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# PSU Student Research from the TRB 2022 Annual Meeting: Drone Facility Location Considering Coverage Reliability: Application to Emergency Medical Scenarios

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# DRONE FACILITY LOCATION CONSIDERING COVERAGE RELIABILITY: APPLICATION TO EMERGENCY MEDICAL SCENARIOS

Darshan Rajesh Chauhan

PSU Friday Transportation  
Seminar

21 January 2022

# ACKNOWLEDGMENTS

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  - CMMI-1636154: Optimal Control of a Swarm of Unmanned Aerial Vehicles for Traffic Flow Monitoring in Post-disaster Conditions
  - CMMI 1562109/1562291: Collaborative Research: Non-Additive Network Routing and Assignment Models
- University Transportation Centers
  - Freight Mobility Research Institute (FMRI)
  - Center for Advanced Multimodal Mobility Solutions and Education (CMMSE)

# OUTLINE

- Emergency services
- Modeling coverage reliability
- The drone facility location problem
- Other considerations
- Results
- Conclusions

# EMERGENCY SERVICES

Need to maintain high level of service:

- US Fire: 90% response rate in 4 minutes response time<sup>a</sup>
- US EMS Act 1997: 95% response rate in 10 minutes<sup>b</sup>
- UK NHS: 75% and 95% response rates in 8 and 14 minutes<sup>c</sup>
- Medical drone applications active in the US: Nevada, North Carolina, North Dakota<sup>d</sup>



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<sup>a</sup> National Fire Protection Agency, 2020. NFPA 1710.

<sup>b</sup> Lutter, P., Degel, D., Büsing, C., Koster, A.M. and Werners, B., 2017. Improved handling of uncertainty and robustness in set covering problems. *European Journal of Operational Research*, 263(1), pp.35-49.

<sup>c</sup> Budge, S., Ingolfsson, A. and Zerom, D., 2010. Empirical analysis of ambulance travel times: The case of Calgary emergency medical services. *Management Science*, 56(4), pp.716-723.

<sup>d</sup> FAA, 2021. UAS BEYOND. [https://www.faa.gov/uas/programs\\_partnerships/beyond/](https://www.faa.gov/uas/programs_partnerships/beyond/)

# MODELING SERVICE RELIABILITY

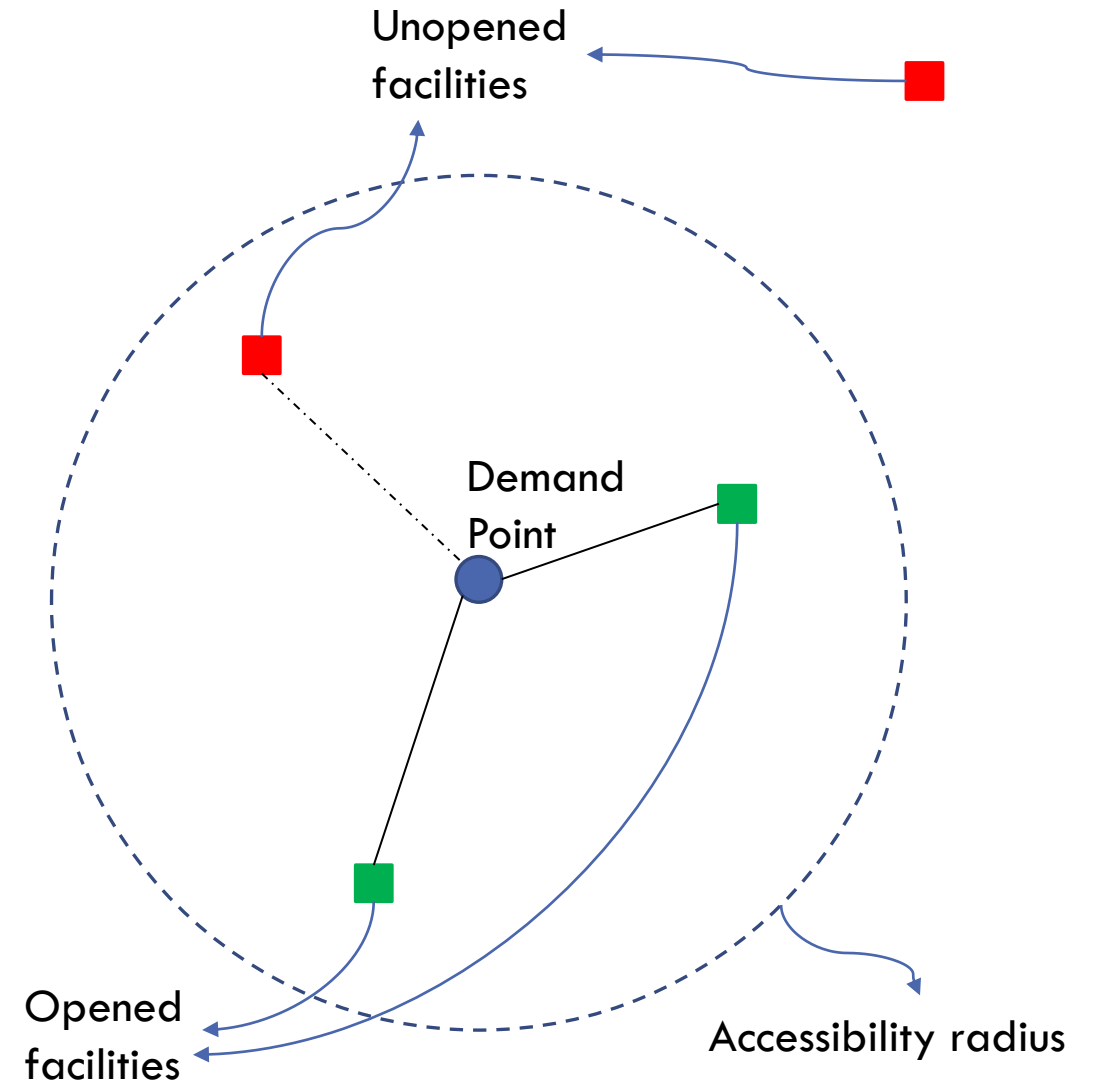
- $S_i$  : Set of open facilities that can access demand point  $i$
- $p_{ij}$  : probability of failing to reach demand point  $i$  from location  $j$
- $a_{ij}$  : 1, with probability  $(1 - p_{ij})$ , and 0 with probability  $p_{ij}$
- $\alpha$  : reliability standard (e.g., 90%)

For demand point  $i$  to be covered:

$$\text{Prob} \left( \sum_{j \in S_i} a_{ij} \geq 1 \right) \geq \alpha$$

Assuming independence:

$$\text{Prob} \left( \sum_{j \in S_i} a_{ij} \geq 1 \right) = 1 - \prod_{j \in S_i} p_{ij} \geq \alpha$$



# A BASIC FACILITY LOCATION MODEL (SP-D)

Objective: Maximize Coverage

$$\text{Max}_{x,y} \sum_{i \in I} c_i x_i$$

Coverage Reliability Constraints for each demand point  $i \in I$

$$\prod_{j \in S_i} (p_{ij})^{y_j} \leq (1 - \alpha)^{x_i}$$

Facility Opening Constraint

$$\sum_{j \in J} y_j \leq q$$

Variable definitions

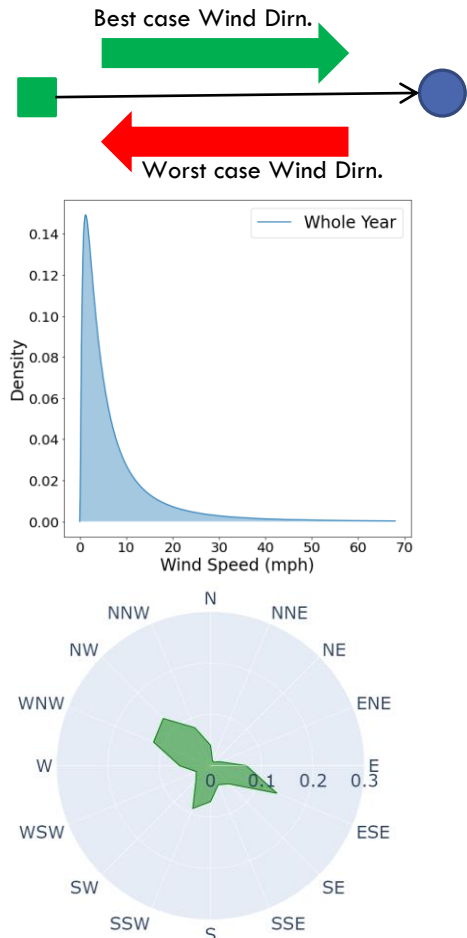
$$x_i, y_j \in \{0,1\}$$

$c_i$  defines importance of covering a demand point  $i \in I$ . Therefore, it is a composite metric and can include factors like:

- Population and demographics
- Emergency calls history
- Equity considerations
- others...

# HOW ARE LOCATION DECISIONS AFFECTED?

## Initial Information



Monte-Carlo Sampling

## Estimating Failure Probabilities

$\bar{p}_{ij}$  is weighted average of  $p_{ij}^{best}$  and  $p_{ij}^{worst}$ .

Weights are decided by the proportion of time wind direction is aligned with delivery direction.

SP-D assumes  $p_{ij} = \bar{p}_{ij}$

Facility Location Model

## Final Output

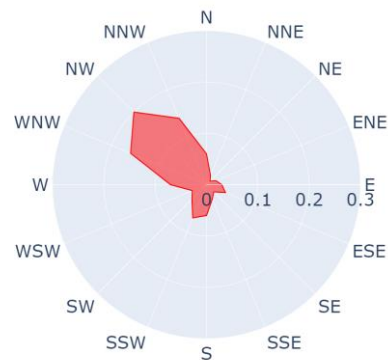
Selected locations for drone operations

Demand Locations that would be "reliably" covered

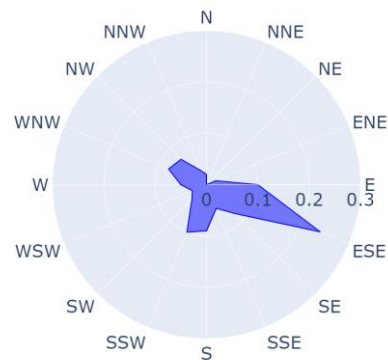


# OTHER CONSIDERATIONS

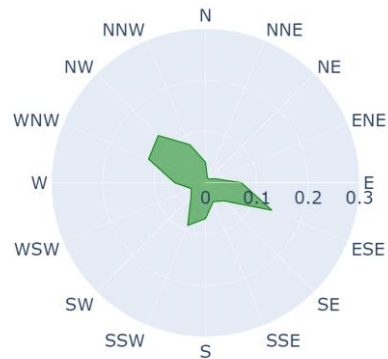
## Seasonality in Wind Directions



Summer Months  
(Apr – Sept)



Winter Months  
(Oct – Mar)



Whole Year

Captured using multiple periods.

Allows opportunity to model changes in facility locations between periods

## Failure Probability Estimation Uncertainty

Assuming  $p_{ij} \in [p_{ij}^{best}, p_{ij}^{worst}]$ , instead of  $p_{ij} = \bar{p}_{ij}$

Use Robust Optimization framework

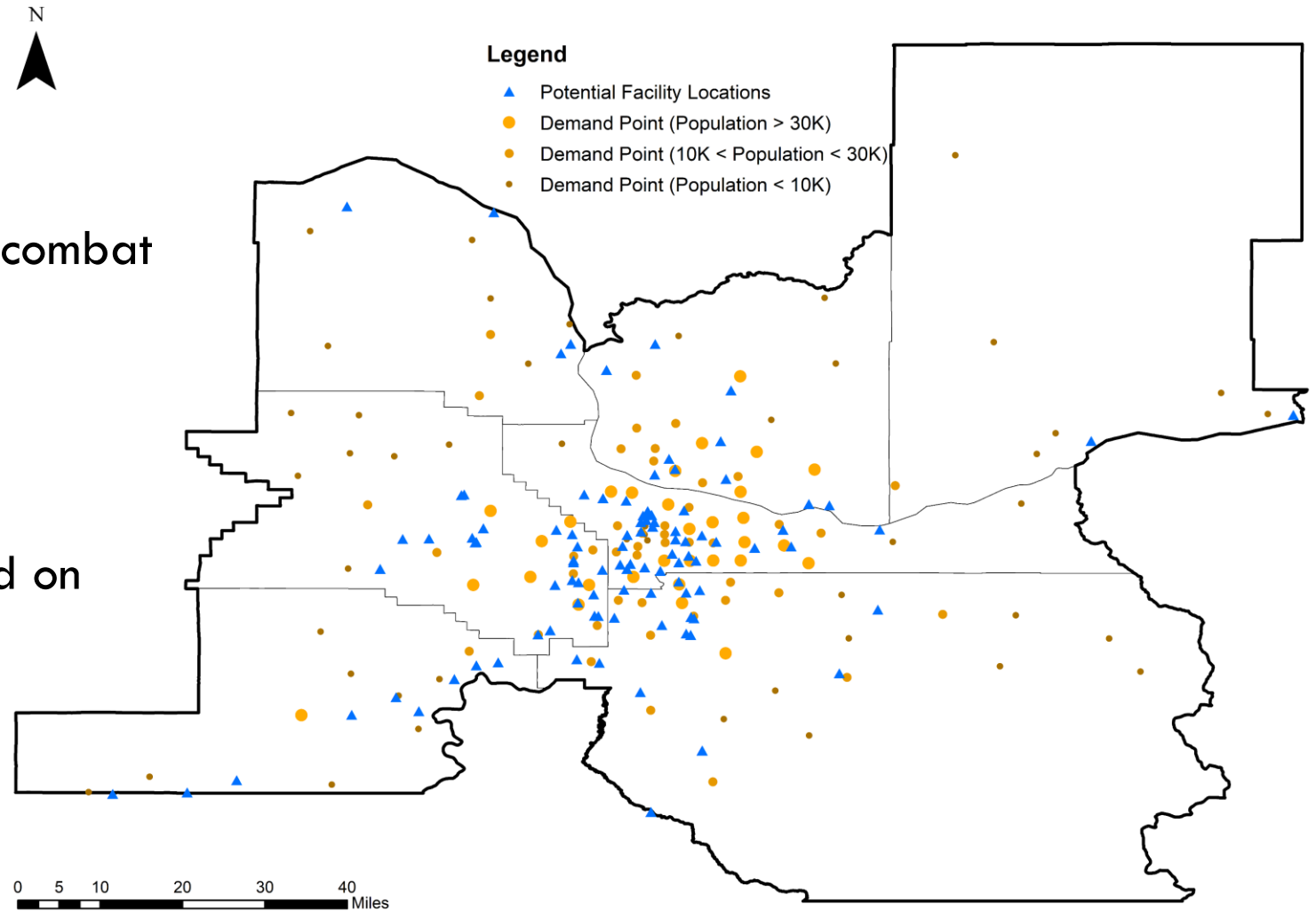
Conservatism induced by capturing uncertainty is controlled using parameter  $\Gamma$

New facility location models developed that capture:

- Seasonality only: MP-D
- Uncertainty only: SP-R
- Both seasonality and uncertainty: MP-R

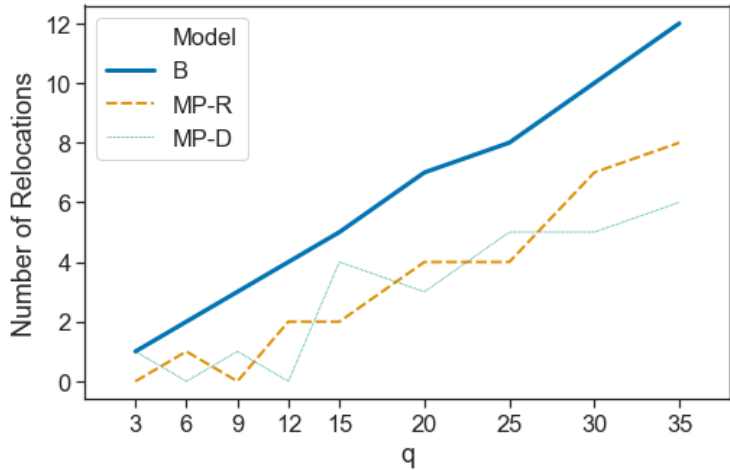
# CASE STUDY

- Deploy AED-enabled drones to combat out-of-hospital cardiac arrests
- 122 demand locations
- 104 potential facility locations
- Coverage importance ( $C_i$ ) based on normalized population
- Two Service Standards:
  - SS1: providing 90% coverage reliability in 4 minutes
  - SS2: providing 95% coverage reliability in 10 minutes

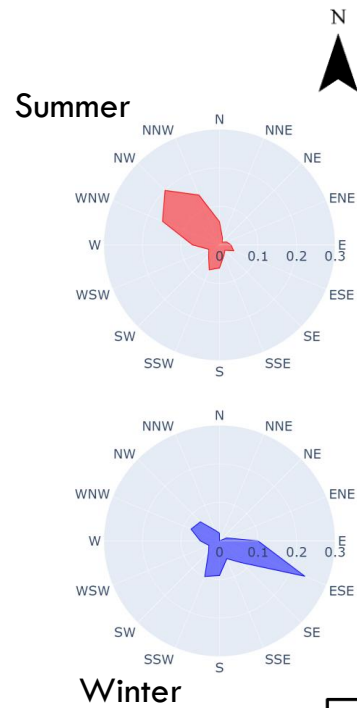
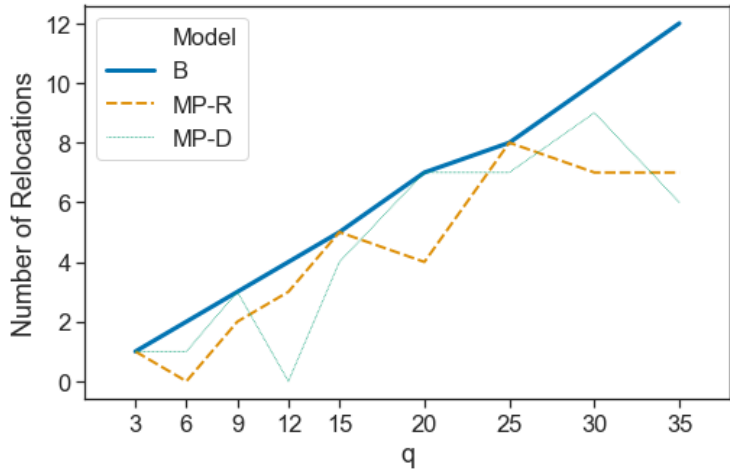


# EXTENT OF FACILITY RELOCATION

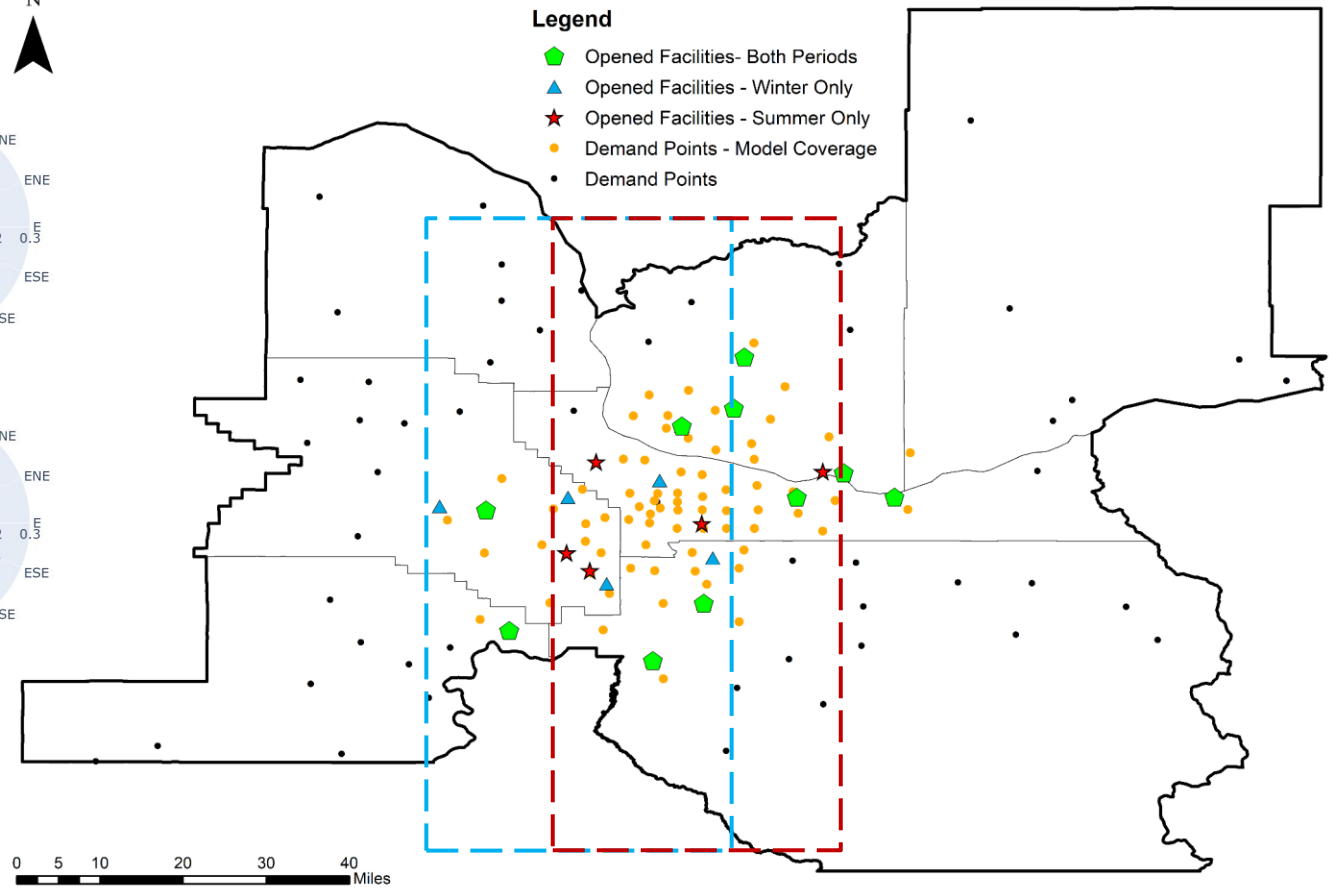
SS1



SS2

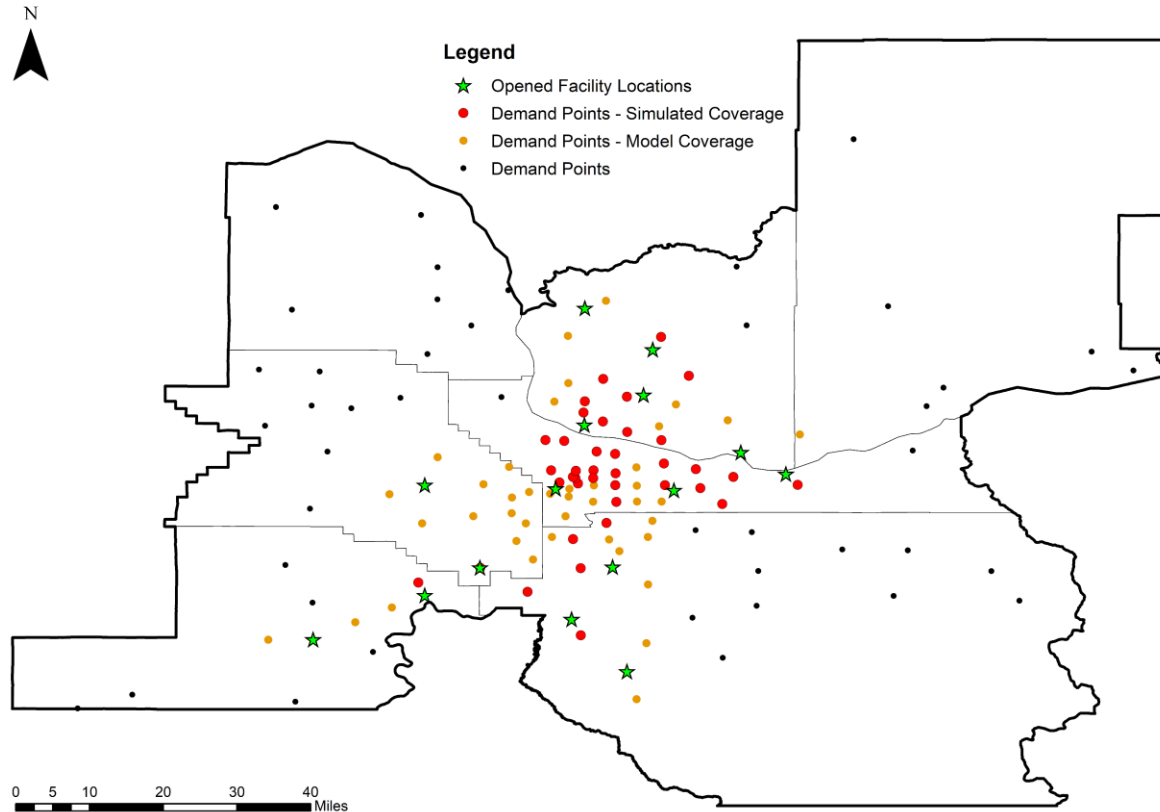


MP-R with  $\Gamma=1$ ; SS2;  $q=15$ ; at most 5 facilities can change locations between Summer and Winter

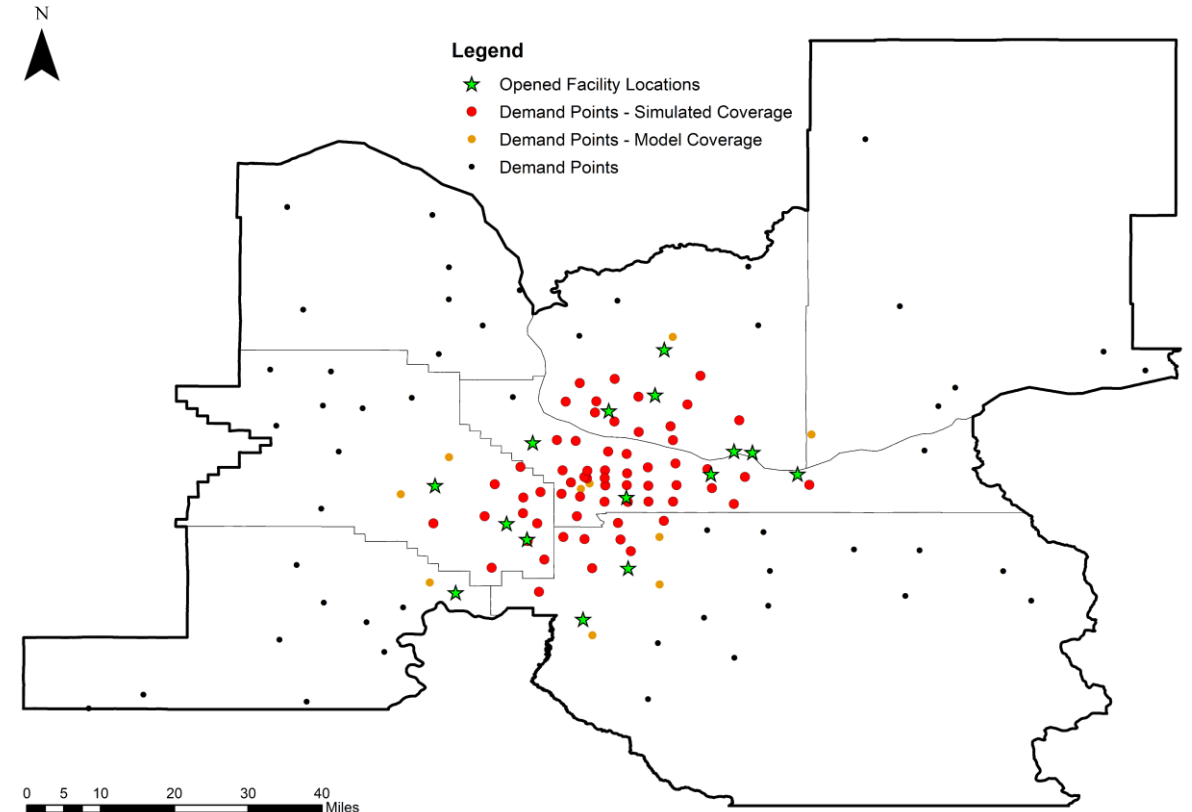


# IMPROVEMENTS IN COVERAGE RELIABILITY

SP-D



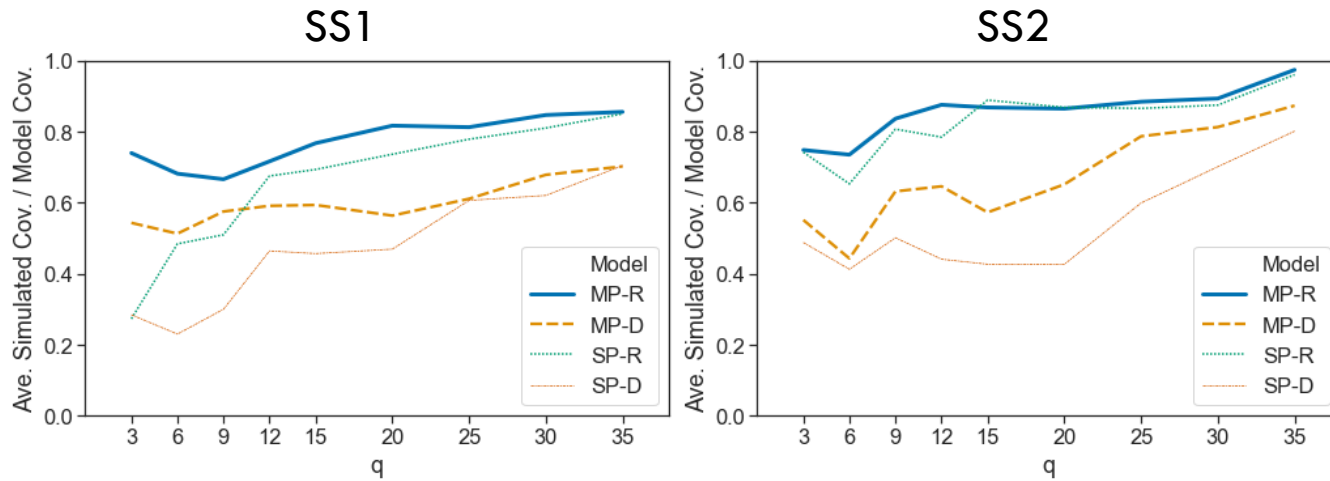
MP-R with  $\Gamma=1$



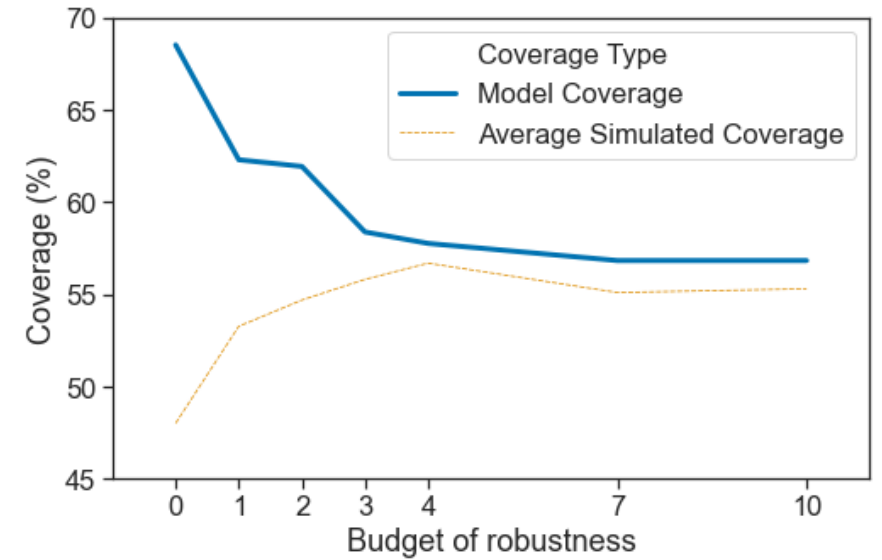
SS2 (95% reliability in 10 minutes);  $q=15$

# REDUCING THE GAP BETWEEN MODEL AND SIMULATED COVERAGE VALUES

Increasing the number of opened facilities ( $q$ )  
(robust models use  $\Gamma_i^t=1$ )



Increasing decision conservatism  
(MP-R; SS1;  $q=35$ ;  $B=12$ )



# CONCLUSIONS

- Facility location problem considering coverage reliability is modeled. The model uses multiple periods to capture seasonality and robust optimization to capture uncertainty in estimation of failure probabilities.
- Capturing both seasonality and uncertainty improves simulated coverage values by 57% (or, 0.57 times), on average.
- Capturing both seasonality and uncertainty are required for best decisions when travel time threshold is small (SS1), while just capturing uncertainty would suffice when travel time thresholds are long (SS2).
- Capturing uncertainty consolidates facilities in the urban core to improve reliability.
- The performance gap between model coverage and simulated coverage can be reduced by either increasing conservatism in decisions, or by opening more facilities.

# THANK YOU!

Contact:

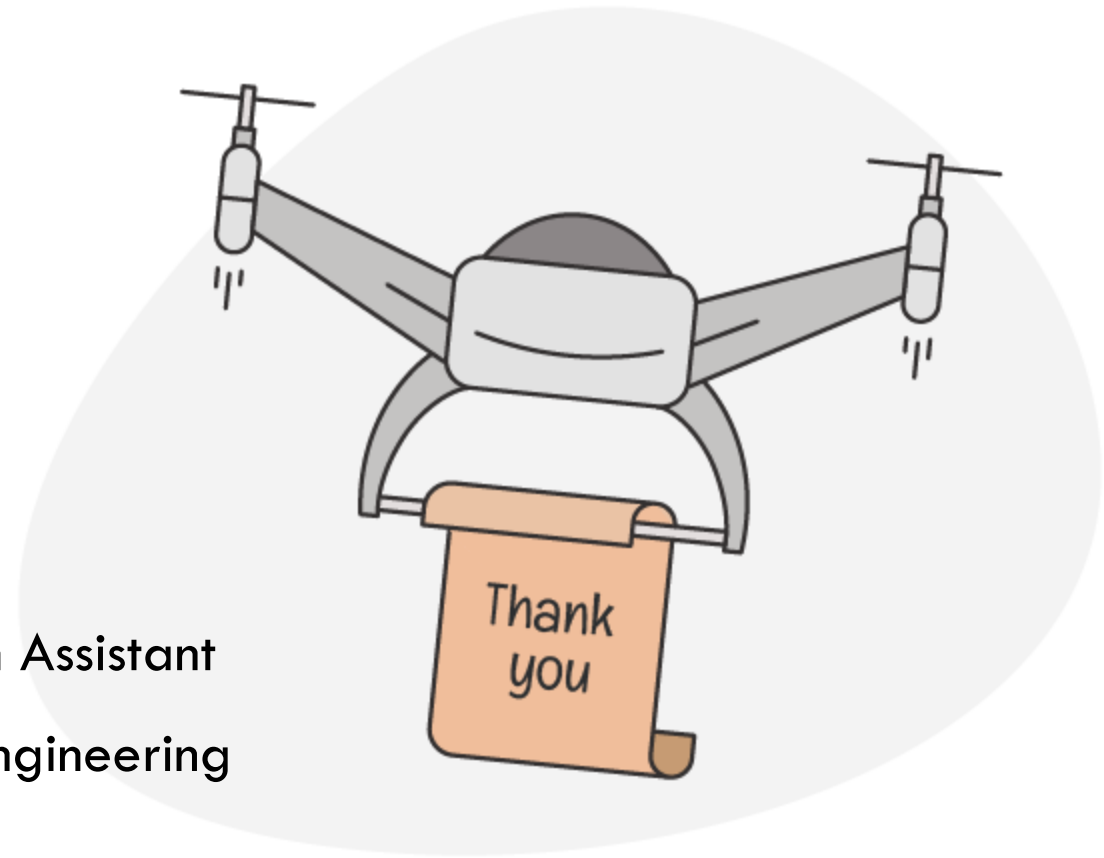
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**SUPPLEMENTARY MATERIAL** |



# MULTI-PERIOD ROBUST (MP-R) FORMULATION

Objective:

$$\text{Max}_{x,y,z} \sum_{i \in I} c_i x_i$$

Coverage Reliability Constraints for each demand point  $i \in I$  and time period  $t \in T$

$$\text{Max}_{\{U \subseteq S_i, |U| \leq \Gamma\}} \left[ \prod_{j \in U} (p_{\text{-worst}}^t_{ij})^{y_j^t} \cdot \prod_{j \in S_i \setminus U} (\bar{p}_{ij}^t)^{y_j^t} \right] \leq (1 - \alpha)^{x_i}$$

Facility Opening Constraint for each time period  $t \in T$

$$\sum_{j \in J} y_j^t \leq q$$

# MULTI-PERIOD ROBUST (MP-R) FORMULATION

Facility Relocation Budget Constraint

$$\sum_{t \in T \setminus \{1\}} \sum_{j \in J} \sum_{k \in J} f_{jk}^t z_{jk}^t \leq B$$

Facility Relocation Logical Constraints

$$\sum_{k \in J} z_{jk}^t = y_j^{t-1} \quad \forall j \in J, t \in T \setminus \{1\}$$

$$\sum_{j \in J} z_{jk}^t = y_k^t \quad \forall k \in J, t \in T \setminus \{1\}$$

Variable Definitions

$$x_i, y_j^t, z_{jk}^t \in \{0, 1\}$$

# MODEL PERFORMANCE RESULTS

- SS1: service standard of providing 90% reliability in 4 minutes

Computational time increment by:

- Adding multiple periods: 37 times
- Adding robustness ( $\Gamma=1$ ): 5.2 times

- SS2: service standard of providing 95% reliability in 10 minutes

Computational time increment by:

- Adding multiple periods: 49.5 times
- Adding robustness ( $\Gamma=1$ ): 24.5 times

# MODEL PERFORMANCE RESULTS

- SS1: service standard of providing 90% reliability in 4 minutes

Improvement in average simulated coverage for SS1:

- Adding multiple periods:
  - Deterministic model: 0.41 times
  - Robust model ( $\Gamma=1$ ): 0.29 times
- Adding robustness ( $\Gamma=1$ )
  - Single period: 0.28 times
  - Multiple period: 0.14 times
- SP-D to MP-R: 0.60 times

- SS2: service standard of providing 95% reliability in 10 minutes

Improvement in average simulated coverage for SS2:

- Adding multiple periods:
  - Deterministic model: 0.24 times
  - Robust model ( $\Gamma=1$ ): 0.02 times
- Adding robustness ( $\Gamma=1$ )
  - Single period: 0.51 times
  - Multiple period: 0.23 times
- SP-D to MP-R: 0.54 times

# WIND SPEED AND DISTRIBUTION DATA

Available openly at <https://github.com/drc1807/RMP-MCFLP-CR>