# Optimization of Emergency Evacuation Planning for Zero-Emission Vehicles

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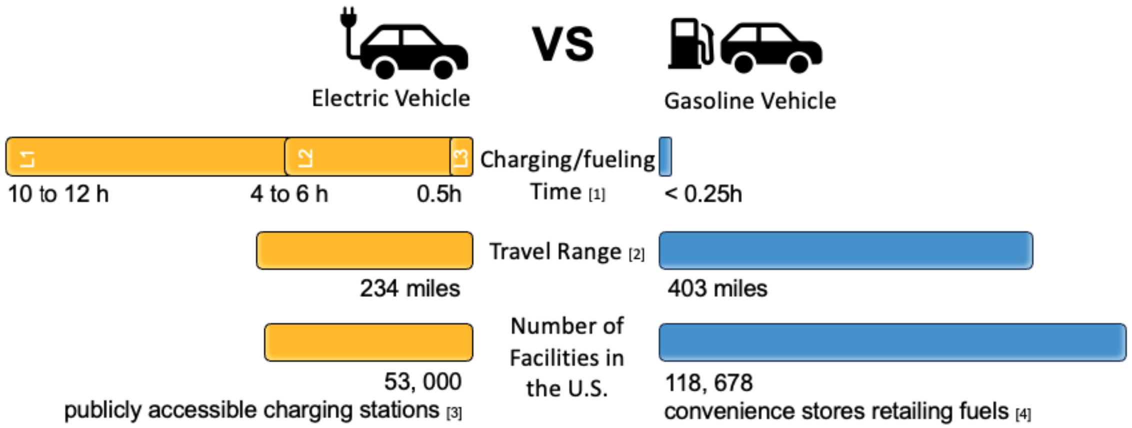
# Agenda

1. Problem: Emergency Evacuation Plans for Zero-Emission Vehicles
2. State of art
3. Methodology
4. Results
5. Conclusions
6. Outlook for future work

# 1. Problem: Emergency Evacuation Plans for ZEVs

- The objective → **safe** and **efficient** evacuation for EVs.
- EVs' **limited range** and **recharging needs** pose challenges.
- **Insufficient**, **daily-use oriented**, or **vulnerable** charging **infrastructure** exacerbates these challenges.




[1] Wildfire Evacuees Fill Lake Tahoe Roads in Rush to Flee


[2] A recent Seattle windstorm caused power outages, delaying EV charging.

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[1] https://www.nbcbayarea.com/news/california/caldor-fire-lake-tahoe-evacuations-traffic/2644500/
[2] https://www.king5.com/article/weather/weather-impact/long-ev-charging-station-lines-washington-power-outages/281-48062fd1-1171-409f-b647-14874ff5fe5f

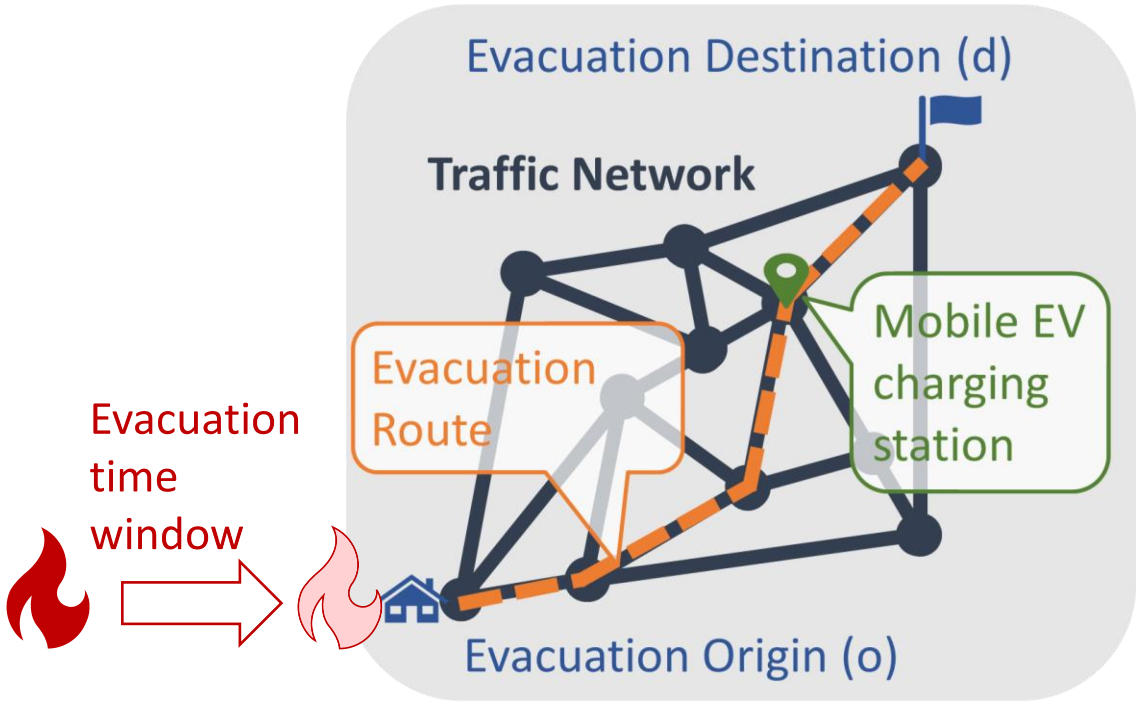
# 1. Problem: Emergency Evacuation Plans for ZEVs

- Mobile charging station (MCS)
  - **Re-deployable** at many locations
  - Does **not** put **stress** on **grid**


# 2. State of Art

| Title | Solution type | Evacuation Use Case | Scheduling and Grouping | Routing | F/MCS Placement | Routing with Recharging/ Refuling | Min travel Time | Min Charging Time | Congestion Aware (consider road capacity) | F/MCS capacity constraint | Microscopic Simulation |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A capacitated network flow optimization approach for short notice evacuation planning | heuristic solution | Yes | Yes | Yes | No | No | No | No | Yes | No | No |
| Dispatch management of portable charging stations in electric vehicle networks | heuristic solution | No | No | No | Yes | No | No | Yes | No | Yes | No |
| Optimal charging facility location and capacity for electric vehicles considering route choice and charging time equilibrium | Decompose optimization problem | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| Optimization methods for the capacitated refueling station location problem with routing | heuristic solution | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| a bilevel ant colony optimization algorithm for capacitated electric vehicle routing problem | Decompose optimization problem | No | Yes | Yes | No | Yes | No | No | No | Yes | No |
| Evacuation route planning for alternative fuel vehicles | heuristic solution | Yes | No | Yes | No | Yes | No | No | Yes | No | No |
| Full cover charging station location problem with routing | Decompose optimization problem | No | No | Yes | Yes | Yes | No | No | No | No | No |
| The p-center flow-refueling facility location problem | Decompose optimization problem | No | No | Yes | Yes | Yes | No | No | No | No | No |
| Location optimization of electric vehicle mobile charging stations considering multi-period stochastic user equilibrium | linearlize | No | No | No | Yes | No | No | No | Yes | Yes | No |
| An optimization model for the temporary locations of mobile charging stations | linearlize | No | No | No | Yes | No | No | Yes | No | Yes | No |
| Dispatch management of portable charging stations in electric vehicle networks | heuristic solution. | No | No | No | Yes | No | Yes | Yes | No | Yes | No |
| Vehicle routing and scheduling for bushfire emergency evacuation | heuristic solution. | Yes | Yes | Yes | No | No | No | No | No | No | No |
| **Our Approaches** | **Heuristic solution** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Planned** |
| | **Decompose optimization problem** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |

# 3. Methodology - Overview



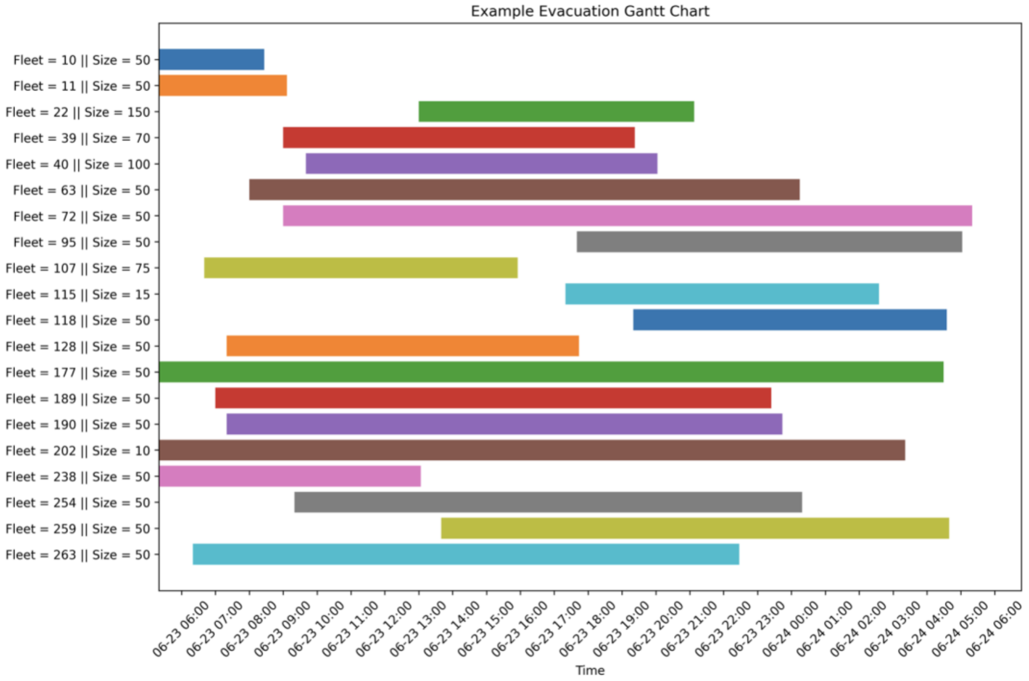

**Objective**:

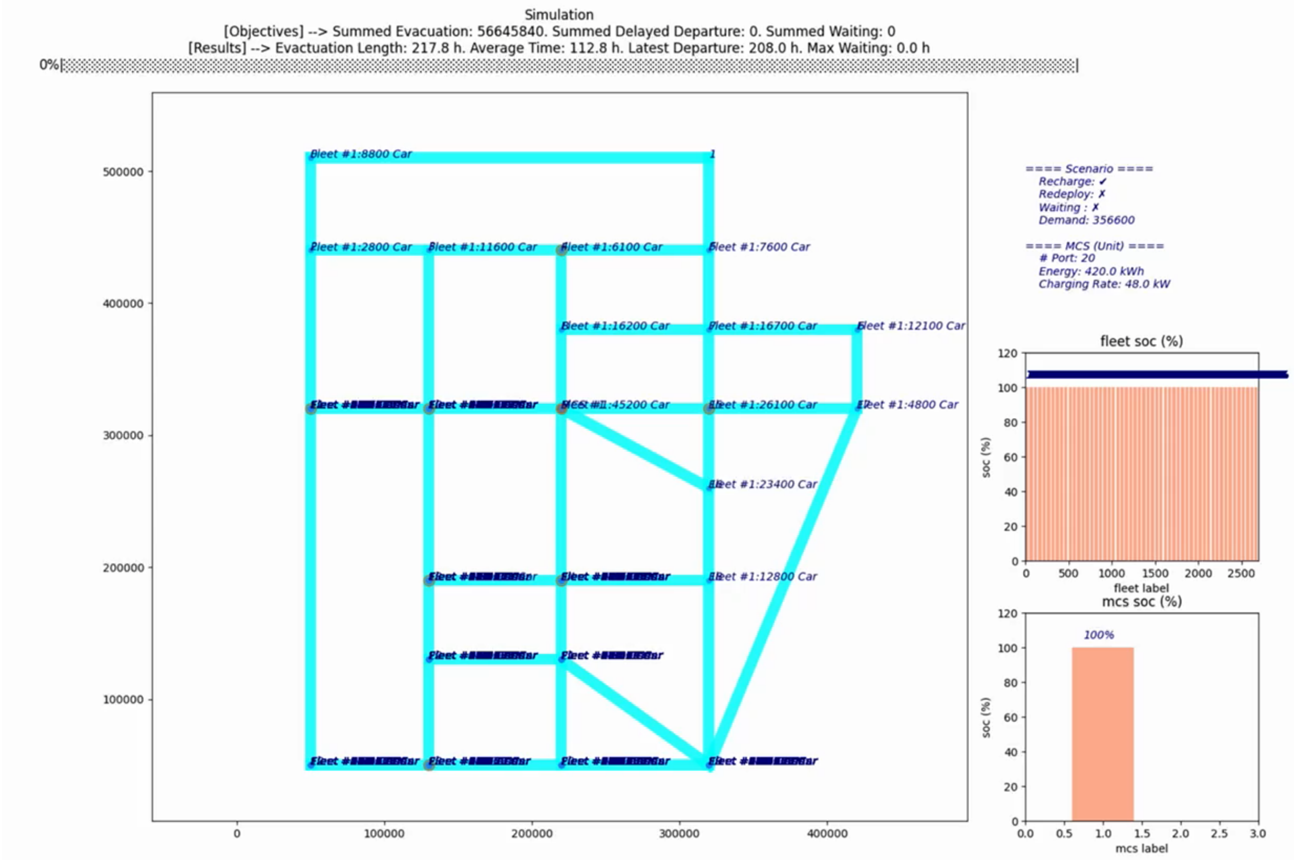
- Minimize the **evacuation time** (travel time + charging time + number of stops made during evacuation).
- Maximize the number of EVs that can be **safely evacuated**.
- Minimize the **traffics** that exceeds road free-flow capacity.

**Constraints**:

- ZEVs should departure before hazard arrives (**scheduling**).
- All EVs can **safely** arrived at evacuation destination without running out of/overcharge the battery.
- Fixed the **number of mobile charging stations (MCS) placed** for evacuation.
- **Conservation of energy**.
- **MCS capacity.**
- …

# 3. Methodology - Goal



# From Previous Workshop

- Formulating in a Mixed Integer linear Programming problem
- Problem:
  - Complexity --> difficult to solve with larger maps
  - Linearity --> difficult to incorporate real-time traffic
  - Global optimum --> not necessary in real-time scenarios

# Optimization Math Engine

## Mixed Integer Linear Programming Formulation

- Decision Variables
  - $x_{wpt}$ : Number of vehicle evacuated between origin-destination (OD) pair $w$ following path $p$ at time $t$
  - $q_{mnt}$: Binary deployment status of MCS labeled $m$ at node $n$ at time $t$
- Objective:
  - Summed evacuation time: $\sum_{w \in \mathbb{W}} \sum_{p \in \mathbb{P}_w} \sum_{t \in \mathbb{T}} (t + \tilde{t}_{wpt}) \times x_{wpt}$
- Constraints
  - Evacuation demand: $\sum_{p \in \mathbb{P}_w} \sum_{t \in \mathbb{T}} x_{wpt} = f_w, \forall w \in \mathbb{W}$
  - MCS single site deployment: $\sum_{n \in \mathbb{N}} |q_{mnt}| = 1, \forall m \in \mathbb{M}, \forall t \in \mathbb{T}$
  - Port limit: $D_{nt} \leq S_{nt}, \forall n \in \mathbb{N}, \forall t \in \mathbb{T}$
  - MCS energy limit: $0 \leq soc_{mt} \leq 1, \forall m \in \mathbb{M}, \forall t \in \mathbb{T}$

# Optimization Math Engine

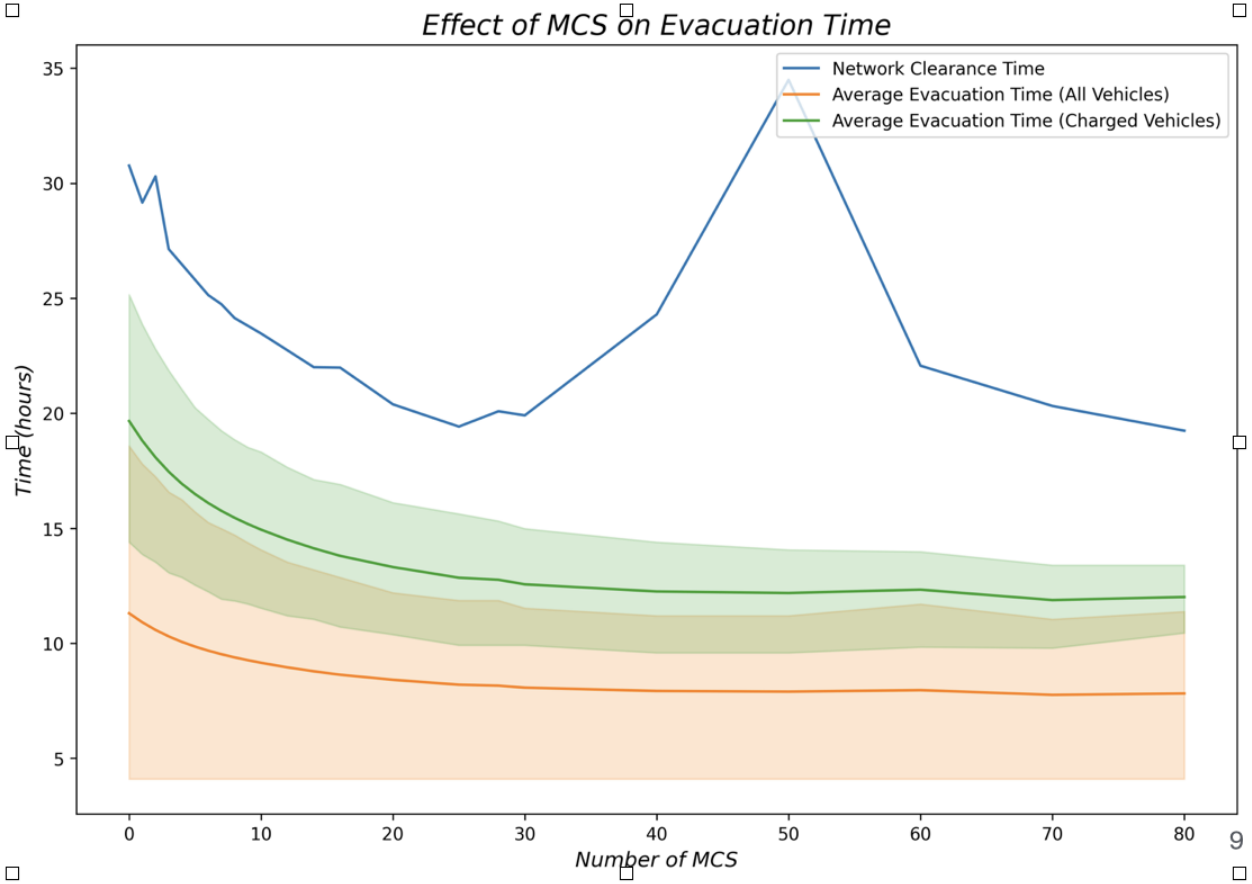
## Mixed Integer Linear Programming Formulation (TLDR)

- Objective —> Minimize the **summed** evacuation time
- Constraints:
  - Fit-the-demand —> **All** registered **vehicles** have to be **evacuated**
  - Pre-deployment —> **MCS** are placed at a **single site** throughout the evacuation
  - Port-limit —> **charging demands** at sites are **bounded** by number of **ports**
  - Energy-limit —> **MCS SOC** is **bounded** between 0 and 1

# Previous Observations

## Reduction of average evacuation time

- Shaded = 25% and 75% quantile
- More MCS = Reduced time
- **Diminishing** effect
- Low average ≠ faster evacuation span
  - Question for focus:
    - Average?
    - Longest?

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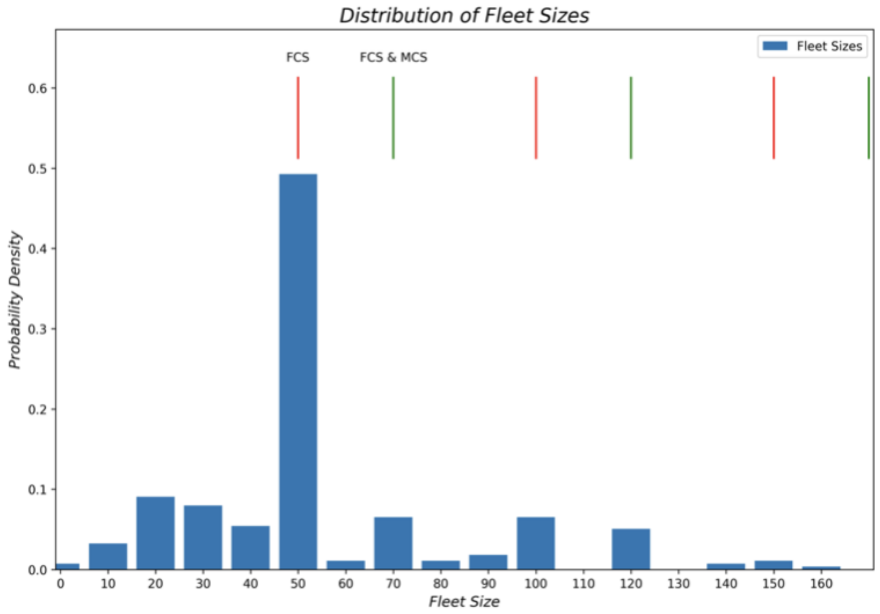
# Previous Observations

## Optimal scheduling strategy

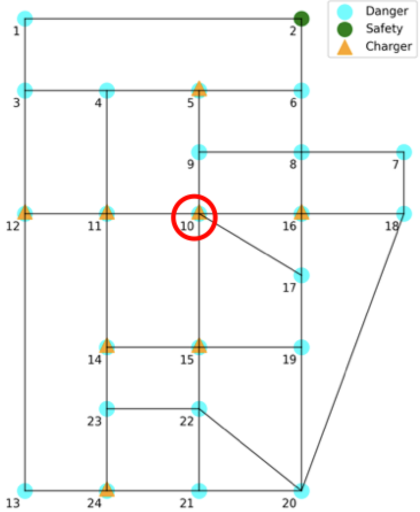
- Vehicle departure
  - Group (fleet) **size** distribution **peaks** at number of **ports**

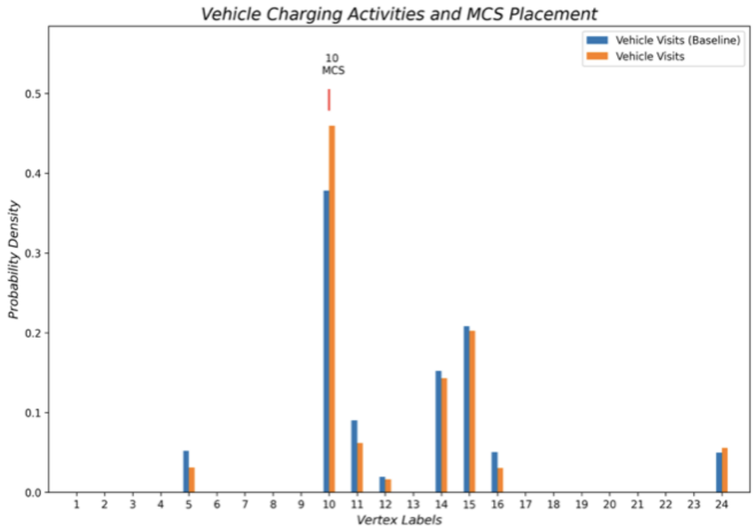


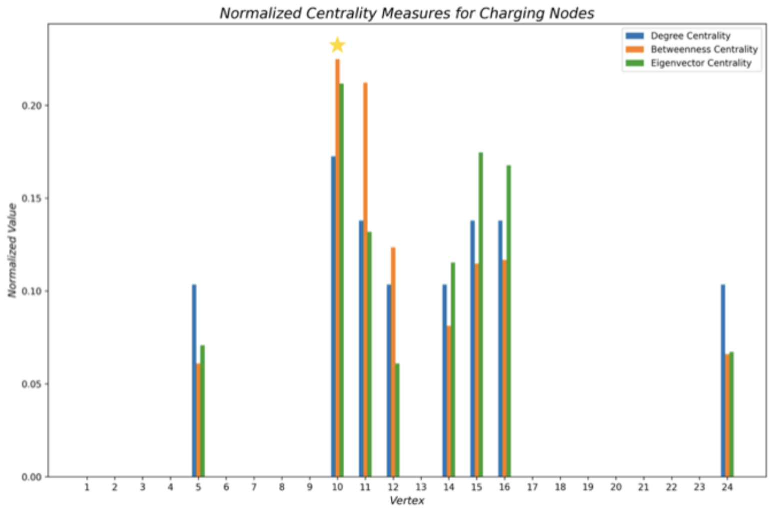
# Previous Observations

## Optimal deployment strategy

- MCS placement
  - All placed at the the **most-visited** node
  - The node also has **highest centrality** measures

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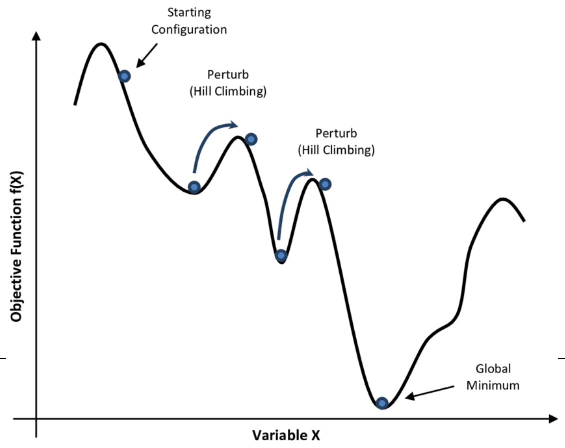
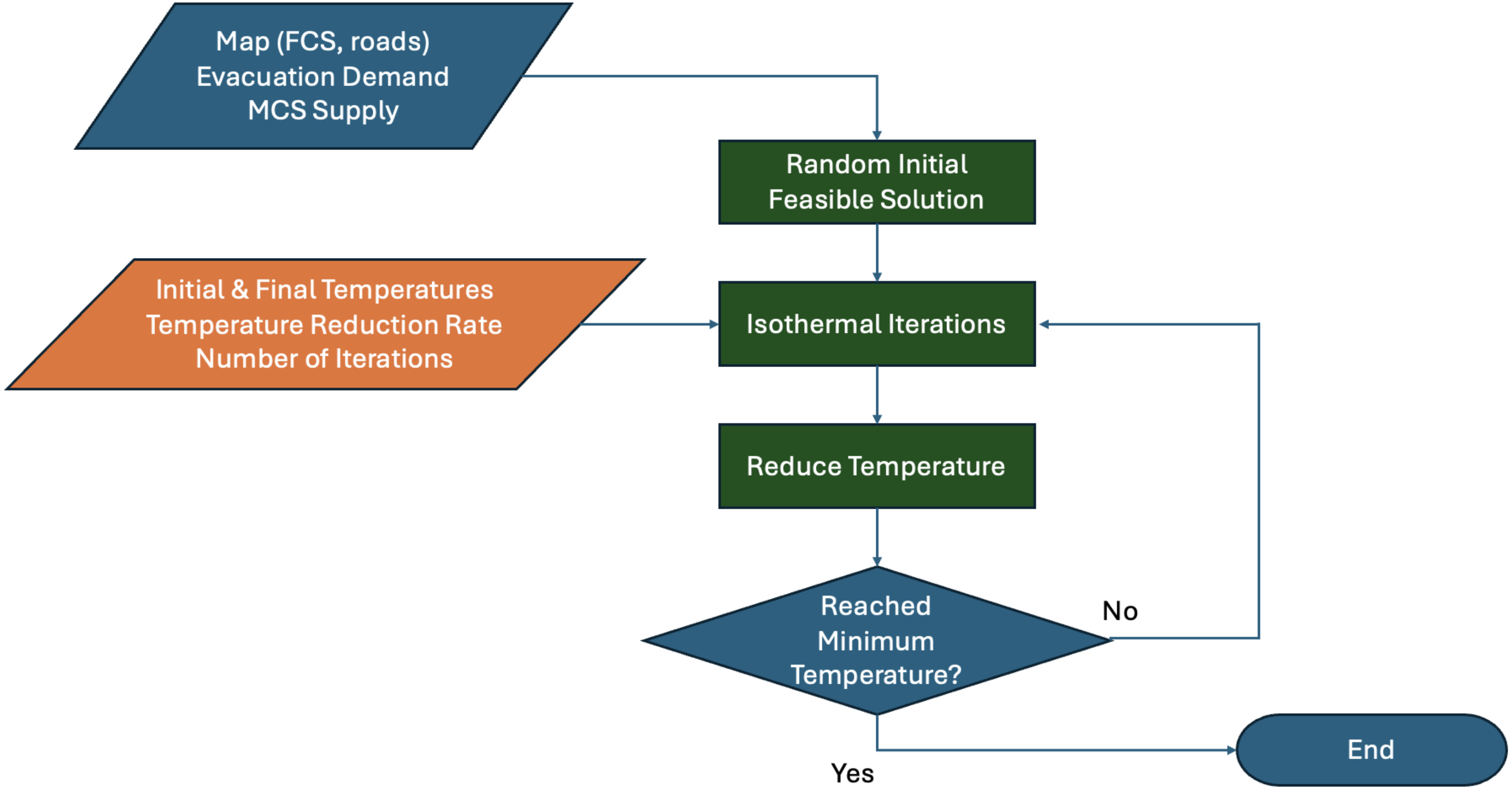
# 3. Methodology – Heuristics: Simulated Annealing

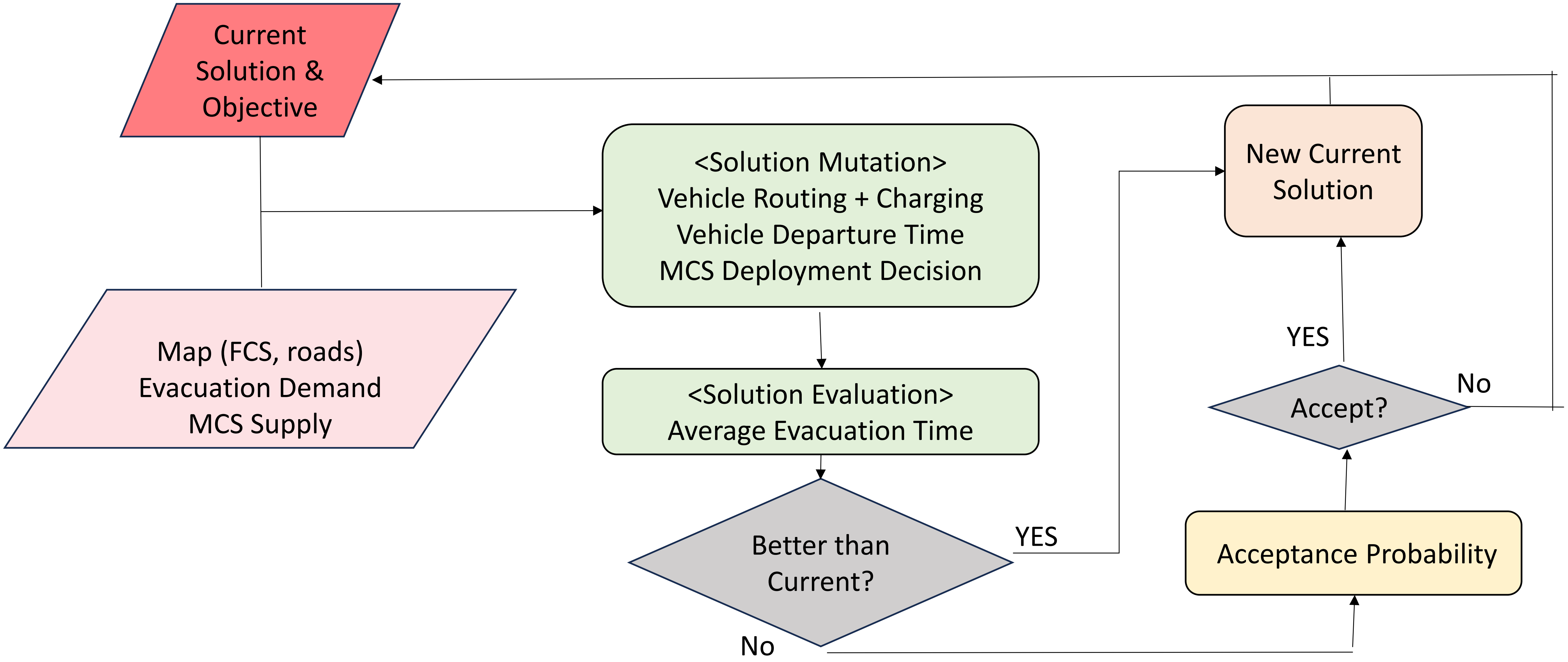
- Annealing:
  - Alters a material's physical properties by heating it to a **specific temperature** and then **cooling it slowly**
- Simulated Annealing (SA):
  - Inspired by annealing process
  - Randomly exploring new solutions by decreasing **temperature**
    - Temperature: **probability of accepting worse solutions**



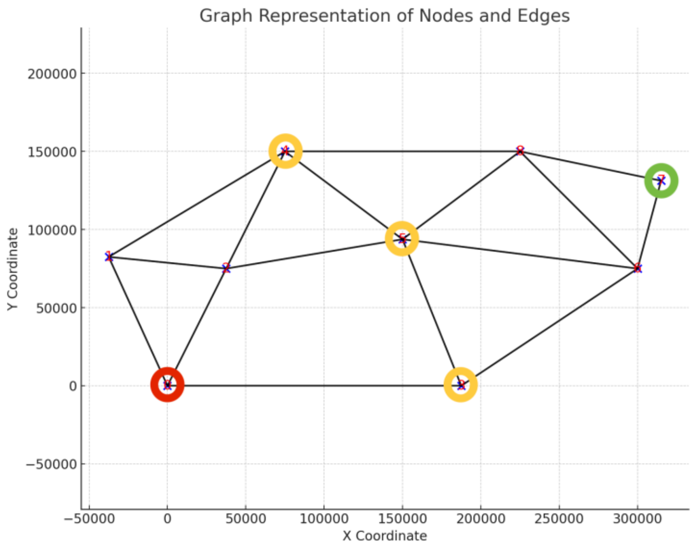
# 3. Methodology – SA Overview



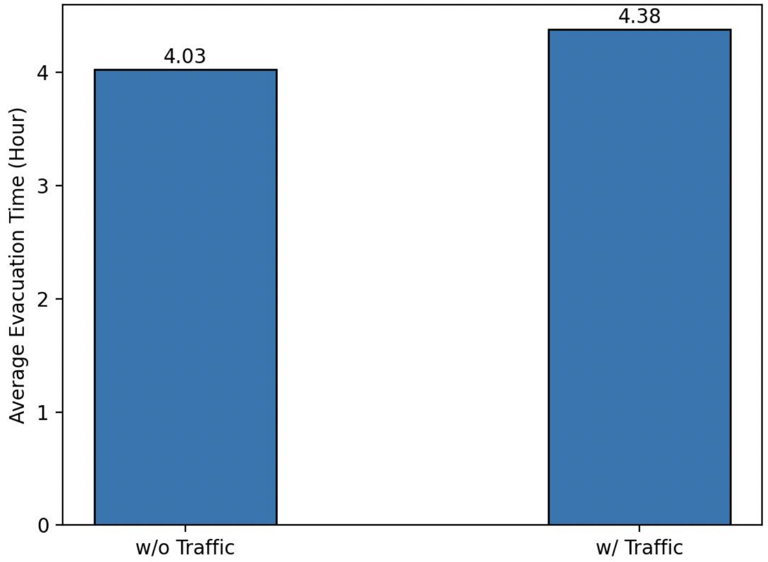
# 3. Methodology – SA "Isothermal" Scheme



# Consideration of Real-time Traffic

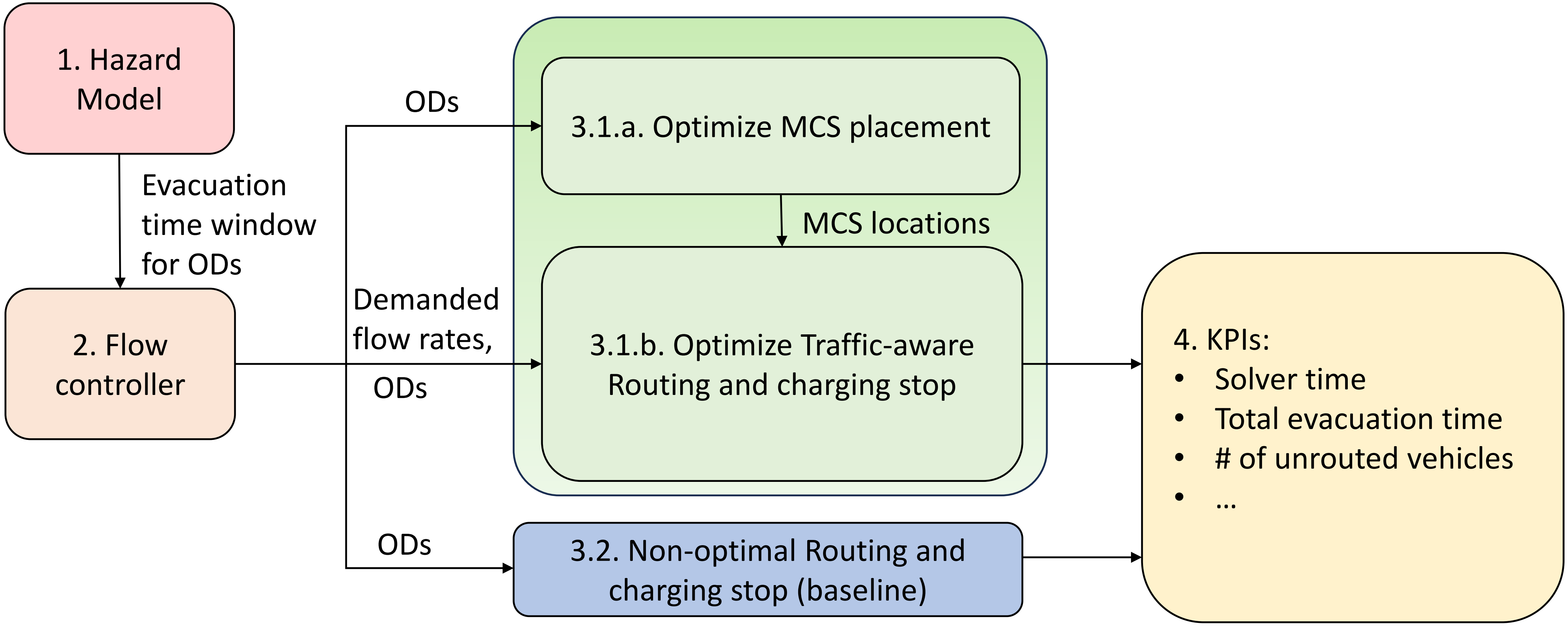



- BPR Function: $t = t_o[1 + \alpha \left(\frac{D}{C}\right)^{\beta}]$
- Sensitivity parameters: $\alpha = 4$ $\beta = 0.15$
- Road Capacity: $C = 10$
- Demand: 10 Vehicles from Red to Green
- FCS: Yellow
- Average Evacuation Time -->

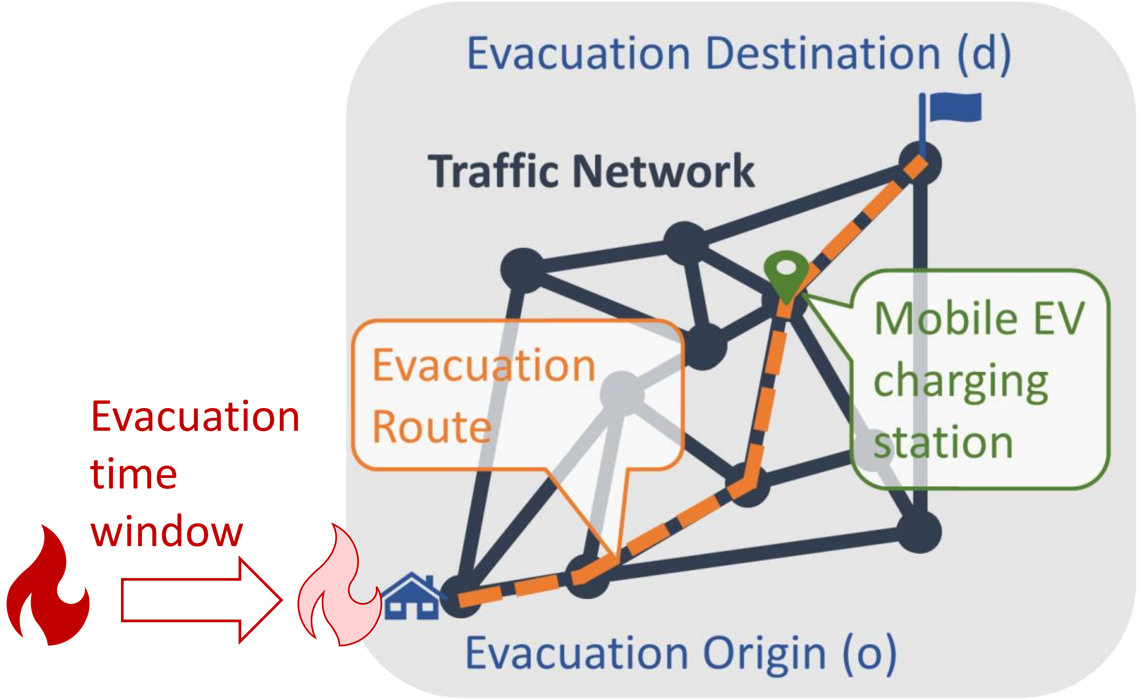


# Decomposed Approach

# 3. Methodology - Decomposition Overview

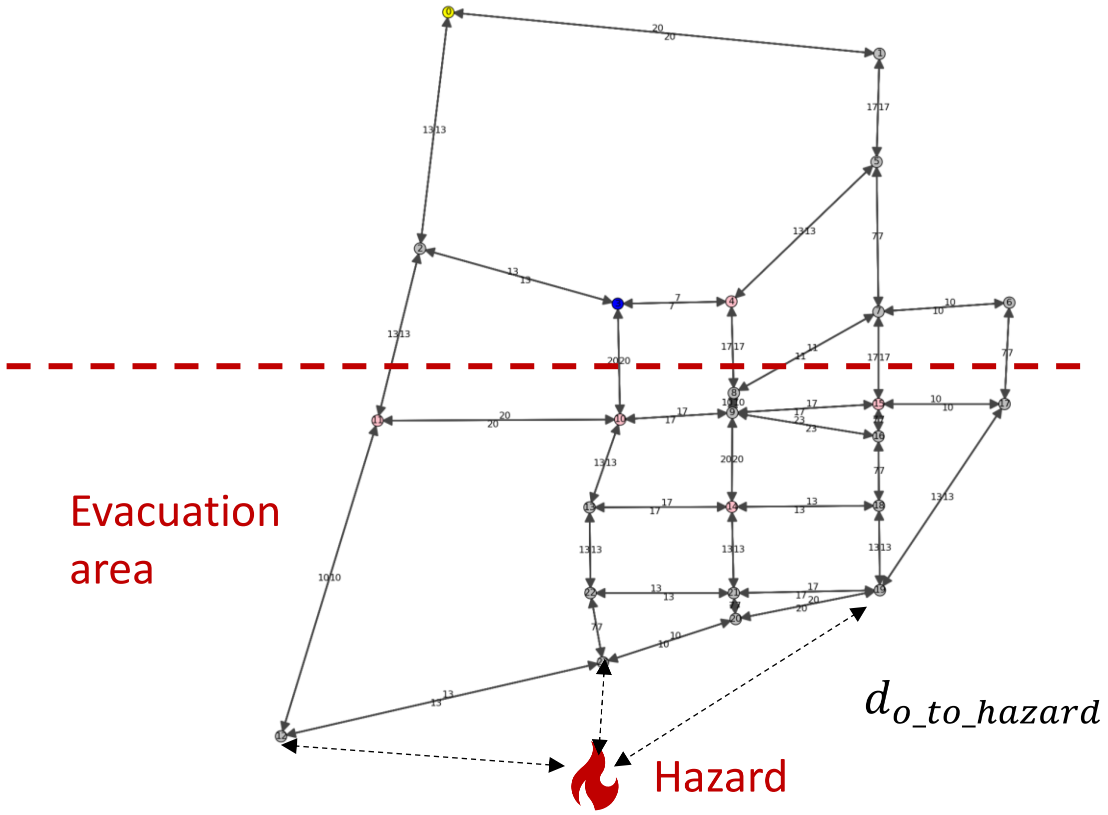


# 3. Methodology – multi-layer optimization problem formulation




- **Layer 1 (feasibility check without MCS)**
  - Check each OD pairs by:
    - **Connectivity** (Dijkstra's algorithm)
    - If **destination is reachable** with existing fixed charging stations (FCS).
- **Layer 2 (if some ODs need MCS to reach destination)**
  - Optimize **MCS location** to minimize travel distance for these ODs.
- **Layer 3 (routing and charging planning)**
  - Optimize the **routes** with shorter driving distance.
  - Optimize the routes for free-flow condition
  - Optimize the **charging stops**:
    - Minimize number of stops made
    - Minimize charging time
  - **Tracking reference flow size** calculated from scheduling layer.

# 3. Methodology – Hazard Modeling and flow control




$$t_{evacuation\ window} = \frac{d_{o\_to\_hazard}}{v_{hazard}}$$

$$n^*_{flow} = \frac{R}{t_{evacuation\ window}}$$

$d_{o\_to\_hazard}$: distance from hazard to evacuation origin node
$R$: remaining demands that required to evacuated
$n^*_{flow}$: desired traffic flow rate for safe evacuation

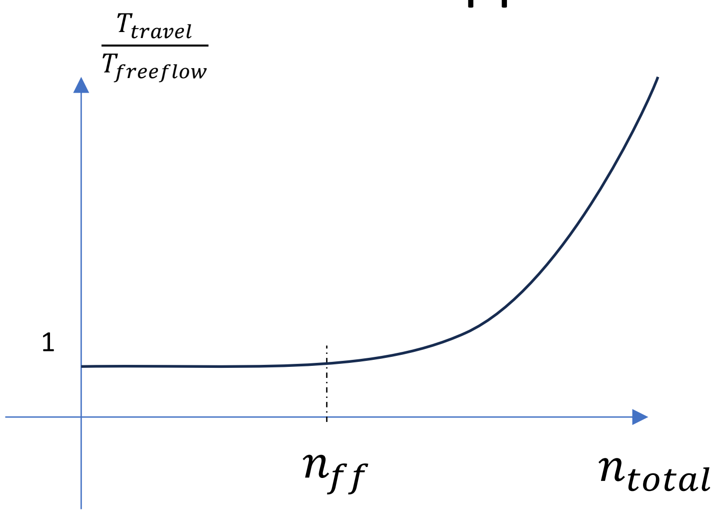
# 3. Methodology – Baseline

- Shortest path from each origin to destination (Dijkstra's algorithm)
  - Maximum of one charging stop at the FCS;
  - Not consider road capacity;
  - No flow size control;

# 3. Methodology – KPI

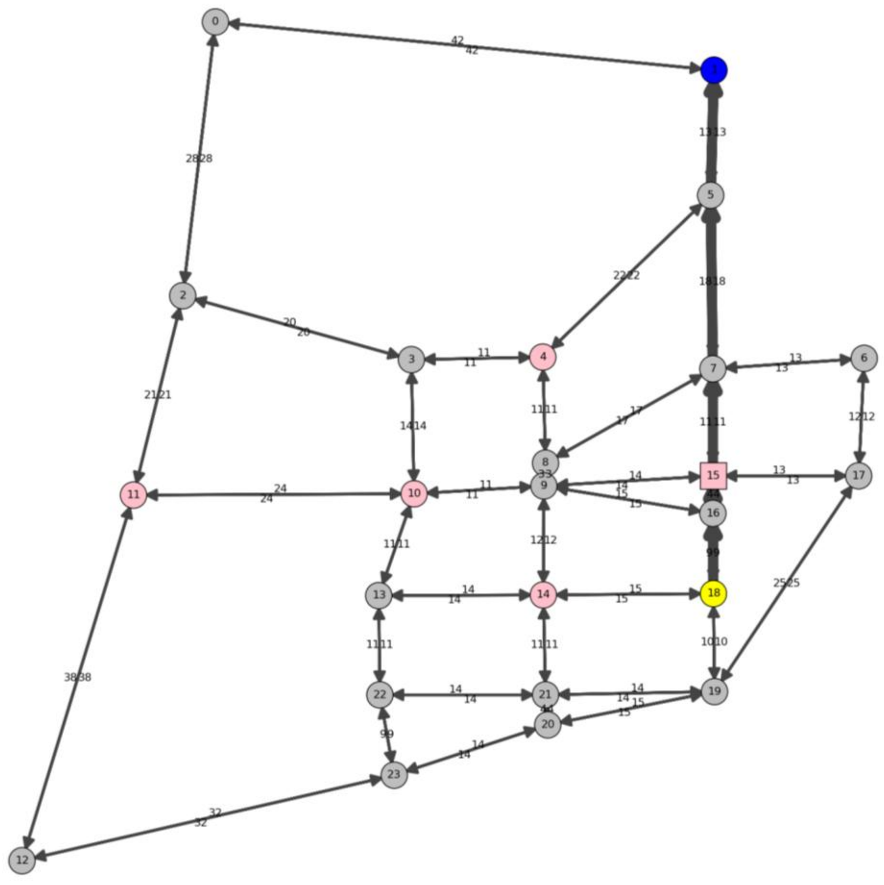
- 1) South Florida case (233 edges, 83 od pairs) with map scaled from x1 to x5, demand scaled down by 1/5. No existing FCS.
  - Solver time: Optimization problems were solved on MacBook Pro with Apple M2 Chip using Gurobi Optimization Solver.
  - Actual evacuation time modeled with BPR function.
  - Charging demand at each MCS.

$$t_{bpr} = \frac{d_{ij}x_{ij}}{s}\left(1 + \alpha\left(\frac{\left(\sum_{od} x_{ij}^{od} m^{od}\right)}{n_{ff}}\right)^{\beta}\right), \alpha = 0.15 , \beta = 4$$

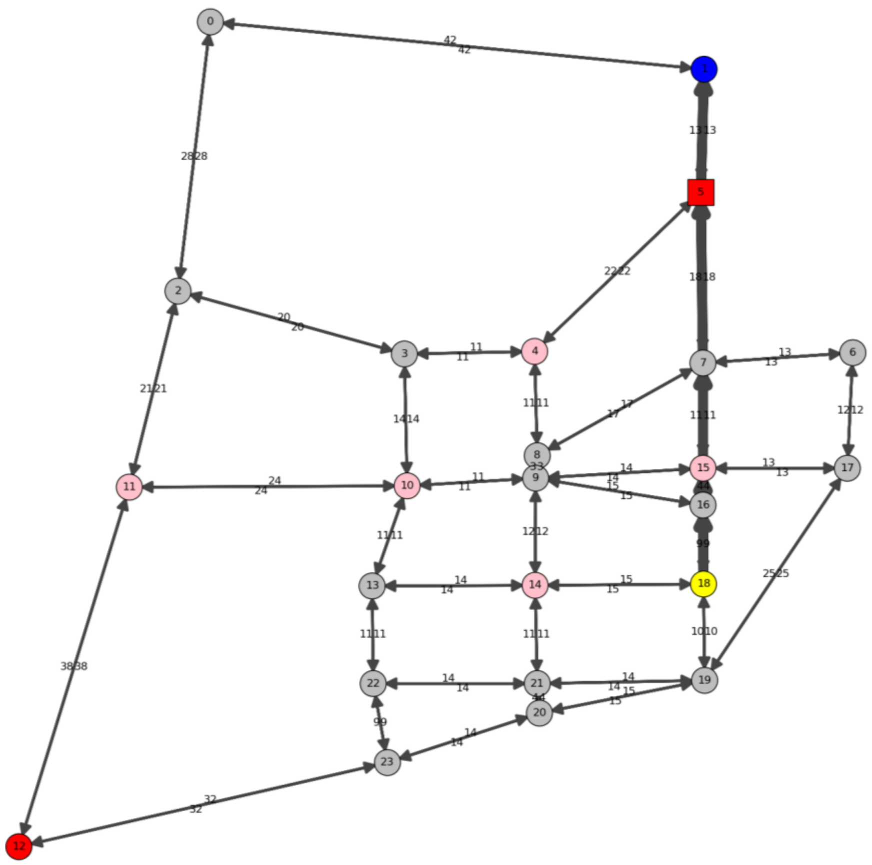



- 2) SiouxFalls case (76 edges) with hazard model
  - Microscopic Traffic Simulation using SUMO

# 4. Results – Routing and charging solution example



Baseline



Optimization

| node | remaining range [mile] | charged range [mile] |
|---|---|---|
| 5 | 7 | 6 |
| 7 | 25 | 0 |
| 15 | 36 | 0 |
| 16 | 40 | 0 |
| 18 | 49 | 0 |

Origin

Destination

FCS

MCS

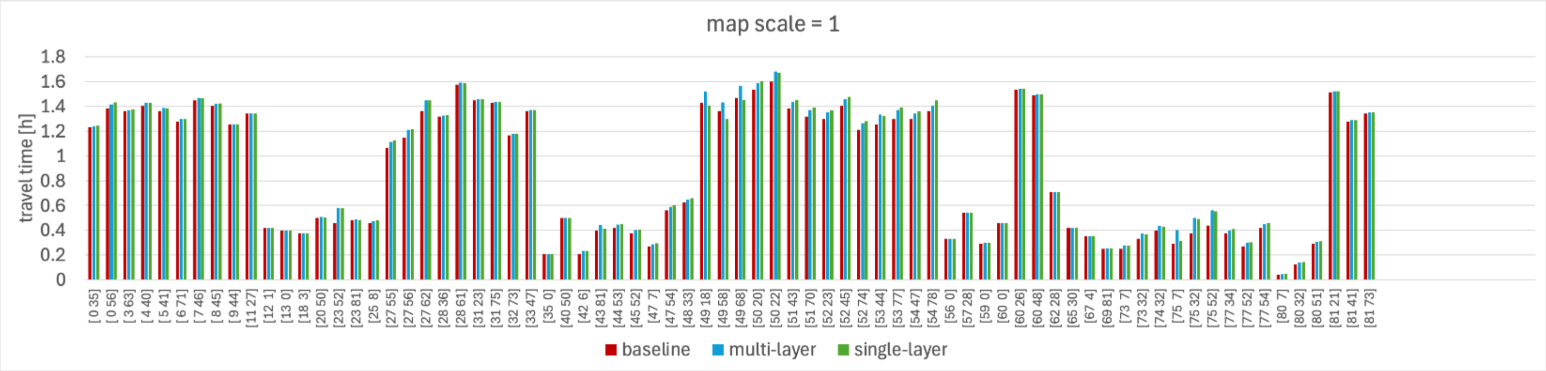
Stop

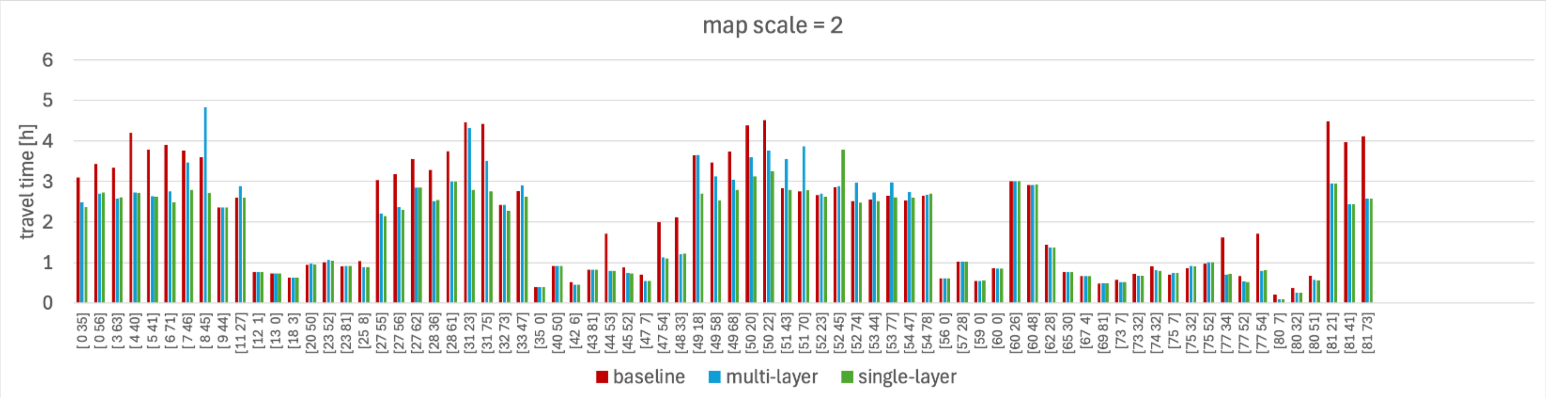
# 4. Results – Optimization vs Baseline

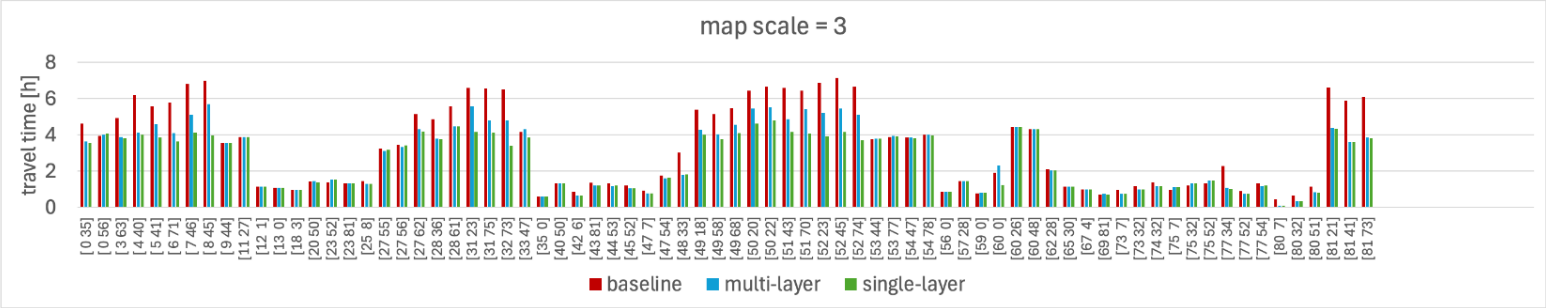
| map scale | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| solver time (s) | | | | | | | |
| baseline | 0.047 | 0.038 | 0.044 | 0.048 | 0.051 | 0.049 | 0.053 |
| layer 1 | | | | | | | |
| layer 2 | | | | 0 | 0 | 0 | 1 |
| layer 3 | | | | 59 | 18 | 3 | 11 |
| layer 2+ 3 | | | | **59** | **18** | **3** | **12** |
| single layer | 1 | 16 | 18 | **15** | **21** | **23** | **26** |
| | | | | | | | |
| number of baseline unrouted OD | | | | **22** | **37** | **40** | **40** |
| | | | | | | | |
| average evacuation time (h) | | | | | | | |
| baseline | 0.9 | **2.2** | **3.4** | | | | |
| layer 2+ 3 | 0.9 | 1.9 | 2.8 | | | | |
| single layer | 0.9 | **1.7** | **2.6** | | | | |
| median evacuation time (h) | | | | | | | |
| baseline | 1.1 | **2.4** | **3.4** | | | | |
| layer 2+ 3 | 1.1 | 2.3 | **3.2** | | | | |
| single layer | 1.1 | **2.2** | 3.3 | | | | |
| total evacuation time (h) | | | | | | | |
| baseline | **65.3** | **159.6** | **249.1** | | | | |
| layer 2+ 3 | **67.6** | 140.6 | 207.8 | | | | |
| single layer | 67.4 | **129.2** | **189.9** | | | | |

- Solver time increased as map scale grew.
- The layered optimization formulation outperformed the single-layer approach in terms of solver efficiency as map scale grew.
- Single layer optimization returns the best evacuation time.
- Baseline returns the longest evacuation time.

# 4. Results – Optimization vs Baseline



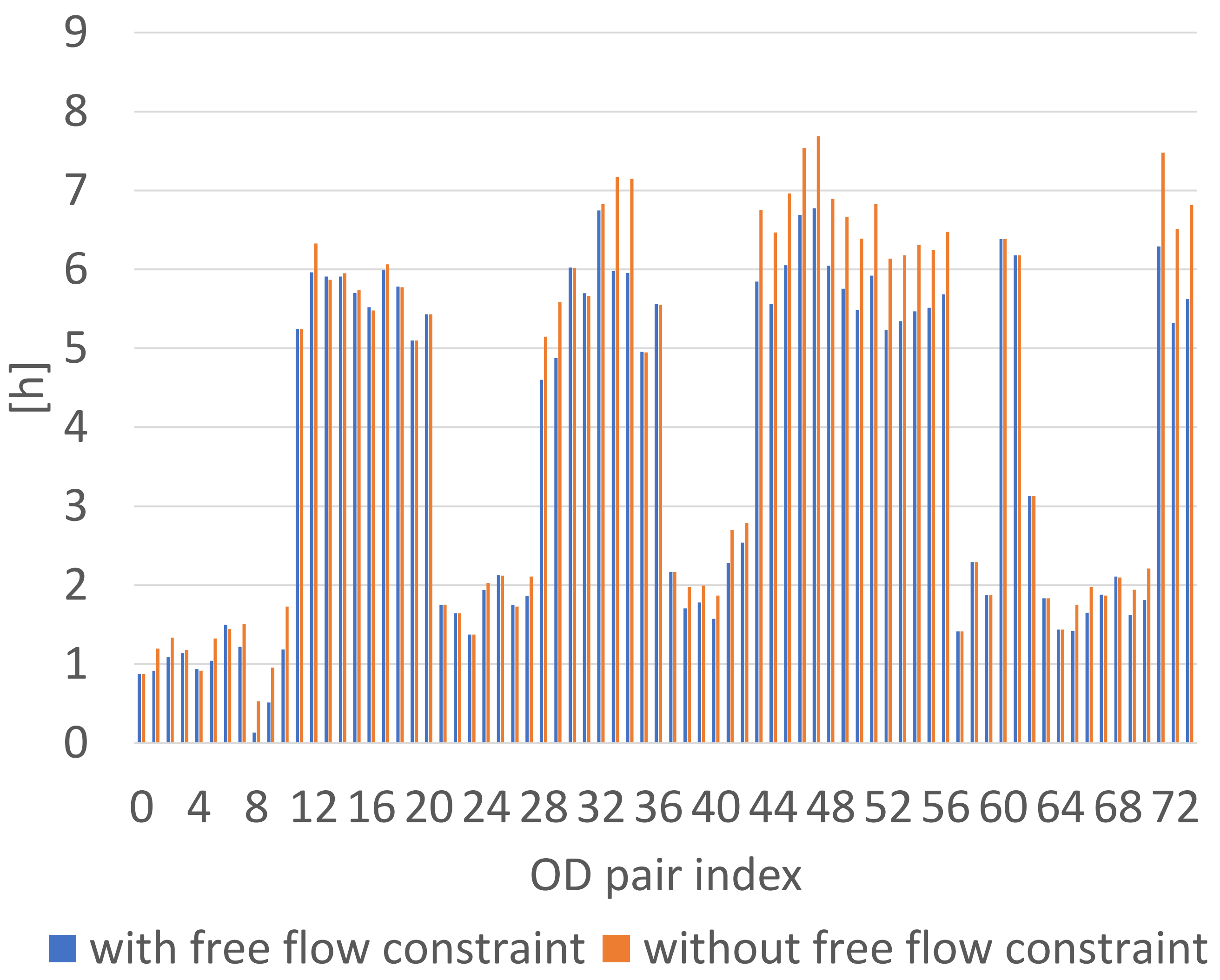



# 4. Results – compare with and without free-flow constraint

- Assume all vehicles departure with 20% battery SoC.
- Assume no pre-exist charging stations.

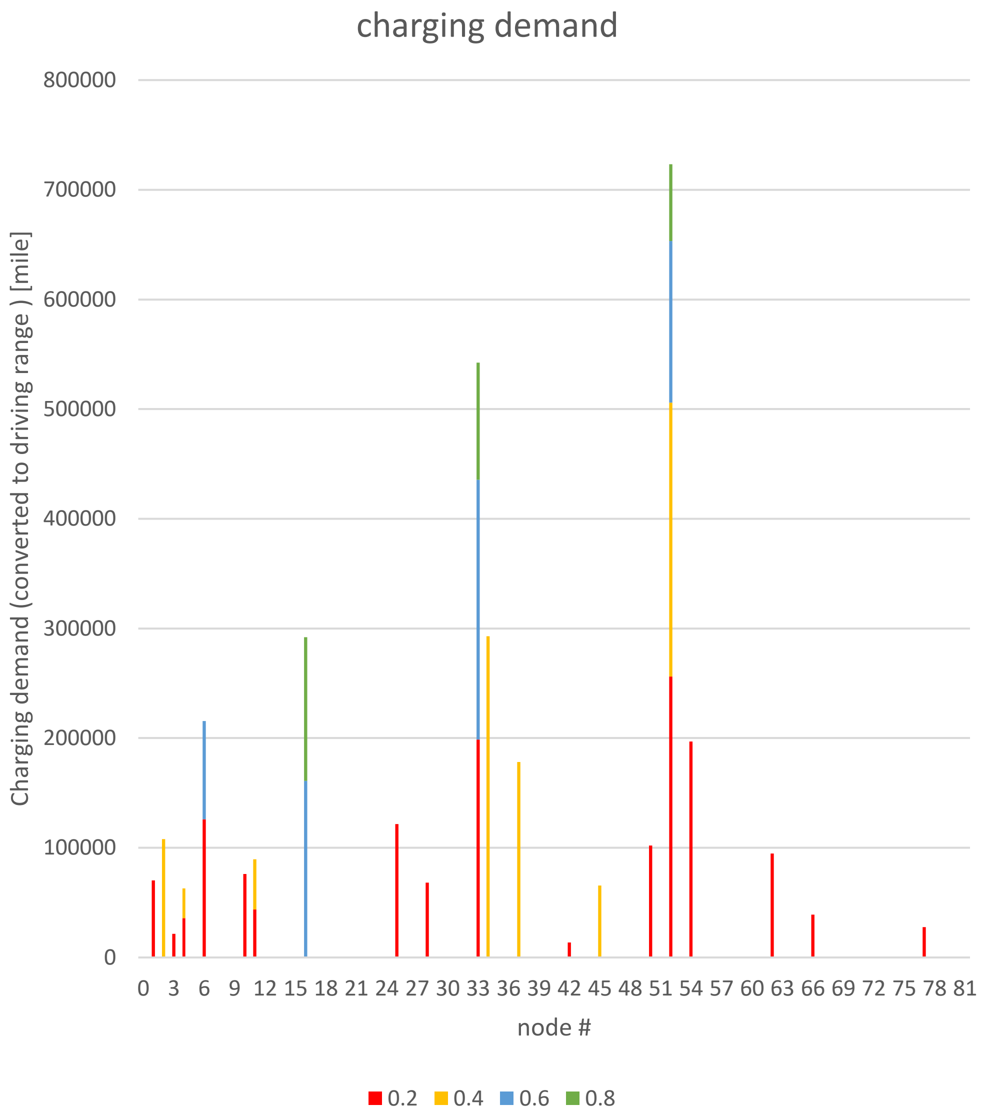
| | with free flow constraint | Without free flow constraint |
|---|---|---|
| max t_bpr [h] | 6.774 | 7.683 |
| std t_bpr [h] | 2.150 | 2.353 |
| average t_bpr [h] | 3.724 | 4.067 |
| total t_bpr [h] | 275.594 | 300.973 |



# 4. Results – battery initial SoC

| | init bat level = 0.2 | init bat level = 0.4 | init bat level = 0.6 | init bat level = 0.8 |
|---|---|---|---|---|
| average t_bpr [h] | 4.786 | 3.723 | 3.728 | 3.724 |
| std t_bpr [h] | 3.493 | 2.153 | 2.147 | 2.150 |
| total t_bpr [h] | 354.129 | 275.536 | 275.879 | 275.555 |
| max t_bpr [h] | 11.830 | 6.771 | 6.769 | 6.783 |

| | init bat level = 0.2 | init bat level = 0.4 | init bat level = 0.6 | init bat level = 0.8 |
|---|---|---|---|---|
| Average t_charging [h] | 0.085 | 0.055 | 0.036 | 0.018 |
| Std t_charging [h] | 0.070 | 0.055 | 0.037 | 0.020 |
| Sum t_charging [h] | 6.316 | 4.093 | 2.687 | 1.301 |
| Max t_charging [h] | 0.182 | 0.143 | 0.107 | 0.070 |

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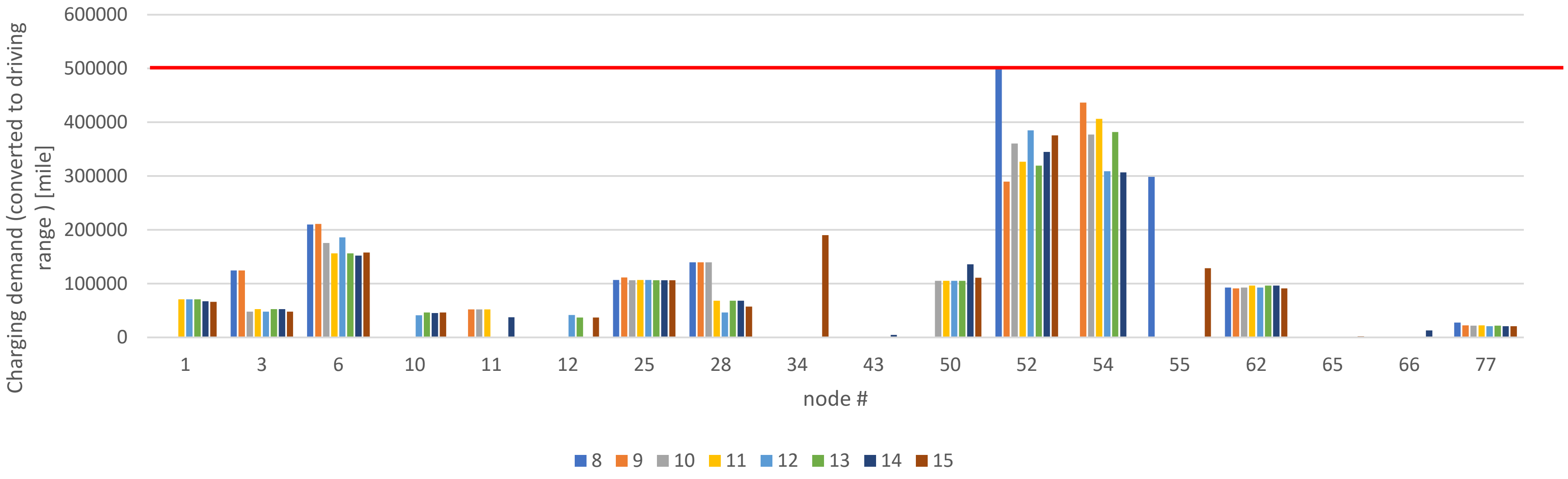
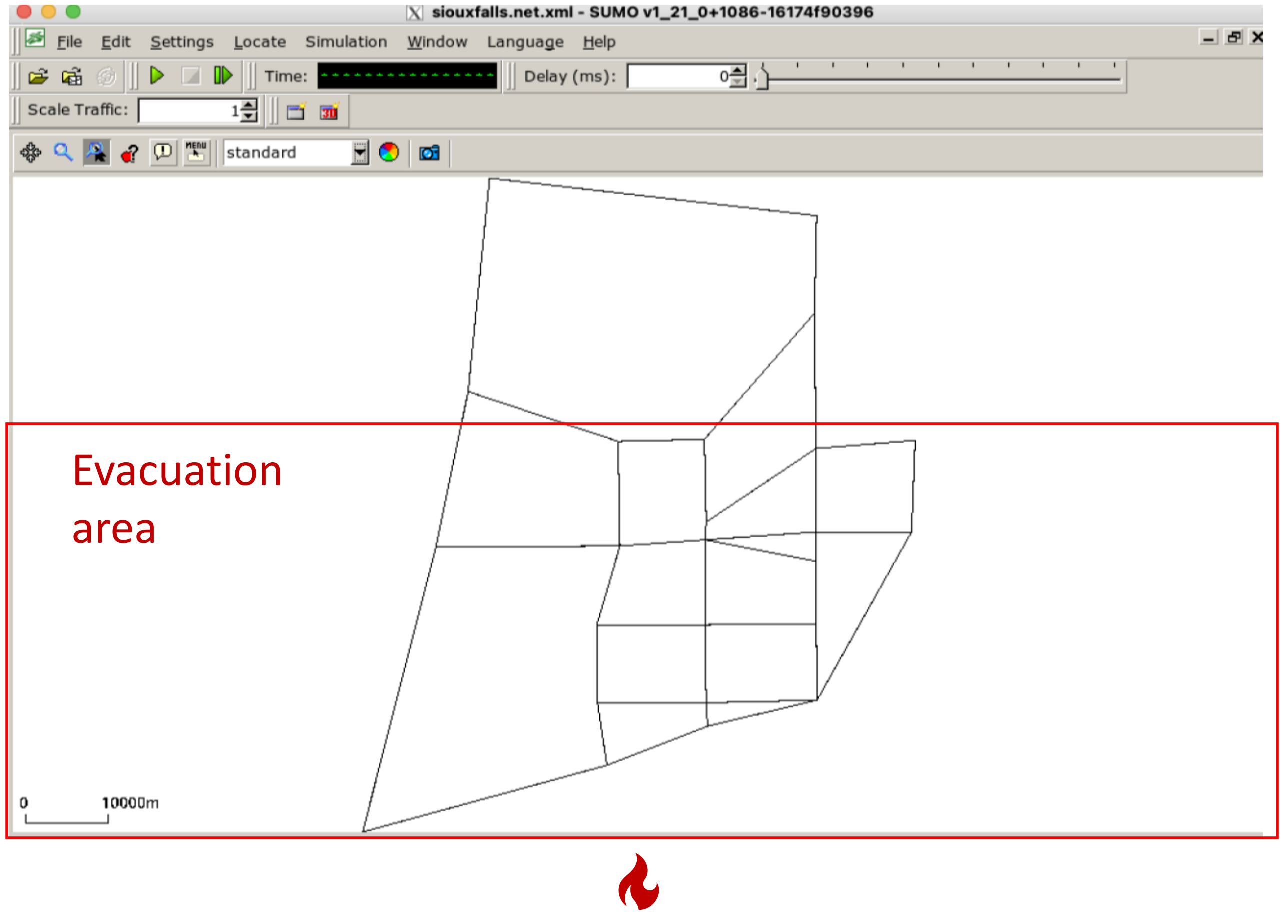
# 4. Results – number of MCS added to the map

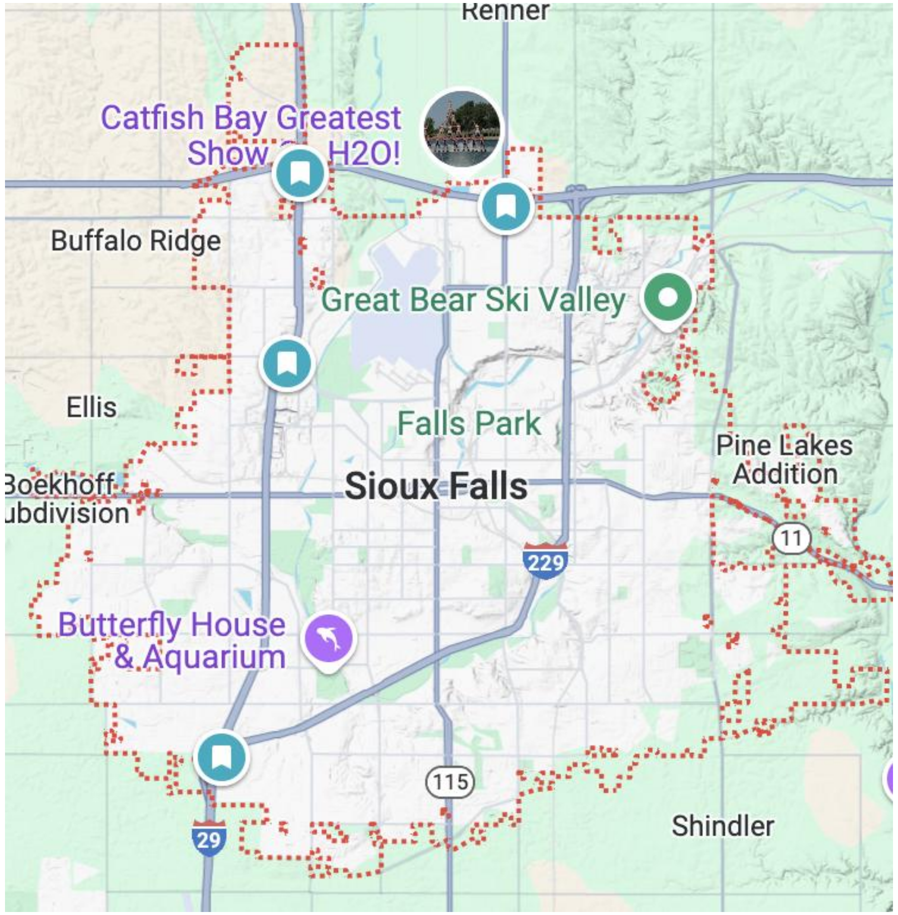
| | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|
| **max t_bpr** | 7.074 | 6.794 | 6.794 | 6.802 | 6.784 | 6.793 | 6.787 | 6.844 |
| **average t_bpr** | 3.876 | 3.831 | 3.811 | 3.791 | 3.777 | 3.780 | 3.774 | 3.750 |
| **std t_bpr** | 2.249 | 2.224 | 2.199 | 2.204 | 2.192 | 2.194 | 2.197 | 2.174 |
| **total t_bpr** | 286.826 | 283.459 | 281.979 | 280.556 | 279.533 | 279.726 | 279.290 | 277.512 |



# 4. Results – SUMO Microscopic Traffic Simulation using SUMO




Sioux Falls map in SUMO (scaled up by x6)




Sioux Falls Google map

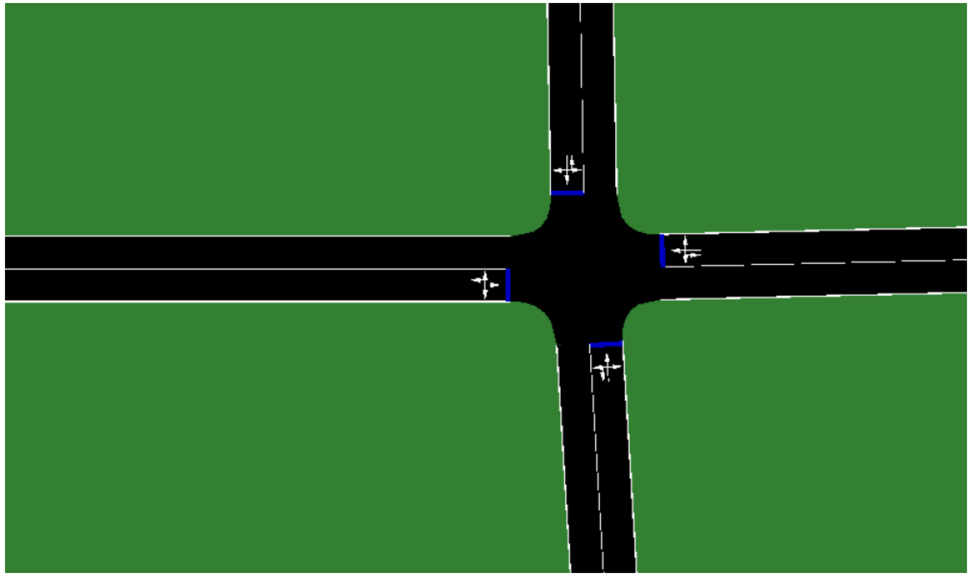
# 5. Results – Microscopic Traffic Simulation using SUMO

Network:

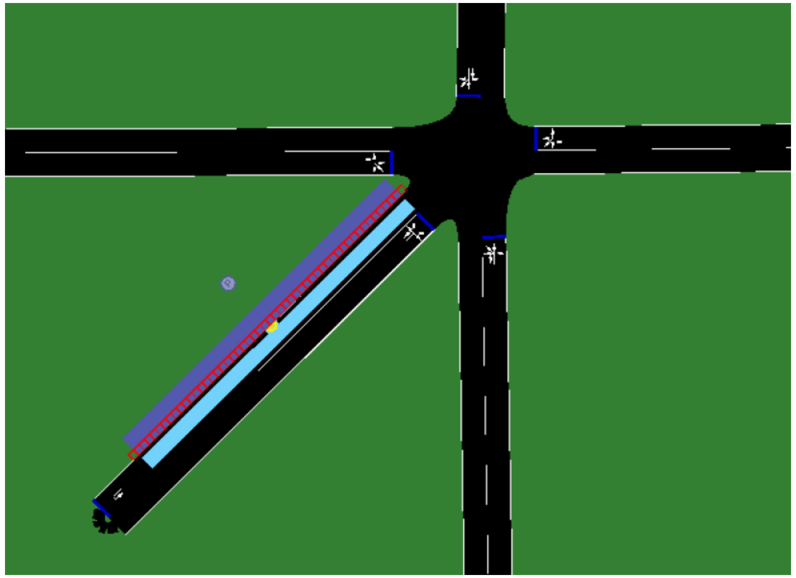
- Traffic Node: All-way stop
- Edge: Single lane roads.
- Charging station: detached from Traffic nodes. 50 parking space with L2 Charger [10kw].

Vehicle model:

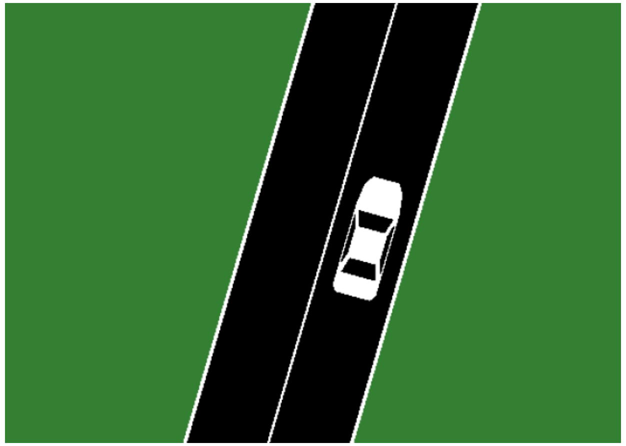
- Kia Soul EV 2020 [1] with 64000 [wh] battery.
- 243 [mile] driving range.



Traffic Node without charging station



Traffic Node with charging station



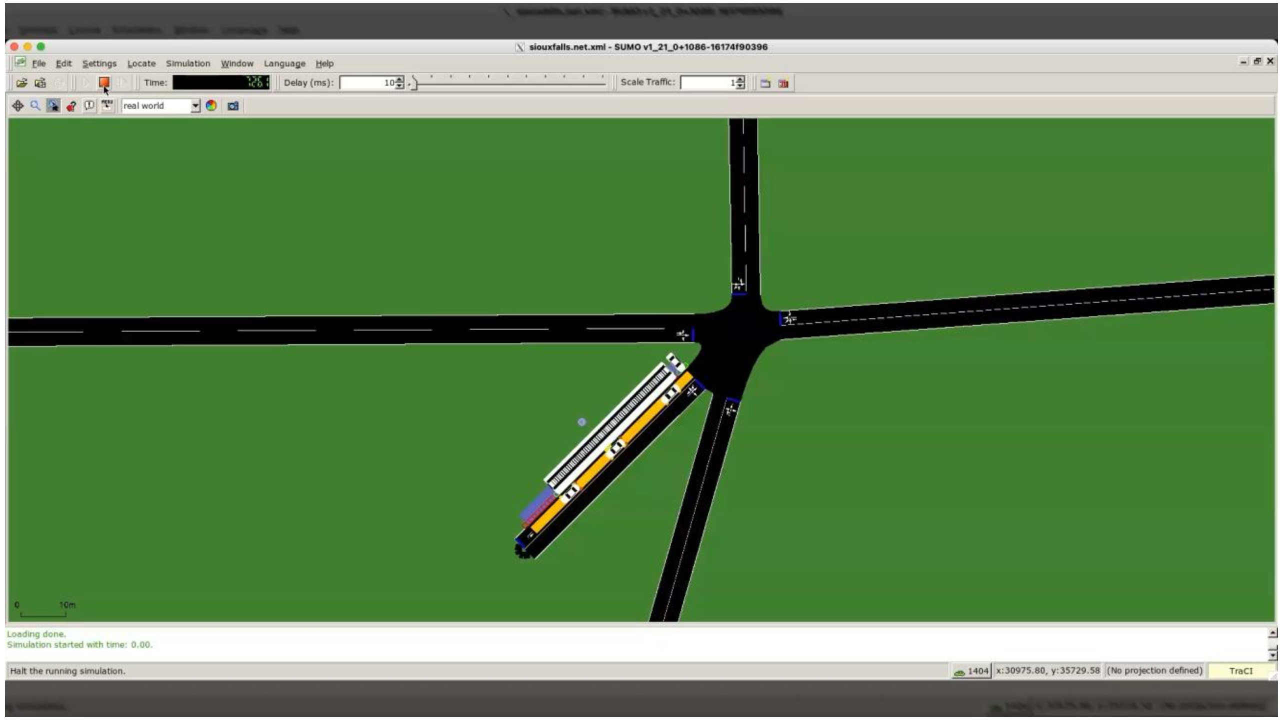
Vehicle

[1] https://sumo.dlr.de/docs/Models/Electric.html

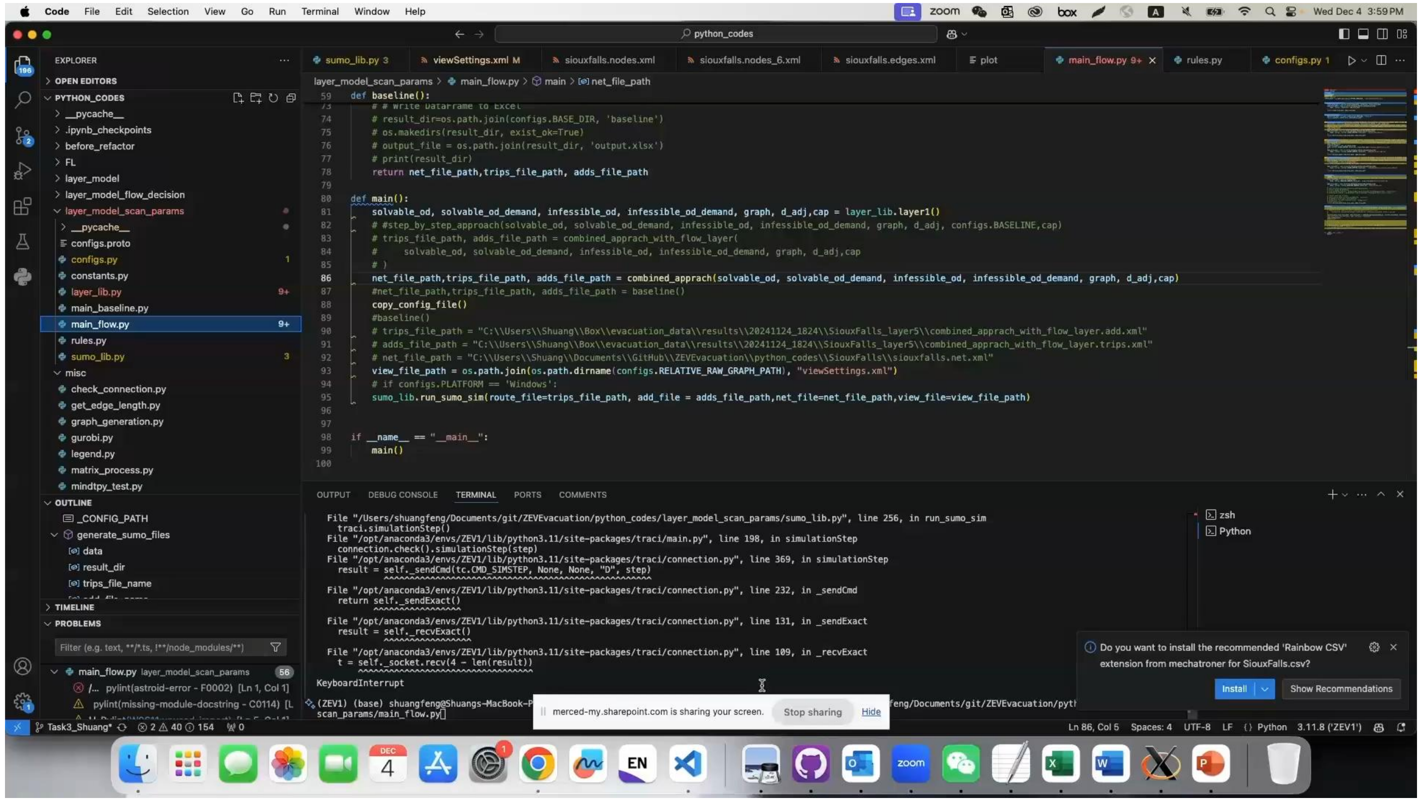
# 5. Results – Microscopic Traffic Simulation using SUMO

Baseline simulation

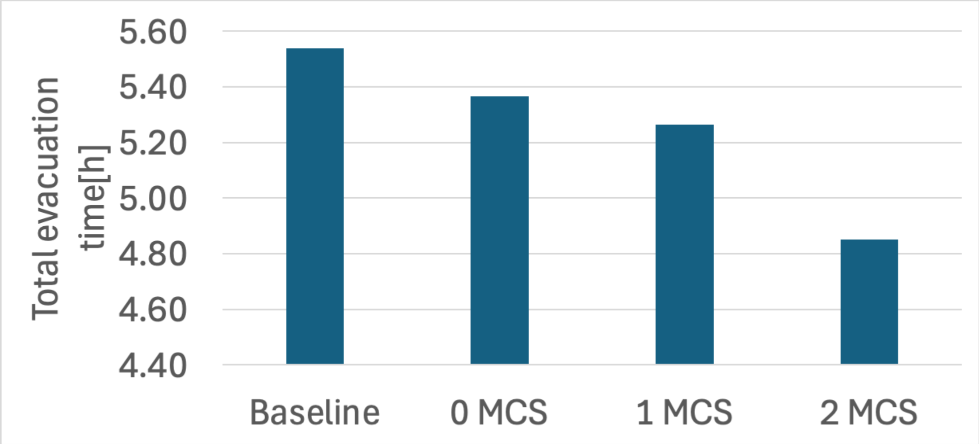
- Traffic Jam due to:
  - Large vehicle flow size
  - High charging demand at charging station

# **5. Results** – Microscopic Traffic Simulation using SUMO



SUMO simulation result (2 MCS added)




evacuation time vs # of MCS added

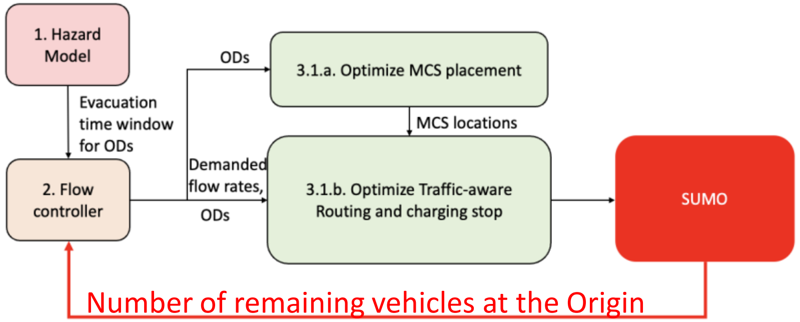
# 5. Conclusions

- MCS Supports ZEV Evacuation During Emergencies:
  - **Reduces** average evacuation **time**
  - **Ensures** EVs can complete evacuation routes.
  - Helps **reduce traffic congestion** and delays.
- Optimization-Based Route and Charging Planning Reduces Evacuation Time:
  - The vehicle **grouping** is affected by **charging infrastructures**
  - **MCS** optimal **placement** correlates with map **centrality** measures
  - Incorporates **congestion-aware planning** with free-flow constraints.
  - Considers limited-capacity **MCS** for realistic charging stop planning.
- Vehicle **initial SOC** affects evacuation time.
- Limitations:
  - Heuristics: no guarantee to find global optimum
  - Decomposed: Lack of feedback loop to update planning basing on the latest evacuation status.

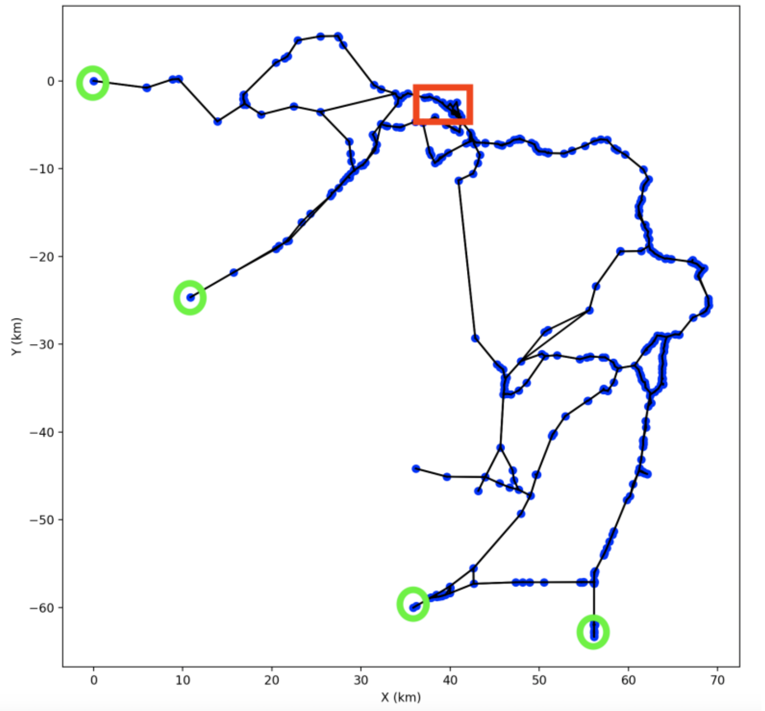
# 6. Outlook for future work

- **Short-term goals**
  - Heuristic Approach:
    - Enable vehicle **grouping**
    - Enable vehicle **waiting** for hazard spreading
    - Apply algorithm on the **Sioux Falls** map
    - **Fine-tune** the hyperparameters
    - **Validate** result with **SUMO**
  - Decomposed Approach:
    - Close the **feedback** loop for **re-planning**.

- **Long-term goals**
  - **Mariposa** use case.




Feedback loop for re-planning




Mariposa map

# Q & A

# Previous Results?

# Optimization Math Engine

## Mixed Integer Linear Programming Formulation

- Decision Variables
  - $x_{wpt}$ : Number of vehicle evacuated between origin-destination (OD) pair $w$ following path $p$ at time $t$
  - $q_{mnt}$: Binary deployment status of MCS labeled $m$ at node $n$ at time $t$
- Objective:
  - Summed evacuation time: $\sum_{w \in \mathbb{W}} \sum_{p \in \mathbb{P}_w} \sum_{t \in \mathbb{T}} (t + \tilde{t}_{wpt}) \times x_{wpt}$
- Constraints
  - Evacuation demand: $\sum_{p \in \mathbb{P}_w} \sum_{t \in \mathbb{T}} x_{wpt} = f_w, \forall w \in \mathbb{W}$
  - MCS single site deployment: $\sum_{n \in \mathbb{N}} | q_{mnt} | = 1, \forall m \in \mathbb{M}, \forall t \in \mathbb{T}$
  - Port limit: $D_{nt} \leq S_{nt}, \forall n \in \mathbb{N}, \forall t \in \mathbb{T}$
  - MCS energy limit: $0 \leq soc_{mt} \leq 1, \forall m \in \mathbb{M}, \forall t \in \mathbb{T}$

# Optimization Math Engine

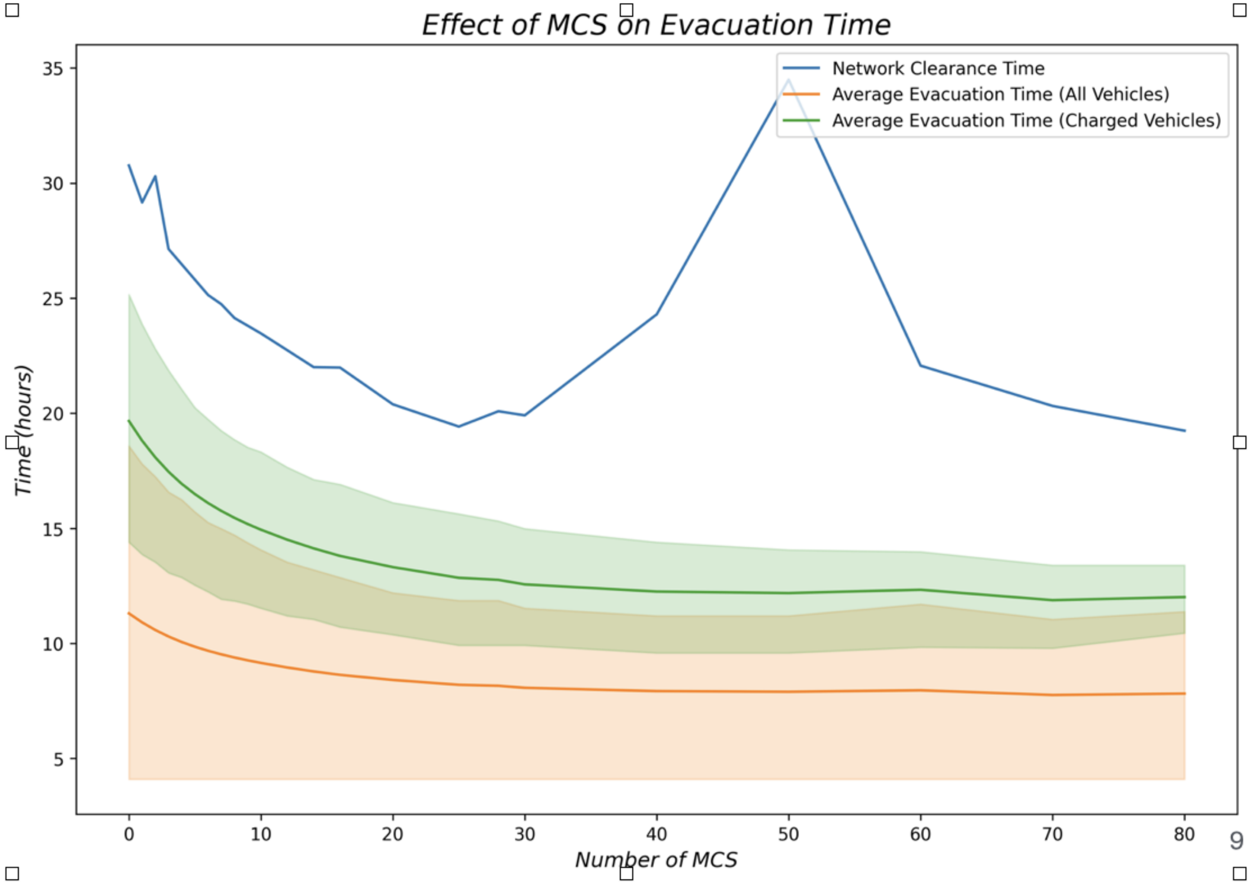
## Mixed Integer Linear Programming Formulation (TLDR)

- Objective —> Minimize the **summed** evacuation time
- Constraints:
  - Fit-the-demand —> **All** registered **vehicles** have to be **evacuated**
  - Pre-deployment —> **MCS** are placed at a **single site** throughout the evacuation
  - Port-limit —> **charging demands** at sites are **bounded** by number of **ports**
  - Energy-limit —> **MCS SOC** is **bounded** between 0 and 1

# Previous Observations

## Reduction of average evacuation time

- Shaded = 25% and 75% quantile
- More MCS = Reduced time
- **Diminishing** effect
- Low average ≠ faster evacuation span
  - Question for focus:
    - Average?
    - Longest?

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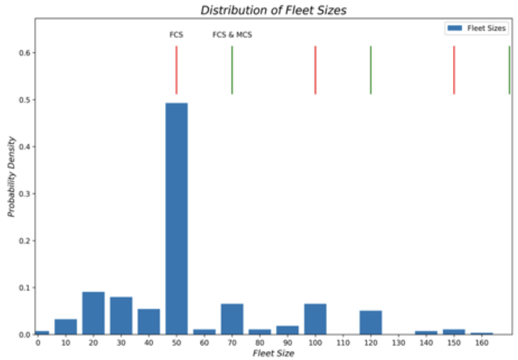
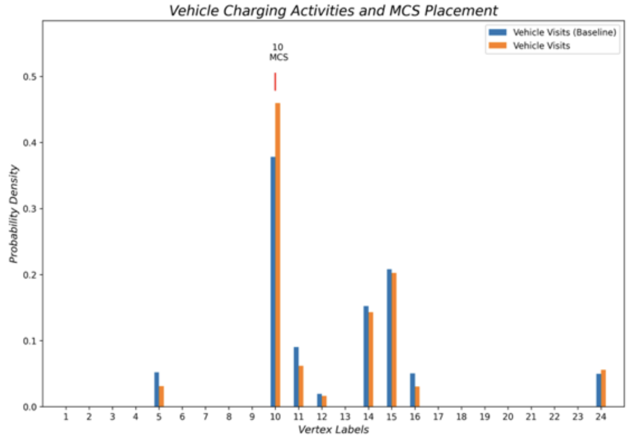
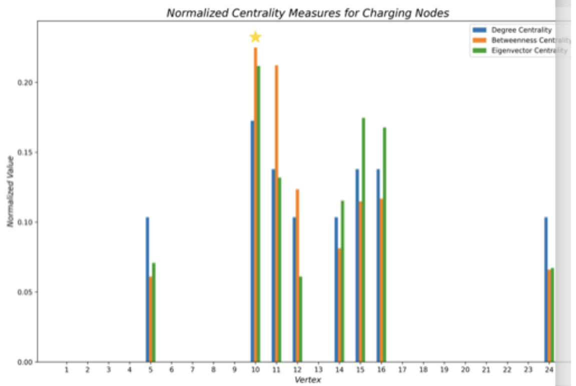
# Previous Observations

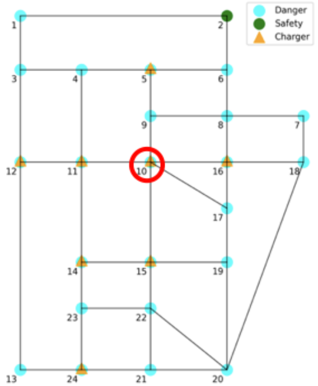
## Optimal scheduling strategy

- Vehicle departure
    - Group (fleet) **size** distribution **peaks** at number of **ports**
- MCS placement
    - All placed at the the **most-visited** node
    - The node also has **highest centrality** measures

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