Optimized path planning of a swarm of drones for massive data collection

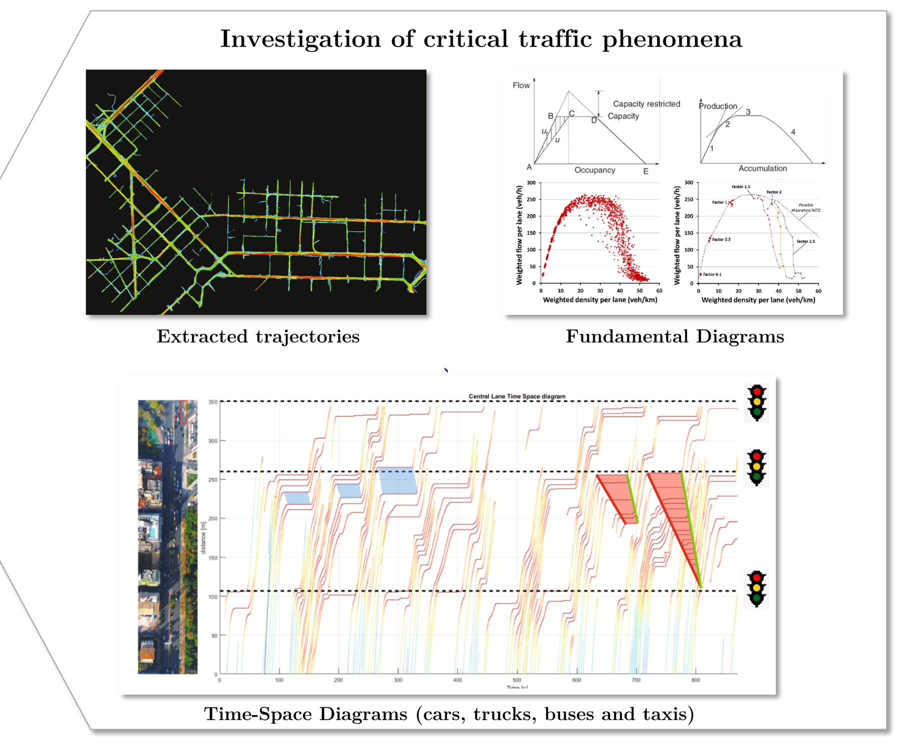
Master Project

Under the supervision of
Prof. Nikolas Geroliminis
Submitted by
Yassine El Ouazzani

Urban Transport Systems Laboratory (LUTS)

Introduction & Challenges

Traffic data collection is the main issue that scientists and researchers are faced to when trying to perform traffic engineering. Traditional manual counting is to forget, given the amount of data to treat. Several mechanical methods are currently tested and established but multiple issues, malfunctions and lack of efficiency are noted. Indeed, fixed sensors, cameras or loop detectors are distributed over urban networks to count down the passing vehicles. These practices are costly, and several malfunctions are noted. An alternative new solution involving a swarm of drones may help and give a real push to the research in this topic. In fact, using drones to film the traffic is a way to collect the data easily, with no heavy cost. The challenge is to find a way to do it appropriately, with the **optimal deployment**.



MILP Modelling

Time consuming problem ⚠

Parameters

t_{ij}	Travel time for arc (i, j)
c_d	Maximum flying time for drone d
I_d	Initial position of drone d
M	Big parameter for time
D_{max}	Maximum number of drones

Sets

N	Set of nodes (= 1, ..., n)
A	Set of arcs (= 1, ..., a)
D	Set of drones (= 1, ..., k)

Decision Variables

$$x_{ij,d} = \begin{cases} 1, & \text{if drone } d \text{ flies over arc } (i,j) \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

$$y_d = \begin{cases} 1, & \text{if drone } d \text{ is used} \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

$$u_{i,d} \in \mathbb{R}^+ = \text{Arrival time at node } i \text{ of drone } d \quad (18)$$

$$\text{Min} \sum_{\forall (i,j) \in A} \sum_{d=1}^{k} x_{ij,d} t_{ij}$$ (4) Objective function

$$\sum_{d=1}^{k} (x_{ij,d} + x_{ji,d}) \geq 1, \quad \forall (i,j) \in A$$ (5) Each edge is visited at least once

$$\sum_{i:(i,j) \in A} x_{ij,d} \leq 1, \quad \forall j \in N, \quad \forall d \in D$$ (6) Each arc cannot be visited more than one time

$$\sum_{j:(i,j) \in A} x_{ij,d} \leq 1, \quad \forall i \in N, \quad \forall d \in D$$ (7) Each arc cannot be visited more than one time

$$\sum_{j:(i,j) \in A} x_{ij,d} = \sum_{j:(j,i) \in A} x_{ji,d}, \quad \forall i \in N, \quad \forall d \in D$$ (8) Flow conservation constraint

$$x_{ij,d} \leq y_d, \quad \forall (i,j) \in A, \quad \forall d \in D$$ (9) Indicates if a drone is used or not

$$\sum_{d=1}^{k} y_d \leq D_{max}, \quad \forall d \in D$$ (10) Gives maximum number of drones at disposal

$$u_{i,d} \leq c_d, \quad \forall d \in D \quad \forall i \in N$$ (11) Capacity constraint

$$u_{j,d} \geq u_{i,d} + t_{ij} - M(1 - x_{ij,d}), \quad \forall i \in N, \quad \forall j \in N \backslash \{I_d\}, \quad \forall d \in D$$ (12) Sub-tour elimination constraint

Column Generation

Restricted Master Problem (RMP):

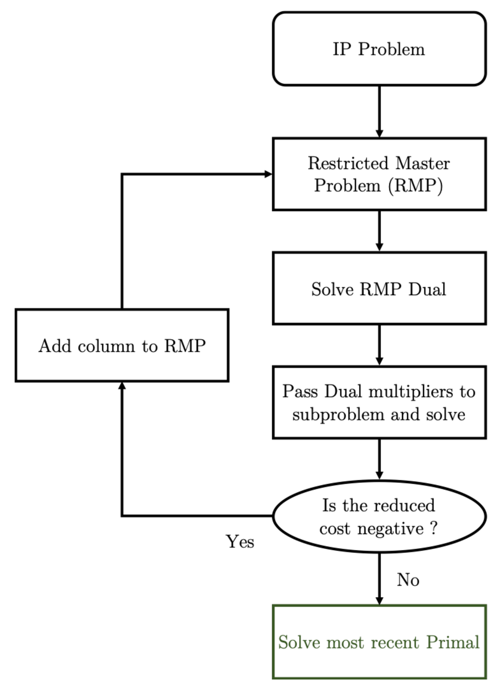
- ✓ Determine optimal number of drone to use given the available fleet
- ✓ Cover the whole network by selecting pre-determined paths generated by the Subproblem
- ✓ Need to be initialized → Generate initial solution (e.g. one drone / arc)

$$\text{Minimize} \sum_{d=1}^{k} c_d y_d$$

$$\sum_{d=1}^{k} (a_{ij,d} + a_{ji,d}) y_d \geq 1, \quad \forall (i,j) \in A$$

$$\sum_{d=1}^{k} y_d \leq D_{max}$$

$$y_d \in \{0, 1\}, \quad \forall d \in D$$



Subproblem:

- ✓ Generate routes using maximum capacity of drones
- ✓ Priorit>ize highly visited arcs (using duals)
- ✓ Continuous closed loops
- ✓ Mathematical Modelling very hard to write down → Use **Heuristics**

Random Heuristic

1. Choose the starting point (manually or randomly)
2. Calculate the shortest path to go from every points to the starting one and save those values in a matrix
3. Inspect the adjacent arcs and randomly choose one of them
4. If possible to comeback to starting point, repeat step 3. Otherwise, stop.
5. Once the last point visited within capacity, build the comeback sequence of node using Dijkstra

Improvement Heuristic

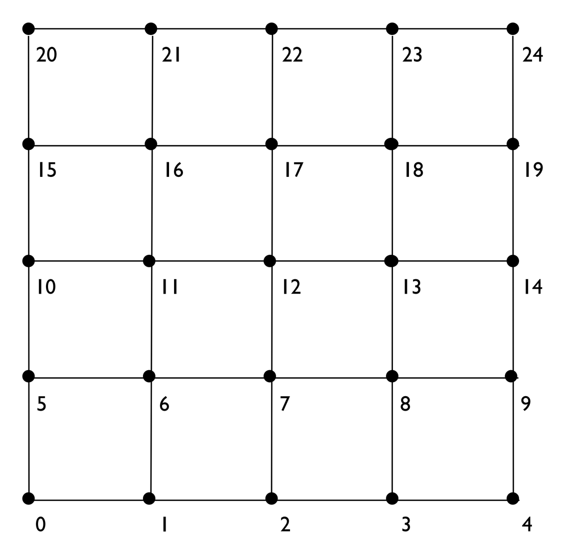
1. Sort the selected set of paths (solution) based on the total travel time, from the shortest to the longest.
2. Mark the shortest path selected and its first arc
3. Force the heuristic to create a path going through the same 1st arc
4. Run the "random heuristic" to build the rest of the path

Lowest cost insertion Heuristic

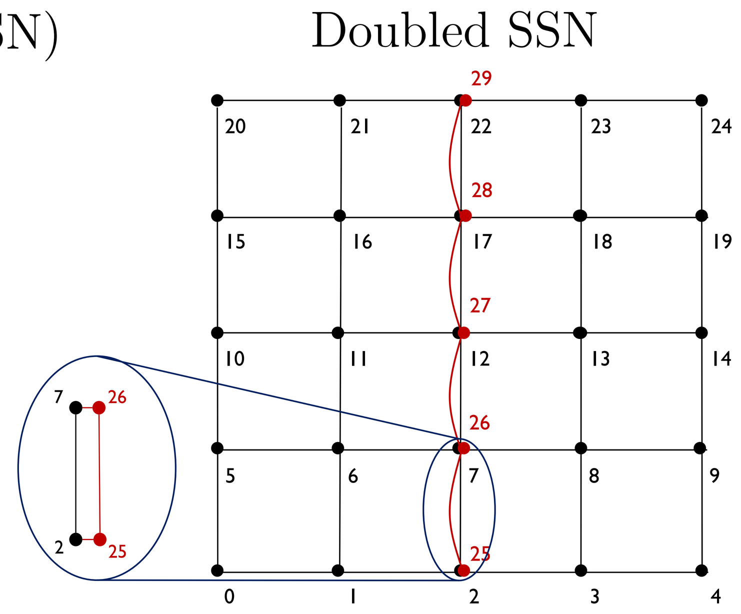
1. Choose starting point
2. Find highest weight next point to visit (using dual multipliers from RMP) and build a 1st arc
3. Find highest weight available point (using dual multipliers from RMP) to visit from any visited points
4. Insert next point by building the most relevant arcs (existing ones can be destroyed)
5. Repeat steps 3. and 4. until capacity is reached

Networks

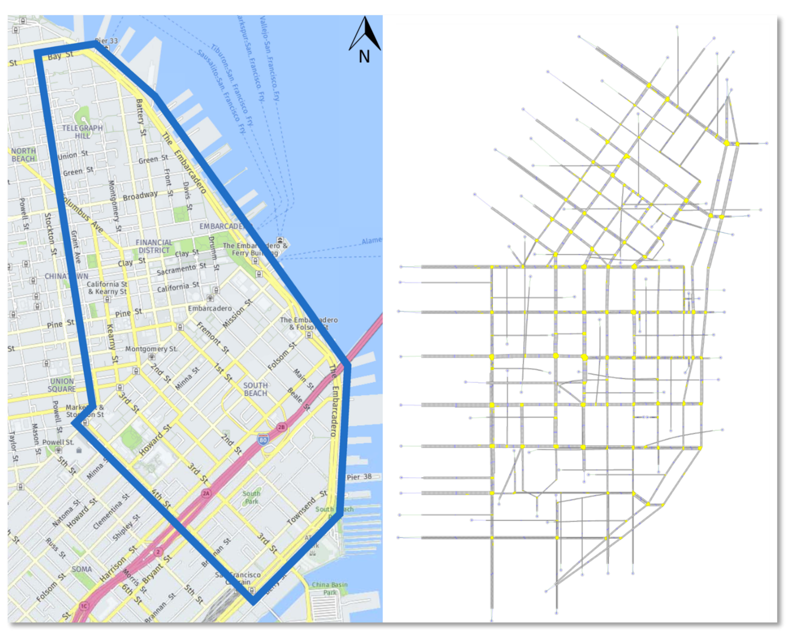
Small Scaled Network (SSN)



Doubled SSN

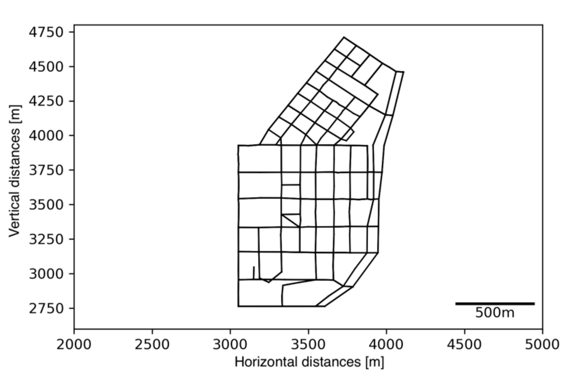


San Francisco Network



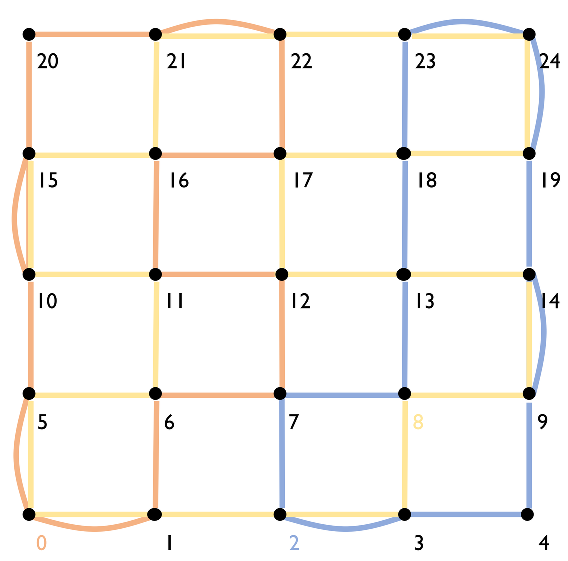
Main Characteristics

Number of nodes	242
Number of arcs	313
Total kilometers	40.8 kms
Lower bond	50 kms



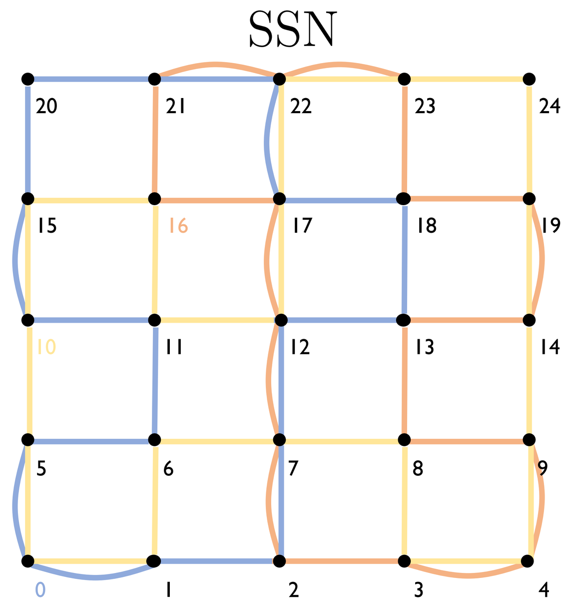
Results

Result 1: MILP SSN



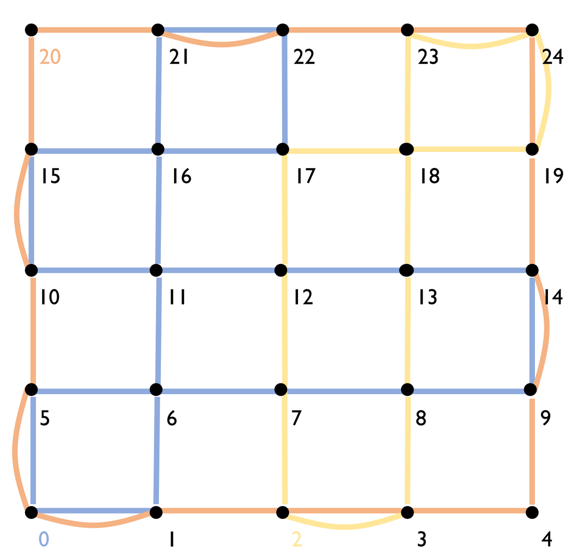
- Objective function = 48
- Optimality Gap = 19.2%
- 6h run (same obj after 20mins)

Result 2: MILP doubled SSN



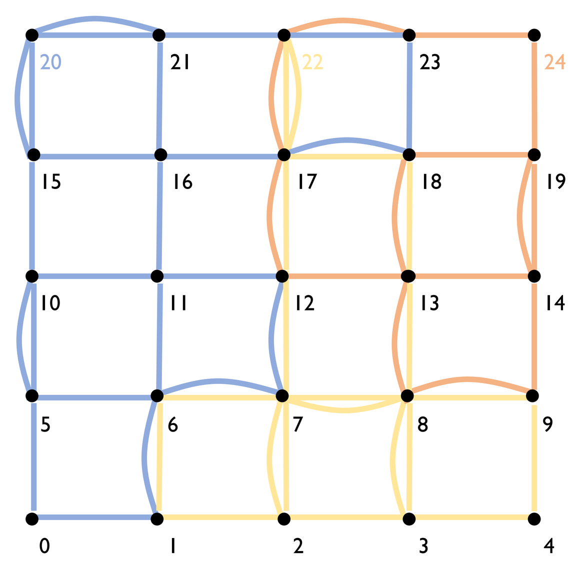
- Objective function = 52
- Optimality Gap = 15.5%
- 6h run (same obj after 20mins)

Result 3: CG SSN



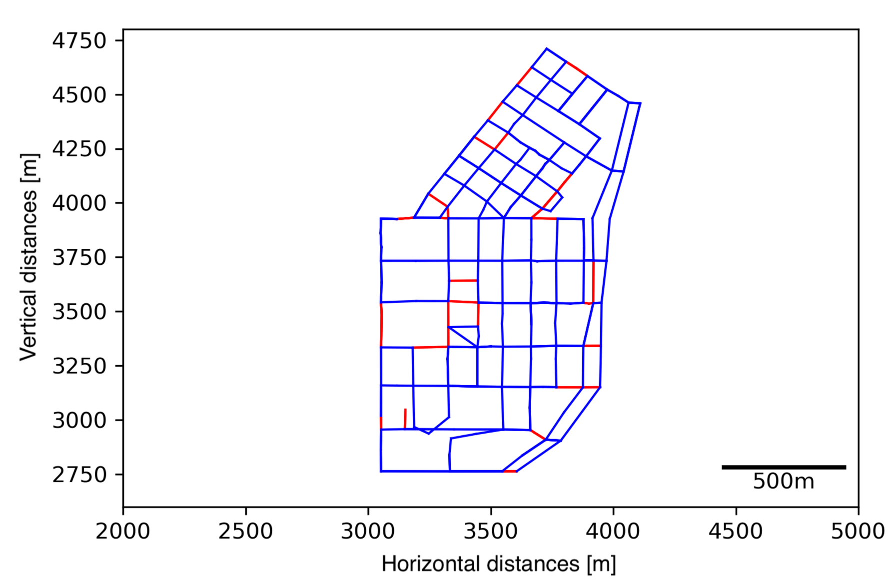
- Objective function = 48
- Optimality Gap = --%
- ~ 1 min run

Result 4: CG doubled SSN

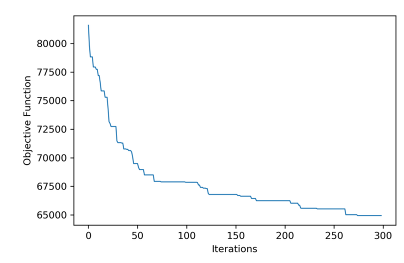


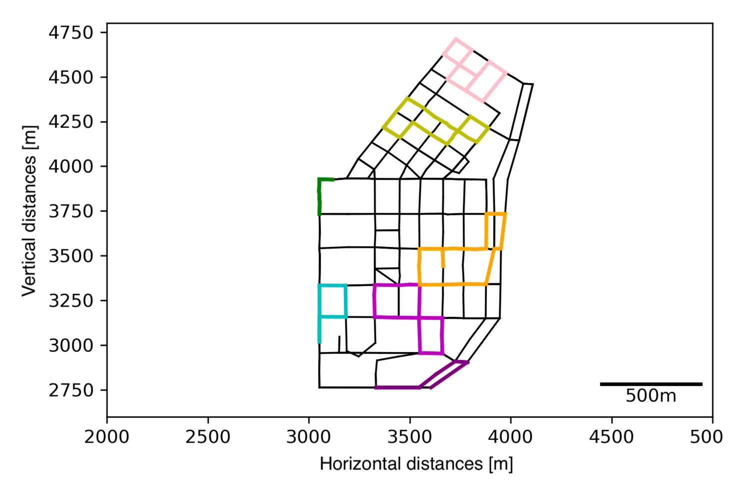
- Objective function = 58
- Optimality Gap = --%
- 1 min 22 s run

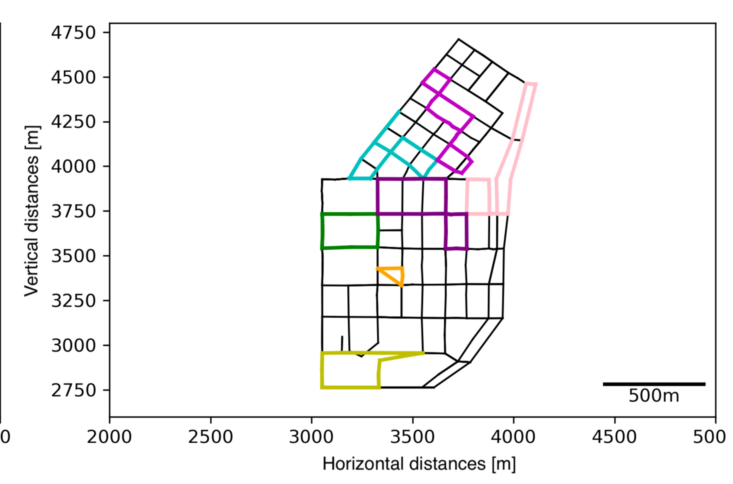
Result 5: Column Generation on San Francisco Network

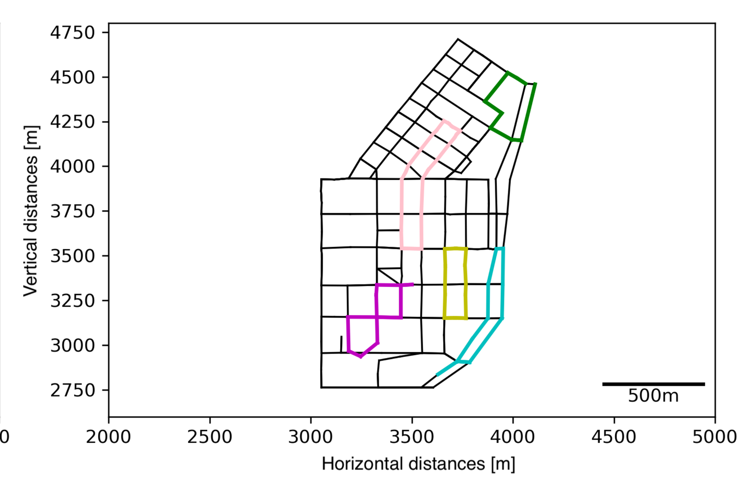


Result 5 Main characteristics	
Number of drones selected	19
Optimality gap estimated	31%
Total kilometers covered	65.5 kms
Total kilometers saved from initial solution	16.1 kms
Running time	31 min 28 sec









Conclusions

MILP Model

✓ Optimal Solution
✓ Not adaptive nor time-efficient
→ Impossible to solve for large scale Network

Column Generation based Model

✓ Adaptive and time efficient
✓ Satisfies most of the objectives
→ Expected to improve (e.g., other improvement heuristics)

References

Barmpounakis, E. and Geroliminis, N. (2020). On the new era of urban traffic monitoring with massive drone data: The pneuma large-scale field experiment. Transportation Research Part C: Emerging Technologies, 111:50–71.

Tsitsokas, D., Kouvelas, A., and Geroliminis, N. (2019). An optimization framework for exclusive bus lane allocation in large networks with dynamic congestion. In 98th Annual Meeting of the Transportation Research Board (TRB 2019), pages 19–02738. The National Academies of Sciences, Engineering, and Medicine.