue. It then repeatedly extracts the minimum-cost state (v, d) and expands it along outgoing edges. When the next node is a charging station, the accumulated distance is reset; otherwise, it is increased by the edge length. Any state exceeding the limit F is discarded, and feasible states are relaxed and inserted back into the queue. This process continues until the destination is reached or the queue is empty.

Algorithm 2: Node-Encoded Shortest Path (NESP)

Inputs:

- A transportation network $G(V, E)$
- Source node o and destination node s
- Set of charging stations CS
- Maximum travel distance between charging-station visits F

Output:

- A charging-feasible evacuation route P

Steps:

1. Initialize the state $(o, 0)$, where the second component represents the distance since the most recent charging-station visit.
2. Create a priority queue for shortest-path exploration.
3. While the queue is not empty do
   (a) Extract the state (v, d) with the minimum travel cost.
   (b) For each neighboring edge $(v, u) \in E$ do
      i. If $u \in CS$, set $d' = 0$; otherwise set $d' = d + w(v, u)$.
      ii. If $d' \leq F$, relax the state (u, d') and update its distance.
4. End while
5. Return the best charging-feasible route reaching the destination node s.

2.3. Time-Expanded Evacuation Scheduling

The second component of TE-CERA schedules the charging-feasible routes produced by NESP while enforcing road-capacity constraints. Since multiple evacuees may attempt to use the same road segment at the same time, a route that is feasible with respect to

driving range may still be infeasible with respect to road capacity. TE-CERA addresses this issue using a time-indexed occupancy table.

For each road segment e and time step t, the occupancy table stores the number of vehicles already assigned to edge e at time t. Before assigning an evacuee to a route, TE-CERA checks whether all edges on the route have available capacity during their corresponding traversal intervals. If any edge would exceed its capacity, the departure time is delayed until the entire route can be reserved without violating road capacity. This procedure produces capacity-feasible schedules for the selected charging-feasible routes.

It is important to note that this scheduling stage is constructive and sequential. The route is first selected by NESP, and capacity conflicts are then resolved mainly by adjusting departure times. Therefore, TE-CERA guarantees feasibility under the stated model, but it does not claim global optimality of the evacuation makespan. A globally optimal solution would require jointly optimizing route choices, departure times, road capacities, and charge states over the full node–time–charge space, which is computationally expensive for large-scale networks.

To show how TE-CERA computes evacuation routes and schedules, consider the evacuation network shown in Figure 4. Nodes represent intersections, and larger-labeled nodes denote charging stations. Each edge is labeled with its travel time and capacity. A candidate evacuation route from node A to node Y is

$$A \to B \to H \to M \to N \to S \to X \to Y.$$

This route is charging-feasible because the vehicle encounters charging stations before exceeding its maximum allowable travel range.

Step-by-Step Toy Example

To illustrate the scheduling procedure, consider two evacuees located at source node A. Both evacuees initially select the same charging-feasible route

$$A \to B \to H \to M \to N \to S \to X \to Y$$

computed by the NESP procedure.

Step 1: Scheduling the first evacuee. The first evacuee departs from node A at time 0 and traverses the route without delay. For each edge (u, v) along the route, TE-CERA records the time interval during which the edge is occupied according to its travel time. Since no other evacuee has been scheduled yet, all edges along the route are available.

Step 2: Attempting to schedule the second evacuee. The second evacuee initially attempts to depart at time 0 and follow the same route. However, when TE-CERA checks the time-indexed occupancy table, it detects that at least one shared edge, such as (H, M), is already occupied during the corresponding time interval.

Step 3: Resolving the capacity conflict. To avoid the capacity violation, TE-CERA postpones the departure time of the second evacuee. The algorithm then recomputes the traversal times along the route and checks the occupancy table again. This process continues until all edges on the route have available capacity for the required traversal intervals.

Step 4: Final feasible schedule. After adjusting the departure time, both evacuees traverse the same route but reach the shared edge (H, M) at different times. As a result, the final evacuation schedule satisfies both the driving-range constraint and the road-capacity constraint.

Figure 12 illustrates the capacity conflict that occurs when two vehicles attempt to traverse the same road segment at the same time. Figure 13 shows the resulting feasible route after scheduling adjustments. This example demonstrates how TE-CERA integrates

charging-feasible routing with time-expanded capacity management to generate evacuation plans that respect both electric-vehicle range limits and shared road capacities.

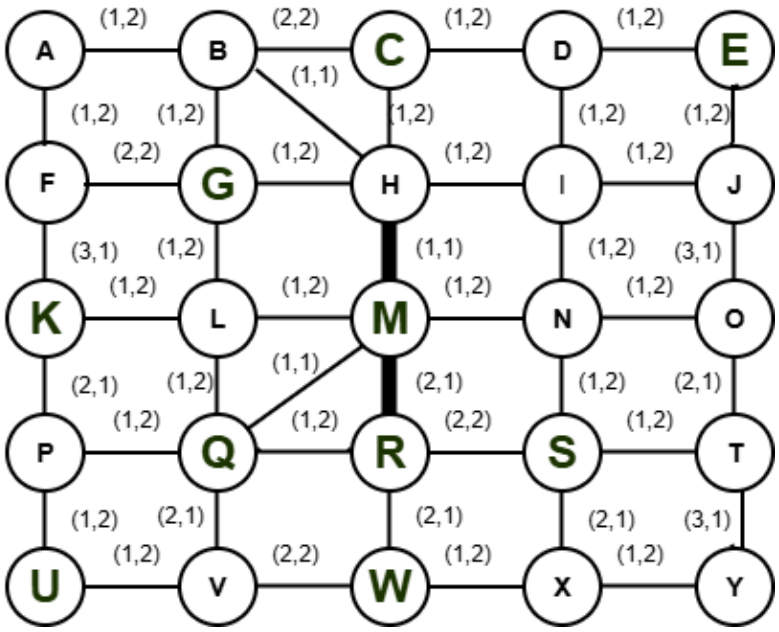


Figure 12. Capacity conflict during evacuation scheduling. The highlighted segment indicates the road segment where two vehicles attempt to traverse simultaneously.

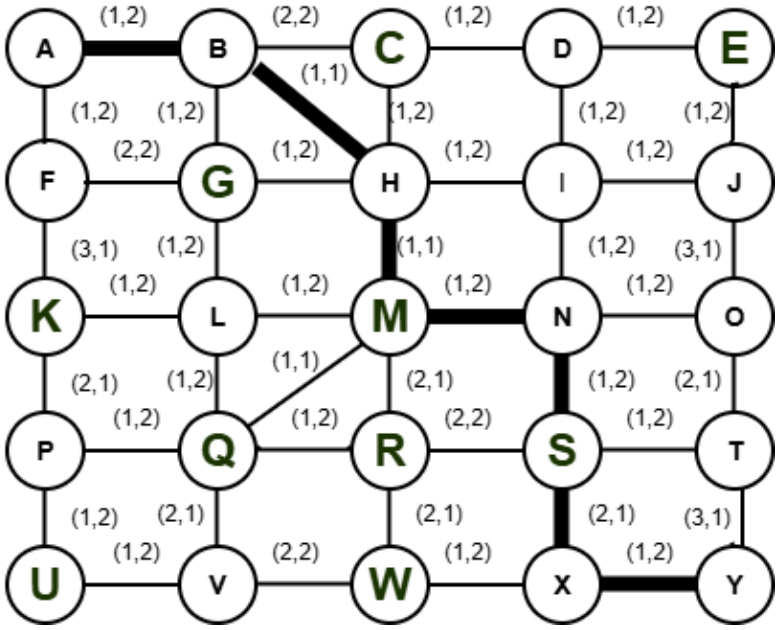


Figure 13. Feasible evacuation route computed by TE-CERA after resolving capacity conflicts through time-expanded scheduling.

Algorithm 3 summarizes the TE-CERA scheduling procedure. The algorithm processes evacuees sequentially. For each evacuee, it obtains a charging-feasible route from NESP and then searches for the earliest departure time that does not violate road-capacity constraints. Once a feasible departure time is found, the corresponding edge-time intervals are reserved in the occupancy table. This procedure continues until all evacuees are assigned routes and departure times. The resulting schedule is feasible with respect to the charging and road-capacity constraints.

Algorithm 3: Time-Expanded Evacuation Scheduling (TE-CERA)

Inputs:

- Set of evacuees K
- Charging-feasible routes computed by NESP
- Edge travel times and edge capacities
- Planning horizon $T_{\max}$: the maximum allowable departure time, set as the sum of all edge travel times on the longest route plus a buffer proportional to the number of evacuees and minimum edge capacity

Output:

- Evacuation schedule containing a route and departure time for each evacuee

Steps:

1. Initialize the time-indexed occupancy table for all edges.
2. For each evacuee $k \in K$ do
   (a) Obtain a charging-feasible route P_k from the NESP procedure.
   (b) Set the initial departure time $t = 0$.
   (c) Check whether each edge along P_k has available capacity during the corresponding traversal interval.
   (d) If any edge capacity would be violated, increment the departure time by one time step and repeat the capacity check. If $t > T_{\max}$, report that no feasible departure time exists within the planning horizon for evacuee k and terminate.
   (e) Reserve the required edge capacities in the occupancy table.
   (f) Record the route and departure time for evacuee k.
3. End for
4. Return the final evacuation schedule.

3. Feasibility and Complexity Analysis

This section analyzes the feasibility guarantees and computational cost of the proposed TE-CERA framework. Since TE-CERA is a constructive heuristic, the analysis focuses on showing that the generated evacuation plans satisfy the driving-range constraint, road-capacity constraint, FIFO assumption, and termination condition.

3.1. Feasibility Analysis

The following lemmas establish that TE-CERA produces evacuation plans that satisfy the main constraints of the RC-ERP problem under the stated modeling assumptions.

Lemma 1. *The routes produced by the NESP procedure satisfy the driving-range constraint.*

Proof. NESP represents each search state as (v, d), where v is the current node and d is the accumulated travel distance since the most recent charging-station visit. When the algorithm considers moving from node v to node u along edge (v, u), the updated distance is computed as $d' = d + W(v, u)$ if u is not a charging station. If u is a charging station, the accumulated distance is reset to $d' = 0$. NESP inserts or relaxes a successor state only when $d' \leq F$. Therefore, every accepted transition satisfies the maximum travel-distance bound between consecutive charging-station visits. Since all routes returned by NESP are composed only of accepted transitions, each returned route satisfies the driving-range constraint. □

Figure 14 shows a charging-feasible route on the evacuation network. Nodes with larger labels represent charging stations.

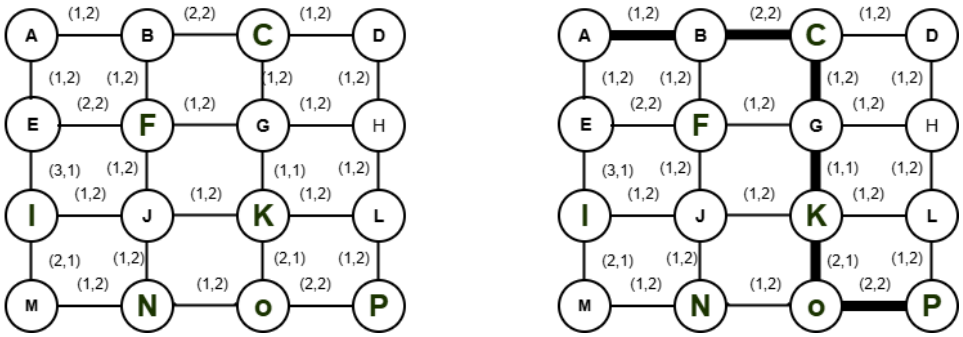


Figure 14. Charging-feasible route on an evacuation network. Nodes with larger labels represent charging stations. The figure size has been increased for readability.

Lemma 2. *The TE-CERA scheduling procedure satisfies the road-capacity constraint for all scheduled evacuees.*

Proof. TE-CERA maintains a time-indexed occupancy table $occ(e, t)$ for each edge e and time step t. Before assigning an evacuee to a departure time, the algorithm checks whether every edge on the selected route has available capacity during the corresponding traversal interval. A reservation is made only if

$$occ(e, t) + 1 \leq C_e$$

for every edge-time pair used by the evacuee. If this condition is not satisfied for any edge-time pair, the departure time is postponed and the capacity check is repeated. Therefore, the algorithm never reserves an edge-time pair beyond its capacity. Hence, the final schedule satisfies the road-capacity constraint. □

Lemma 3. *The TE-CERA scheduling procedure preserves the FIFO property under fixed positive edge travel times.*

Proof. In the time-expanded representation, movement along an edge e connects time t to time $t + T_e$, where $T_e > 0$ is fixed. Thus, if two vehicles traverse the same edge and one vehicle departs earlier, the earlier vehicle reaches the end of the edge no later than a vehicle departing later on that same edge. Since TE-CERA only delays departures to avoid capacity violations and does not allow overtaking on an edge, the FIFO property is preserved. □

Lemma 4. *TE-CERA terminates for a finite number of evacuees and a finite planning horizon.*

Proof. The number of evacuees is finite. For each evacuee, NESP searches over a finite charge-encoded state space because the graph is finite and the accumulated-distance state is bounded by F. After a charging-feasible route is obtained, the scheduling procedure checks departure times within a finite planning horizon. Therefore, each evacuee requires a finite number of route-generation and scheduling operations. Since the algorithm processes a finite number of evacuees, TE-CERA terminates. □

In practice, the planning horizon $T_{\max}$ is set conservatively as the sum of all edge travel times along the longest computed route multiplied by the number of evacuees sharing that route, divided by the minimum edge capacity. This upper bound guarantees that sufficient

time steps exist to schedule all evacuees sequentially without exceeding capacity, and is the value used in our experiments.

Lemma 5. *If NESP finds a charging-feasible route for each evacuee and the planning horizon is large enough to accommodate the required capacity reservations, then TE-CERA returns a feasible evacuation plan.*

Proof. By Lemma 1, each route returned by NESP satisfies the driving-range constraint. By Lemma 2, the scheduling stage reserves edge-time intervals only when road capacity is available. By Lemma 3, scheduled movements preserve FIFO under fixed positive travel times. Therefore, if a charging-feasible route exists for each evacuee and the planning horizon is sufficient, the plan returned by TE-CERA satisfies the driving-range, road-capacity, and FIFO constraints. □

3.2. Complexity Analysis

Let $n = |N|$ be the number of nodes, $m = |E|$ be the number of edges, $p = |K|$ be the number of evacuees, and F be the maximum accumulated-distance bound. In NESP, each physical node may be represented by multiple charge-encoded states. In the worst case, each node can have up to F accumulated-distance states. Therefore, the number of charge-encoded states is $O(nF)$, and the number of charge-encoded edge relaxations is $O(mF)$.

Using a priority queue, the cost of one NESP route computation is

$$O(F(n \log n + m)).$$

If a route is computed for each evacuee, the total routing cost is

$$O(pF(n \log n + m)).$$

The scheduling stage checks the time-indexed occupancy table for the edges on each selected route. Let L denote the maximum number of edges in a selected route and let H denote the maximum number of departure-time shifts checked before a feasible departure time is found. The scheduling cost is then

$$O(pLH).$$

Thus, the overall computational cost of TE-CERA can be written as

$$O(pF(n \log n + m) + pLH). \tag{10}$$

A direct node–time–charge expansion would require maintaining states over node, time, and accumulated-distance dimensions, resulting in a storage requirement of $O(nT_{\max}F)$. TE-CERA avoids constructing this full three-dimensional state space by decoupling charge-feasible route generation from time-expanded capacity scheduling. The route-generation stage stores charge-encoded spatial states, while the scheduling stage stores edge-time occupancy information. This decoupled structure improves memory efficiency for large transportation networks while preserving the feasibility guarantees proved above.

4. Experimental Evaluation

We conducted experiments to evaluate the feasibility, scalability, and evacuation performance of the proposed TE-CERA framework. The experiments focus on three main questions. First, can TE-CERA produce evacuation schedules with no driving-range violations while

respecting road-capacity constraints? Second, what is the computational cost of enforcing the charging constraint compared with a capacity-constrained evacuation routing baseline? Third, how do the number of evacuees, source nodes, charging stations, and destination nodes affect runtime, evacuation completion time, and charging-feasibility violations?

We compare TE-CERA with the Capacity-Constrained Route Planner (CCRP), a representative capacity-constrained evacuation routing baseline. CCRP is included because it is designed for evacuation scheduling under road-capacity constraints. However, CCRP does not explicitly model electric-vehicle driving-range constraints or charging-station visits. In this sense, CCRP can be viewed as a conventional-vehicle or infinite-range baseline. Therefore, the comparison should be interpreted as evaluating the additional effect and computational cost of adding driving-range feasibility to capacity-aware evacuation routing, rather than as a claim that CCRP is a charging-aware method.

The experiments are organized around four research questions:

(1) What is the effect of the number of evacuees?
(2) What is the effect of the number of source nodes?
(3) What is the effect of the number of charging stations?
(4) What is the effect of the number of destination nodes?

4.1. Experiment Layout

Figure 15 shows the experimental setup for the RC-ERP problem. We selected four municipal road networks from OpenStreetMap [34], ranging from a small urban network to a large regional network. Table 5 shows the number of nodes and edges in each network. Road-property information, such as road type and number of lanes, was used to construct edge travel times and road-capacity values. In all experiments, travel times and capacities were fixed according to the extracted road-network properties.

The algorithms were implemented in Java 1.8. All experiments were performed on an Intel Core i7-10510U CPU at 1.80 GHz with 16 GB of RAM, running Windows 11. The reported runtimes were averaged over 10 runs.

In the main experiments, the maximum travel distance between consecutive charging-station visits was set to $F = 15$ miles. This value is intentionally conservative and is used as a stress-test setting to evaluate algorithm behavior under restrictive driving-range conditions. It should not be interpreted as the typical full range of a modern electric vehicle. Rather, it represents a planning scenario in which the usable range may be reduced by emergency conditions, congestion, detours, battery reserve requirements, or conservative safety margins. This setting follows prior work on resource-constrained routing under emergency conditions, where reduced effective range values are used to stress test algorithm robustness [18,29]. The evacuee counts (500–2500) and source-node counts (500–2500) were chosen to span a range from small local evacuations to large regional events, consistent with the network sizes in Table 5 and with parameter ranges used in prior capacity-constrained evacuation studies [13,14]. The destination-node count (100) reflects a typical number of designated safe zones in regional emergency plans.

For the New Orleans experiments, the number of candidate charging-station nodes was set to $CS = 500$ unless otherwise stated. This value was selected to represent a plausible density of charging infrastructure relative to the New Orleans network size (134,621 nodes), yielding approximately one candidate charger per 270 network nodes. While this does not reflect the exact deployed infrastructure, it falls within the range of EV charging densities studied in urban transportation networks [24,26]. These charging stations are modeled as candidate range-reset locations for algorithmic evaluation. The purpose is to evaluate the effect of charging-feasibility constraints on evacuation routing under a controlled network setting.

Some figures also report evacuation completion time with a penalty delay for charging violations. This penalty is used only as an illustrative measure of the possible operational impact of assigning an electric vehicle to a route that exceeds its driving-range limit. Such delay may arise from vehicle stalling, emergency assistance, rerouting, or unplanned charging. Because the exact penalty depends on incident-specific operating conditions, penalty-based results should be interpreted as sensitivity indicators rather than fixed real-world delay estimates.

Table 5. Transportation network datasets (source: OpenStreetMap).

Area	No. of Nodes ($\|V\|$)	No. of Edges ($\|E\|$)
Jacksonville, FL, USA	17,461	50,194
New Orleans, LA, USA	134,621	382,484
Miami, FL, USA	220,632	627,976
Central Florida, USA	329,929	935,490

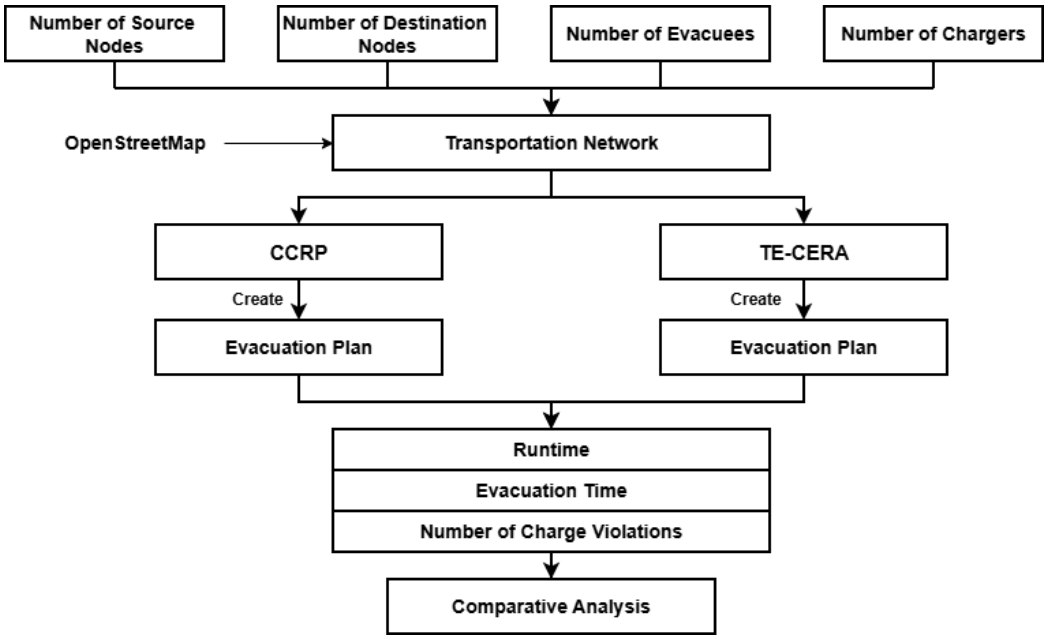


Figure 15. Experimental layout for evaluating evacuation routing algorithms.

4.2. Baseline and Evaluation Scope

We compare TE-CERA with the Capacity-Constrained Route Planner (CCRP), a representative capacity-constrained evacuation routing baseline. CCRP considers road capacity during evacuation scheduling, but it does not explicitly model electric-vehicle driving-range constraints or charging-station visits. Therefore, in this study CCRP is interpreted as a conventional-vehicle or infinite-range baseline. The purpose of the comparison is not to treat CCRP as a charging-aware competitor, but to evaluate the effect of adding driving-range feasibility to capacity-constrained evacuation routing.

The comparison reports runtime, evacuation completion time, and the number of charging-constraint violations. TE-CERA eliminates charging-constraint violations because the NESP route-generation stage explicitly enforces the maximum travel-distance bound F. CCRP may produce charging-constraint violations because it does not track accumulated travel distance between charging-station visits.

We also report evacuation completion time with penalty delay as an illustrative measure of the possible operational impact of charging-constraint violations. The penalty represents additional delay that may occur due to vehicle stalling, emergency assistance,

rerouting, or unplanned charging. Since the exact delay depends on operational conditions, the penalty-based results should be interpreted as a sensitivity indicator rather than as a fixed real-world delay estimate.

We acknowledge that a charging-aware baseline comparison would further strengthen the evaluation. However, to our knowledge, no existing publicly available evacuation routing method simultaneously enforces both a maximum inter-charger travel-distance constraint and shared time-dependent road-capacity constraints at the scale of the networks used here. Existing EV routing methods such as those in [18,20,21,29] are designed for individual vehicle or small-fleet logistics and do not incorporate large-scale capacity scheduling. Adapting these methods to handle hundreds or thousands of simultaneous evacuees sharing road capacity would require non-trivial re-engineering that goes beyond the scope of the present paper. The primary purpose of the current comparison is therefore to quantify the computational overhead and feasibility benefit of adding driving-range enforcement to a well-established capacity-aware evacuation planner. A rigorous comparison against charging-aware multi-vehicle routing methods, including potential ablation studies that isolate the NESP and scheduling components independently, is planned as a direct extension of this work.

4.3. Experiment Results and Analysis

The following experiments compare TE-CERA with CCRP under different evacuation settings. Since CCRP does not model electric-vehicle driving range, the number of charging-constraint violations for CCRP is reported to show the limitation of applying an infinite-range capacity-constrained evacuation planner to electric-vehicle evacuation. TE-CERA explicitly enforces the maximum travel-distance bound F through NESP; therefore, it produces no charging-constraint violations under the stated range-reset charging model. The main interpretation of the experiments is the trade-off between additional computational cost and improved driving-range feasibility.

The penalty-delay plots are included as illustrative sensitivity results. They show how evacuation completion time may increase if a charging-constraint violation causes vehicle stalling, unplanned rerouting, emergency assistance, or unplanned charging. The penalty is not part of the TE-CERA optimization objective and should not be interpreted as a fixed real-world delay value.

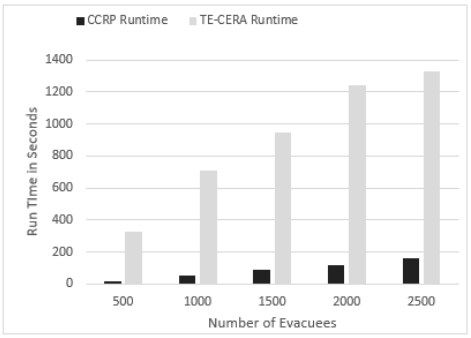
4.3.1. Effect of the Number of Evacuees

The first experiment evaluated the effect of the number of evacuees on algorithm performance. The performance measurements were runtime, evacuation completion time, and number of charging-constraint violations. We used the road networks listed in Table 5. In this experiment, Dataset 2 (New Orleans) was used. We fixed the number of source nodes to $|S| = 2000$ and the number of destination nodes to $|D| = 100$. The number of charging stations was set to $CS = 500$, and the maximum feasible travel distance without recharging was set to $F = 15$ miles. The number of evacuees was varied from 500 to 2500 in increments of 500. The execution times were averaged over 10 test runs.

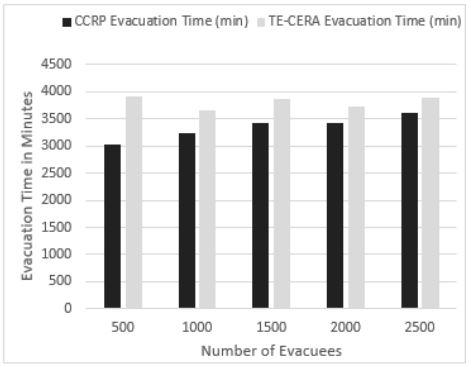
Figure 16a shows the runtimes. As the number of evacuees increases, the runtime for both approaches increases. CCRP requires less computation time because it does not enforce the driving-range constraint. TE-CERA requires additional computation to track accumulated travel distance and generate charging-feasible routes. Figure 16b shows the evacuation completion time, and Figure 16c shows the number of charging-constraint violations. TE-CERA produces evacuation routes with no charging-constraint violations, while CCRP produces violations because it assumes conventional or infinite-range vehicles.

As the number of evacuees increases, the number of CCRP charging-constraint violations also increases.

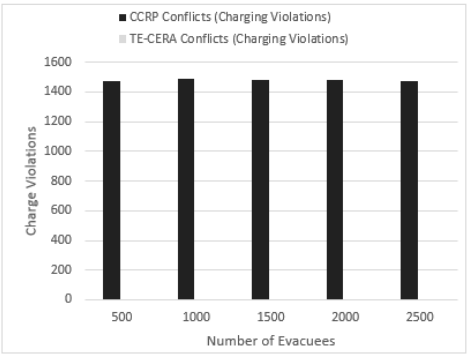
Figure 16d shows evacuation completion time with penalty delay for charging-constraint violations. The penalized completion time of CCRP increases as the number of evacuees increases because more routes may violate the driving-range bound. TE-CERA is not affected by this penalty because it produces charging-feasible routes under the stated model. This result illustrates the potential operational cost of ignoring driving-range feasibility in electric-vehicle evacuation planning.



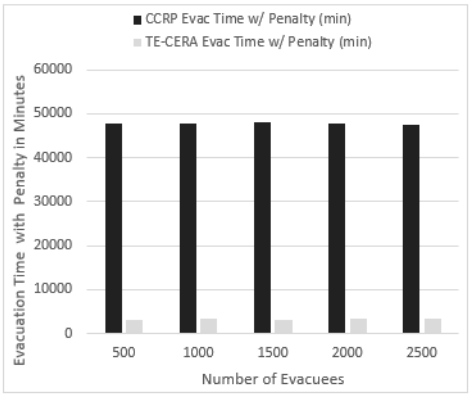
(**a**) Runtime



(**b**) Evacuation Time



(**c**) Charge Violations



(**d**) Evacuation Time with Penalty

Figure 16. Effect of the number of evacuees ($|S| = 2000$, $|D| = 100$).

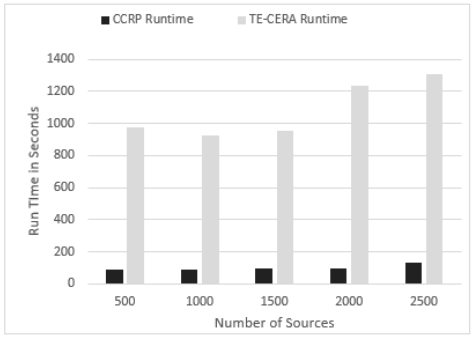
4.3.2. Effect of the Number of Source Nodes

The second set of experiments evaluated the effect of the number of source nodes on algorithm performance. The performance measurements were runtime, evacuation completion time, and number of charging-constraint violations. We used the road networks listed in Table 5. We fixed the number of destination nodes to $|D| = 100$ and the number of evacuees to $|P| = 2000$. The number of charging stations was set to $CS = 500$, and the maximum feasible travel distance without recharging was set to $F = 15$ miles. The number of source nodes was varied from 500 to 2500. The execution times were averaged over 10 test runs.

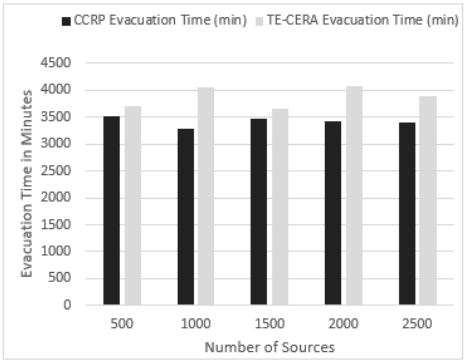
Figure 17a shows the runtimes of the two approaches. As the number of source nodes increases, the runtime of both approaches increases. CCRP is faster because it does not track the accumulated travel distance between charging-station visits. TE-CERA has additional computational overhead because it enforces driving-range feasibility during route generation. Figure 17b shows the evacuation completion time, and Figure 17c shows the number of charging-constraint violations. As the number of source nodes increases,

evacuation completion time slightly decreases because evacuees are distributed across more starting locations. CCRP may produce a large number of charging-constraint violations because it does not model electric-vehicle range feasibility, whereas TE-CERA produces no such violations under the stated model.

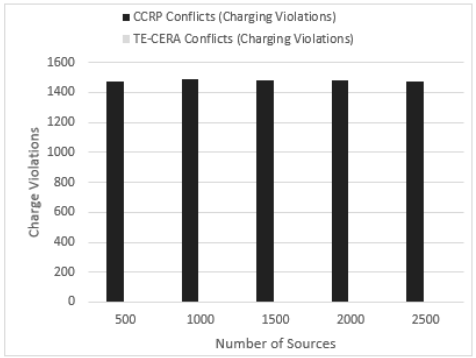
Figure 17d shows evacuation completion time with penalty delay for charging-constraint violations. The penalized completion time of CCRP reflects the possible delay caused by range-infeasible assignments. TE-CERA remains stable because its route-generation stage enforces the driving-range constraint. This result should be interpreted as evidence that adding charging-feasibility enforcement improves the operational feasibility of evacuation schedules for electric vehicles.



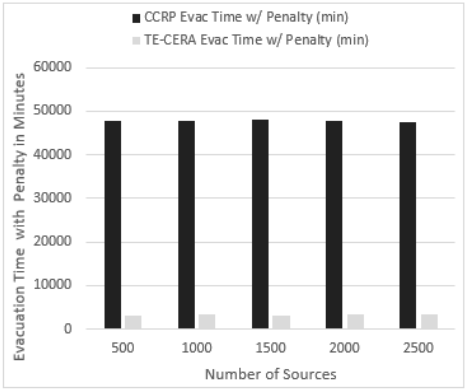
(**a**) Runtime



(**b**) Evacuation Time



(**c**) Charge Violations



(**d**) Evacuation Time with Penalty

Figure 17. Effect of the number of source nodes ($|P| = 1000$, $|D| = 100$).

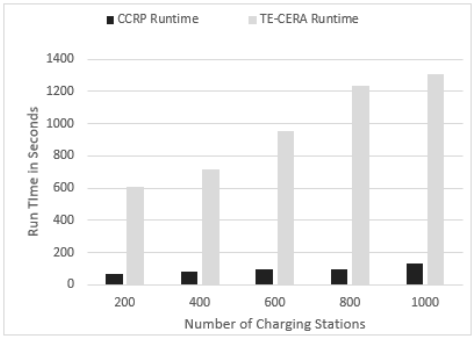
4.3.3. Effect of the Number of Charging Stations

The third set of experiments evaluated the effect of the number of charging stations on algorithm performance. The performance measurements were runtime, evacuation completion time, and number of charging-constraint violations. We used Dataset 2 (New Orleans) from Table 5. We fixed the number of source nodes to $|S| = 1000$, the number of destination nodes to $|D| = 100$, and the number of evacuees to $|P| = 2000$. The number of charging stations was varied from 200 to 1000 in increments of 200. The execution times were averaged over 10 test runs.

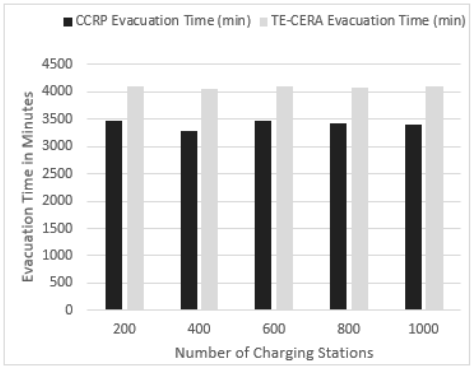
Figure 18a shows the runtimes of the two approaches. As the number of charging stations increases, the runtime for both approaches slightly increases. CCRP requires less computation time because it does not enforce the charging constraint. Figure 18b shows the evacuation completion time, and Figure 18c shows the number of charging-constraint violations. As the number of charging stations increases, evacuation completion time

slightly decreases because more range-reset locations become available for electric vehicles. CCRP can still generate charging-constraint violations because it does not explicitly track charging-station visits. In contrast, TE-CERA produces routes with no charging-constraint violations by construction under the range-reset model.

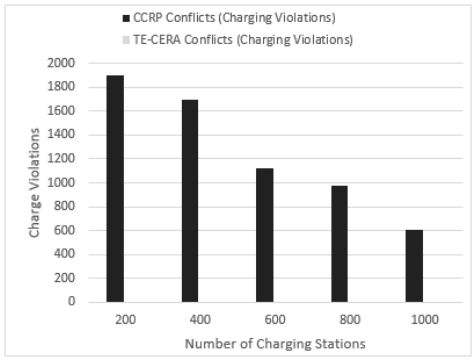
Figure 18d shows evacuation completion time with penalty delay. As the number of charging stations increases, driving-range feasibility becomes easier to satisfy because more range-reset locations are available. The penalized completion time of CCRP reflects the possible operational impact of range-infeasible route assignments. TE-CERA avoids such violations because NESP explicitly checks the maximum travel-distance bound F.



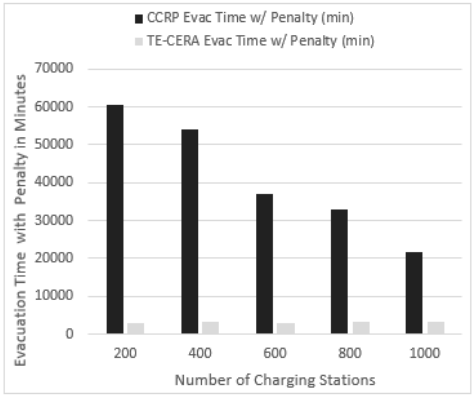
(**a**) Runtime



(**b**) Evacuation Time



(**c**) Charge Violations



(**d**) Evacuation Time with Penalty

Figure 18. Effect of the number of charging stations ($|P| = 2000$, $|S| = 1000$, $|D| = 100$).

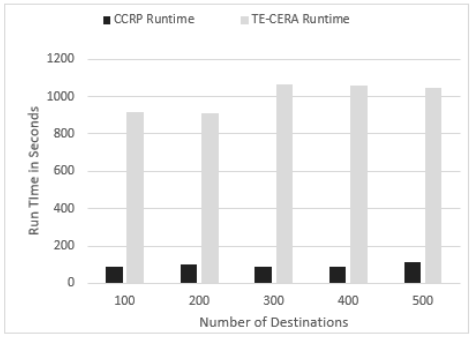
4.3.4. Effect of the Number of Destinations

The fourth set of experiments evaluated the effect of the number of destination nodes on algorithm performance. The performance measurements were runtime, evacuation completion time, and number of charging-constraint violations. We used the road networks listed in Table 5. We fixed the number of source nodes to $|S| = 1000$ and the number of evacuees to $|P| = 2000$. The number of charging stations was set to $CS = 500$, and the maximum feasible travel distance without recharging was set to $F = 15$ miles. The number of destination nodes was varied from 500 to 1000. The execution times were averaged over 10 test runs.

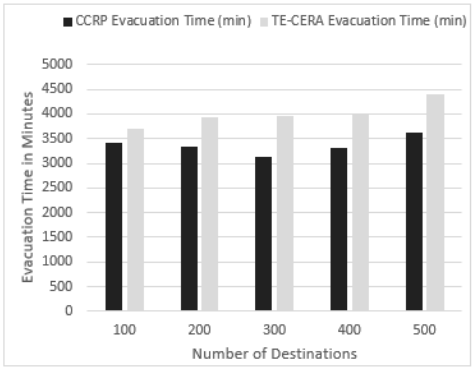
Figure 19a shows the runtimes of the two approaches. As the number of destination nodes increases, the runtime of the algorithms slightly decreases because more destination choices become available for distributing evacuees. CCRP is faster because it does not enforce the driving-range constraint. Figure 19b shows the evacuation completion time, and Figure 19c shows the number of charging-constraint violations. As the number of destination nodes increases, evacuation completion time slightly decreases because evacuees

can be distributed across more safe locations. CCRP may produce charging-constraint violations because it assumes conventional or infinite-range vehicles. TE-CERA produces no charging-constraint violations because each route is generated using the NESP procedure before capacity scheduling.

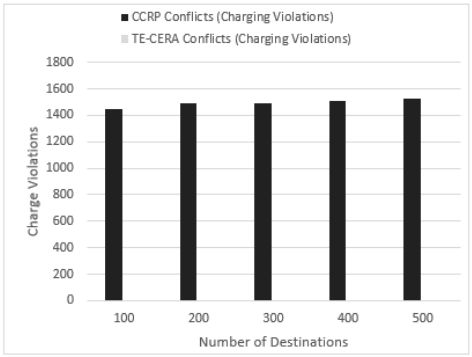
Figure 19d shows evacuation completion time with penalty delay for charging-constraint violations. CCRP may experience increased penalized completion time because it does not enforce the electric-vehicle driving-range bound. TE-CERA maintains charging-feasible schedules because NESP enforces the maximum travel-distance constraint between charging-station visits. This result highlights the benefit of incorporating driving-range feasibility into evacuation routing.



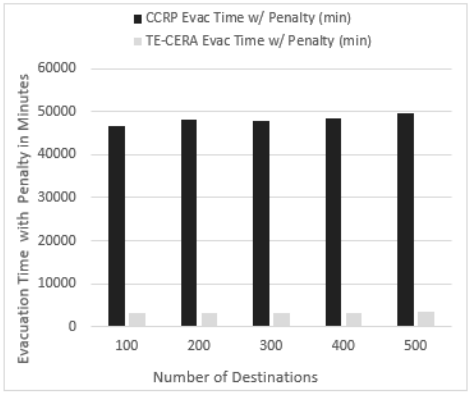
(**a**) Runtime



(**b**) Evacuation Time



(**c**) Charge Violations



(**d**) Evacuation Time with Penalty

Figure 19. Effect of the number of destination nodes ($|P| = 2000$, $|S| = 1000$).

4.4. Discussion

The experimental results show that TE-CERA consistently produces evacuation routes with no charging-constraint violations under the stated range-reset charging model. This result is expected because the NESP component explicitly prunes route states that exceed the maximum travel-distance bound F. CCRP, in contrast, is a capacity-constrained evacuation routing baseline that assumes conventional or infinite-range vehicles. Therefore, its charging-constraint violations demonstrate the limitation of applying a capacity-only evacuation planner directly to electric-vehicle evacuation.

The results also show a computational trade-off. CCRP generally has lower runtime because it does not track accumulated travel distance or enforce charging-station visits. TE-CERA requires additional computation to generate charging-feasible routes and then schedule them using time-expanded capacity management. This additional cost is the price of enforcing driving-range feasibility. In the tested networks, TE-CERA maintains comparable evacuation completion times while eliminating charging-constraint violations.

The slight decreases in evacuation completion time observed when the number of source nodes, charging stations, or destinations increases deserve specific attention. When source nodes increase, evacuees originate from more spatially distributed locations, reducing contention on individual road segments near high-density departure zones, which slightly shortens the overall makespan. When charging stations increase, NESP can find shorter charging-feasible routes because more range-reset points are available, reducing the detours needed to reach the nearest charger. When destination nodes increase, evacuees can be assigned to closer safe locations, directly reducing individual travel distances. In all three cases, the magnitude of change is modest because road-capacity bottlenecks remain the dominant constraint on evacuation completion time, and these bottlenecks are not eliminated by adding sources, chargers, or destinations alone. The practical implication is that infrastructure investments that relieve road-capacity bottlenecks—such as contraflow lane activation or staged departure scheduling—are likely to have greater operational impact on evacuation time than increasing the number of chargers or destinations within the ranges tested here.

The penalty-delay results should be interpreted carefully. They are included to illustrate the possible operational impact of range-infeasible assignments, such as vehicle stalling, emergency assistance, unplanned rerouting, or unplanned charging. The penalty is not part of the TE-CERA optimization objective, and its exact value depends on incident-specific conditions. Therefore, the primary conclusion of the experiments is that TE-CERA provides feasible evacuation schedules that satisfy both driving-range and road-capacity constraints under the stated assumptions, with comparable evacuation completion times to the baseline.

We note that the current experimental design does not include a dedicated charging-aware multi-vehicle routing baseline, as no such method is directly applicable to large-scale evacuation scheduling with shared time-dependent road capacities at the network scales considered here. An ablation study that evaluates the contribution of the NESP component independently of the time-expanded scheduling stage, for example by replacing NESP with a standard shortest-path that ignores charging feasibility and measuring the resulting violation rate and runtime difference, would provide additional insight into the isolated benefit of each component. Such ablation experiments, together with a comparison against adapted single-vehicle EV routing methods extended to multi-vehicle capacity-aware settings, are planned as immediate future work and will be reported in a follow-up study.

Finally, the experiments use a simplified charging model in which charging stations act as range-reset nodes. Charging duration, charger capacity, station-level queues, and power-grid limitations are not explicitly modeled. Therefore, the results should be viewed as evaluating driving-range feasibility rather than detailed charging-station operations. Extending the framework to incorporate charging-service time and station-level capacity is an important direction for future work.

The modeling assumptions of fixed travel times, fixed road capacity, and FIFO ordering warrant discussion in the context of real disaster evacuations. In practice, road congestion can dynamically alter effective travel times, road closures can eliminate segments from the network, and driver behavior may not follow FIFO order strictly. Similarly, charging stations may become unavailable due to power outages or damage. The present framework treats these as static inputs, which is appropriate for pre-event planning scenarios where planners construct schedules before a disaster strikes [9,10]. Under such conditions, fixed parameters represent the best available estimates, and the framework can be rerun as conditions change to generate updated plans. For real-time or dynamic replanning scenarios where conditions change continuously during an evacuation, extensions of TE-CERA

incorporating adaptive routing and dynamic capacity updates would be needed, and this is identified as an important direction for future work.

5. Conclusions and Future Work

Evacuation route computation is a critical component of emergency transportation planning during natural and human-made disasters such as hurricanes, floods, wildfires, and hazardous chemical incidents. As electric vehicles become more common, evacuation planning must account not only for road-capacity constraints but also for driving-range feasibility. Traditional capacity-constrained evacuation routing methods can generate road-capacity-aware schedules, but they may assign electric vehicles to routes that exceed the maximum feasible travel distance between charging-station visits.

In this paper, we studied the Resource Constraint Evacuation Route Planning (RC-ERP) problem, which combines evacuation routing, road-capacity constraints, and electric-vehicle driving-range constraints. We proposed the Time-Expanded Charge-Encoded Routing Algorithm (TE-CERA), a scalable constructive heuristic for generating evacuation schedules under these constraints. TE-CERA first uses the Node-Encoded Shortest Path (NESP) procedure to compute charging-feasible spatial routes by tracking the accumulated travel distance since the most recent charging-station visit. It then applies a time-expanded scheduling procedure to assign departure times while respecting road-capacity constraints.

Theoretical analysis showed that TE-CERA terminates and produces evacuation plans that satisfy the driving-range constraint, road-capacity constraint, and FIFO assumption under the stated model. The analysis also clarified that TE-CERA is a feasibility-oriented constructive heuristic rather than an exact global optimization algorithm for evacuation makespan minimization. This distinction is important because the proposed framework decouples charging-feasible route generation from capacity-aware scheduling in order to improve scalability on large transportation networks.

Experiments on real-world road networks demonstrated that TE-CERA produces evacuation routes with no charging-constraint violations under the range-reset charging model. Compared with CCRP, which is interpreted as a capacity-constrained conventional-vehicle or infinite-range baseline, TE-CERA incurs additional computational cost because it explicitly enforces driving-range feasibility. However, this additional cost allows the framework to avoid range-infeasible route assignments while maintaining comparable evacuation completion times in the tested scenarios.

This study uses a simplified charging model in which charging stations act as range-reset nodes. Therefore, the current formulation enforces driving-range feasibility but does not explicitly model charging duration, charger capacity, station-level queues, or power-grid limitations. These factors are important for real-world electric-vehicle evacuation operations and will be addressed in future work. Future extensions will incorporate charging-service time, charger availability, station-capacity constraints, and queueing effects. We also plan to investigate adaptive and real-time versions of TE-CERA that can update evacuation schedules in response to road closures, charging-station failures, traffic changes, and dynamic charging availability. A component-level ablation study and a comparison against charging-aware multi-vehicle routing methods adapted to large-scale evacuation settings are also planned to further validate the contribution of each algorithmic component. Finally, parallel and distributed implementations of the framework will be explored to improve scalability for regional-scale evacuation planning.

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X.J., T.K., and K.Y.; supervision, K.Y.; project administration, K.Y. All authors have read and agreed to the published version of the manuscript.

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