Route Optimization using Reinforcement Learning and Metaheuristic Approach

publicis
sapient

September 8, 2022

About the Speakers

Ravi Ranjan is working as Manager Data Science at Publicis Sapient (India) with expertise in budling scalable ML solutions. He is a certified Google Cloud Architect. He has done proficiency course in Reinforcement Learning from IISc, Bangalore. He is contributor and member at Kubeflow (ML Platform by Google).

Sushant has a bachelor's in Materials Engineering from the Indian Institute of Technology, Kharagpur. He has extensive work experience in Reinforcement Learning, Computer Vision with AR technologies and created end-to-end pipelines and data products from conceptualization to deployment phase for various engagements. He is currently working as a Senior Data Scientist at Publicis Sapient.

publicis
sapient

Session Logistics

1. Access to the session environment using the following link. [https://bit.ly/join-the-ODSC-session]
2. Presentation and research paper will be available at link. [https://bit.ly/ODSC-conference-India-2021]
3. Connecting to the speaker [Please send introductory note in LinkedIn invite]

   https://bit.ly/ravi-ranjan-03

   https://bit.ly/ravi-ranjan-03
4. Don't forget to tweet and share the session with #ODSCAPAC

publicis
sapient

Learning Outcome

1. Gain an understanding of Recommendation Systems.
2. How to transform the concepts and build Recommendation Systems?
3. Gain a detailed understanding of deep reinforcement learning-based recommendation system.
4. How to recommend using the deep RL based model with distributed Q-table?
5. Reference architecture of recommendation engines.

Session Agenda

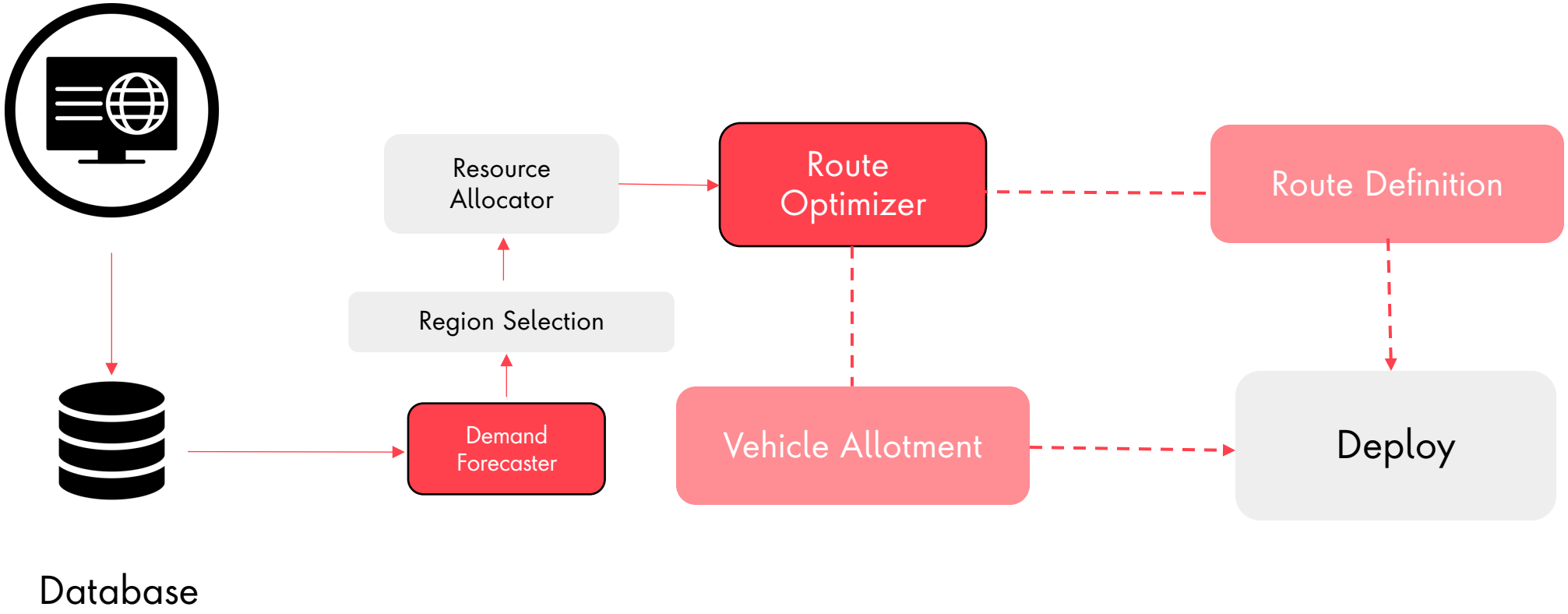
1. Introduction to Route Optimization
2. Why we need Route Optimization?
3. The classical approach to Multi-vehicle route optimization and its limitations
4. Introduction to the key concepts of
    - Multi-objective Optimization
    - Reinforcement Learning
    - Genetic Algorithms and other Metaheuristics
4. Combination of a Deep RL-based algorithm with a metaheuristic approach
5. Training Methodology and Result Discussion
6. Business Impacts and Outcomes
7. Question - Answers

Section 1

Route Optimization

The background to our problem is...

The business flow...

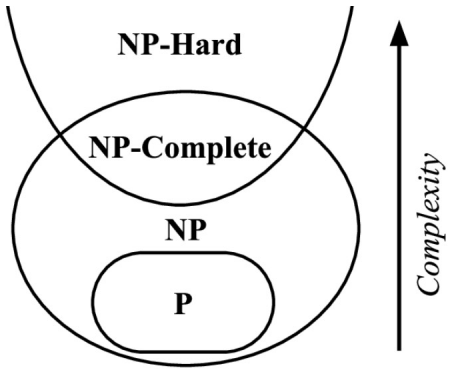


Daily based Model

Classifying the decision problems into the complexity classes

P(Polynomial Time)

NP(Non-deterministic Polynomial Time)



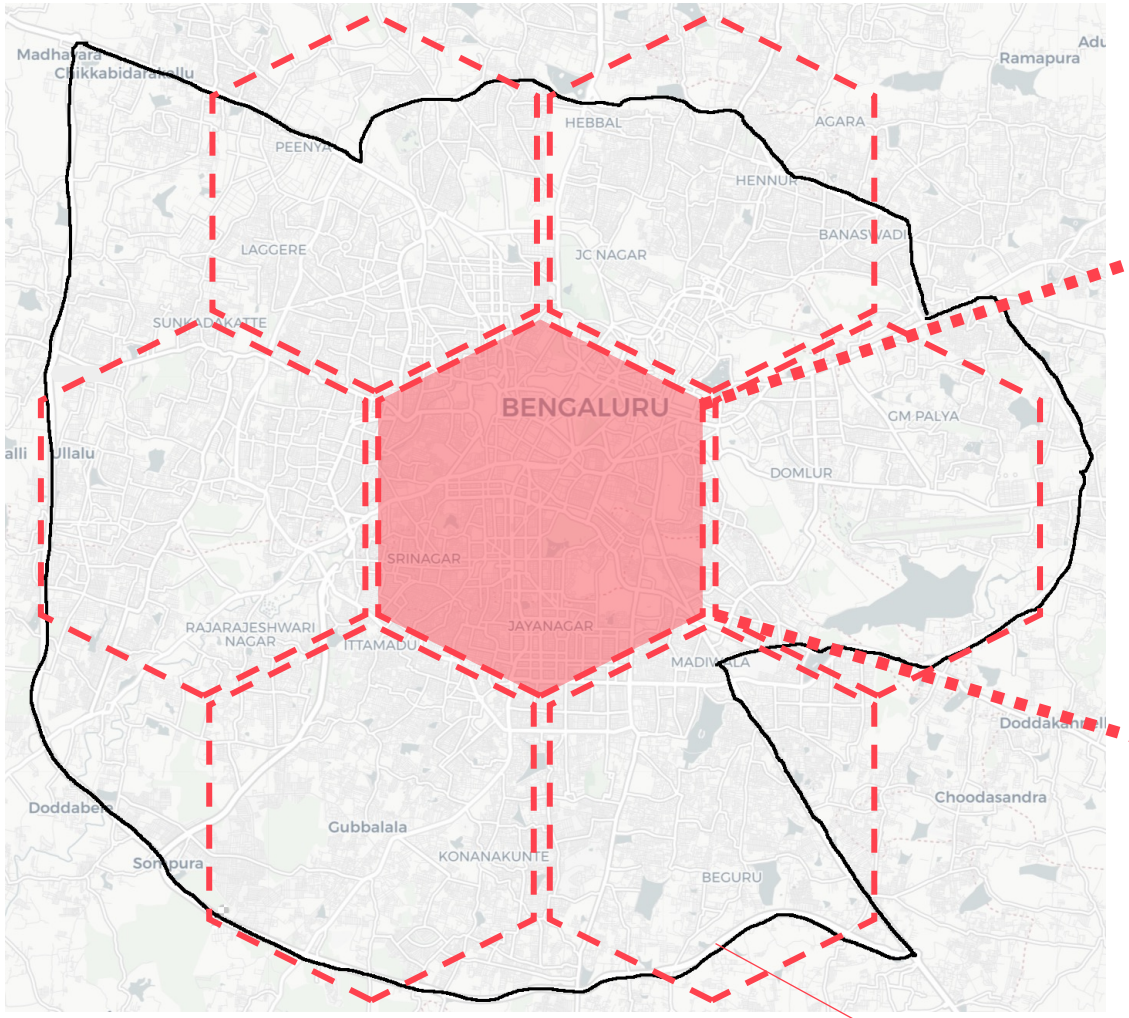
NP-Hard

NP-Complete

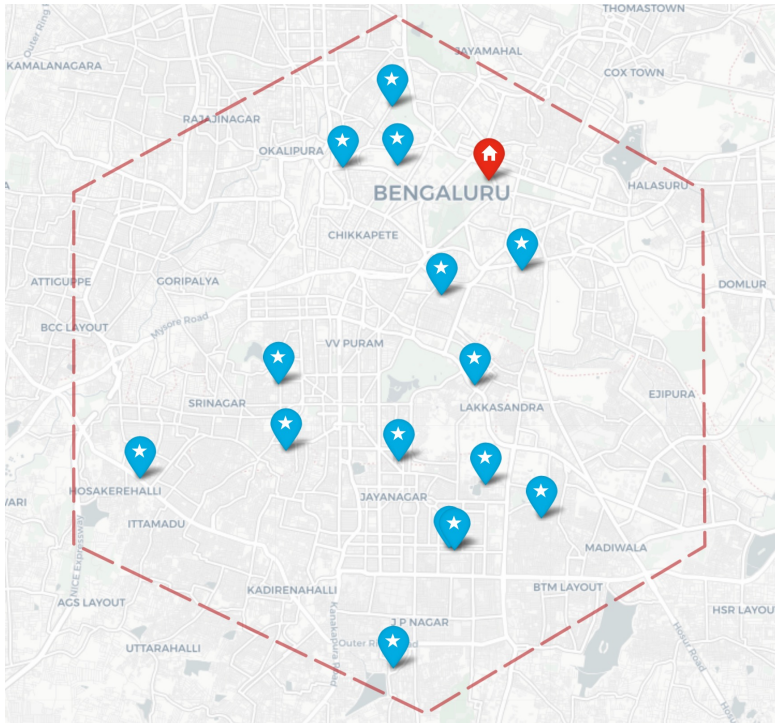
Section 1

Scaling the solution using Primary Cells

Creating a Scalable Architecture...



Central Bangalore

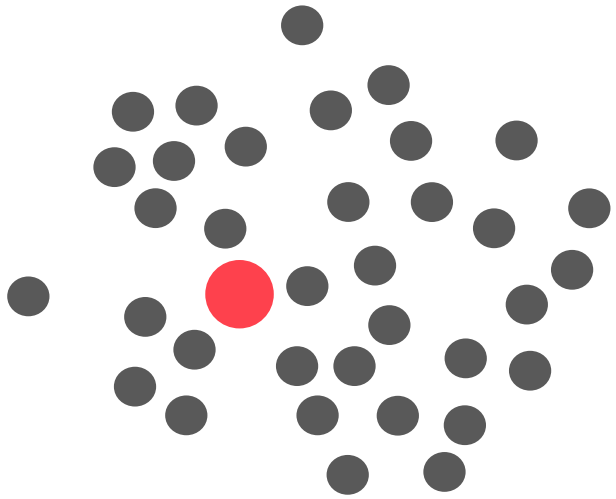


Outer ring road

Section 1

Route Optimizer Module - Explanation

Problem we are facing now...classic derivation of NP- hard



Distribution of customers or delivery points

Depot → $n = 0$

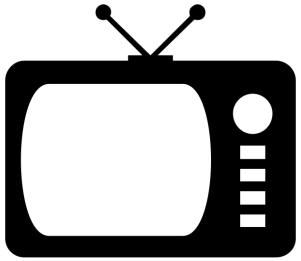
Customer → n, $weight = 1, w_1$
$2, w_2$
.
.
.
k, w_k

Set of customers along with their demands

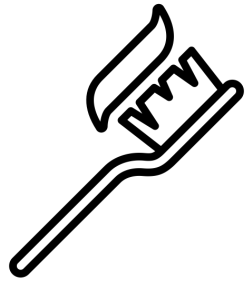
(Q) : Each vehicle has a fixed Capacity

"Television" v/s "toothbrush“ v/s “cabbage”....

- Each object is allotted a corresponding size e.g.



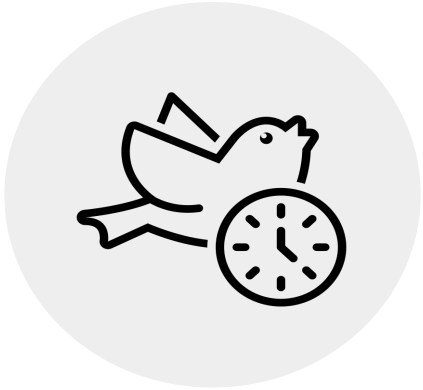
size = 90 units



size = 1 unit

Time Durations to keep in mind …

Time Window-early



The earliest time that a vehicle can arrive

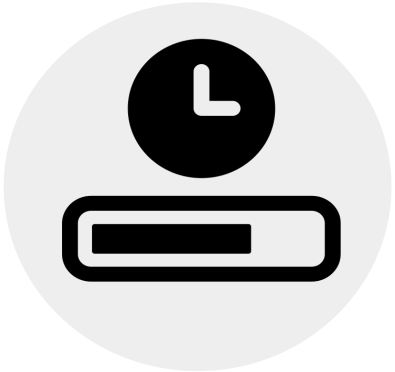
Time Window-late

The latest time that a vehicle can arrive

Time Window-service Time

Time needed to unload the goods

Time Window – wait cost

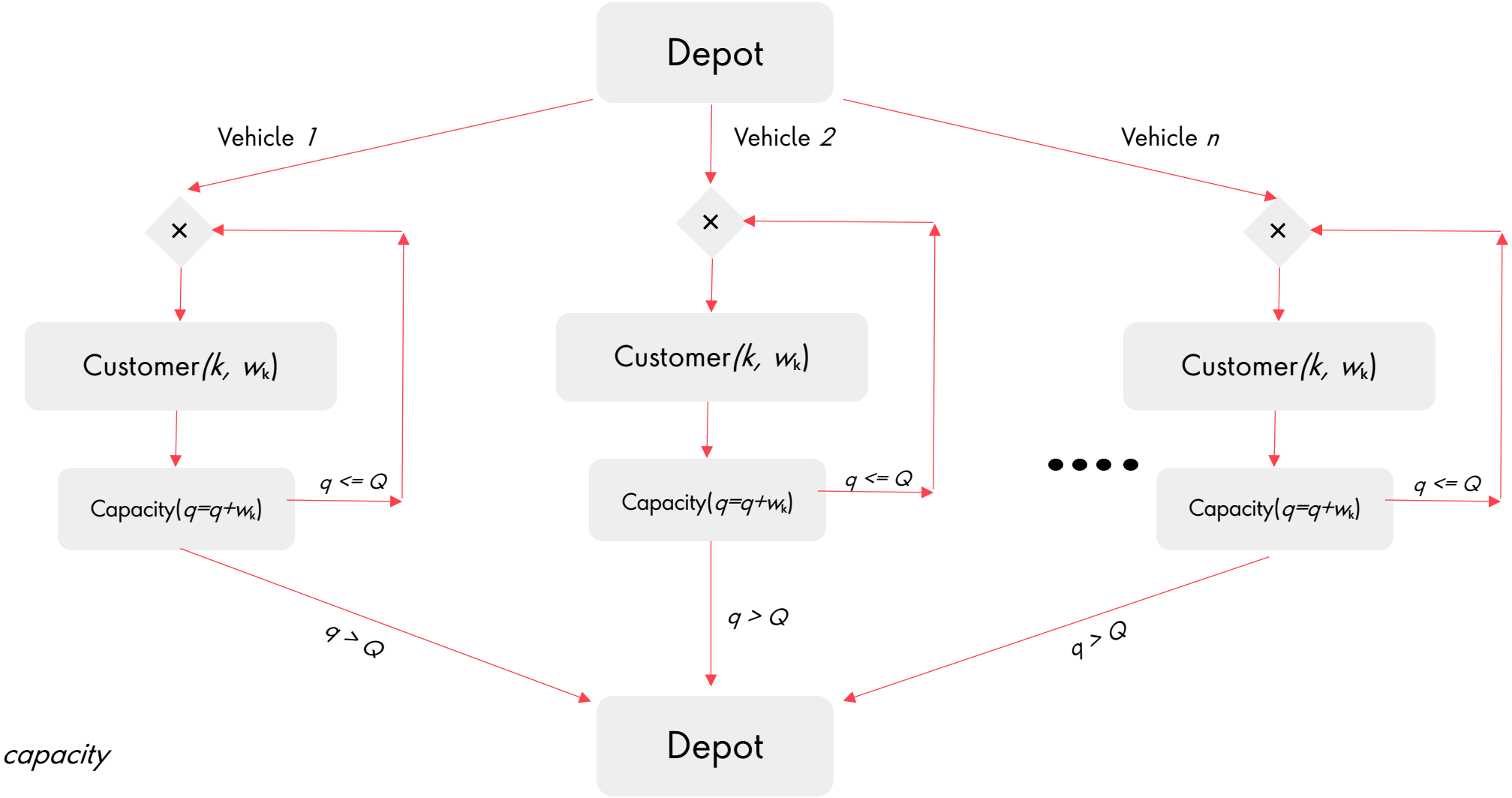


Cost for waiting for a client to be available

Types of vehicles in use...

	Store-owned vehicles 	Rented vehicles 
Size	To satisfy average demand	To satisfy large demand
Fixed Cost	Lower	Higher
Variable Cost	Lower	Higher
Velocity	Same	Same
Fleet Size	Same	Same

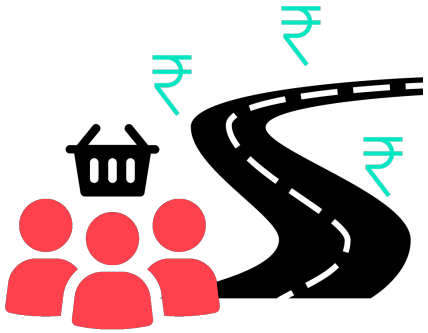
Continuing with the detailed workflow...



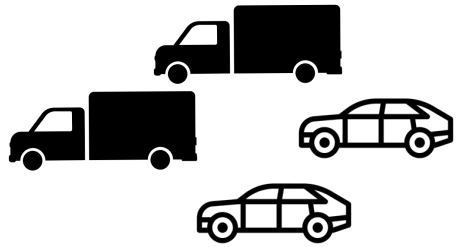
q = current capacity

The objectives…

- Optimization has been performed on the following two objectives:

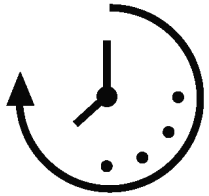


The cost to deliver

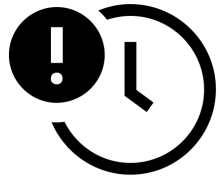


Number of vehicles

- Objectives omitted :



Total time



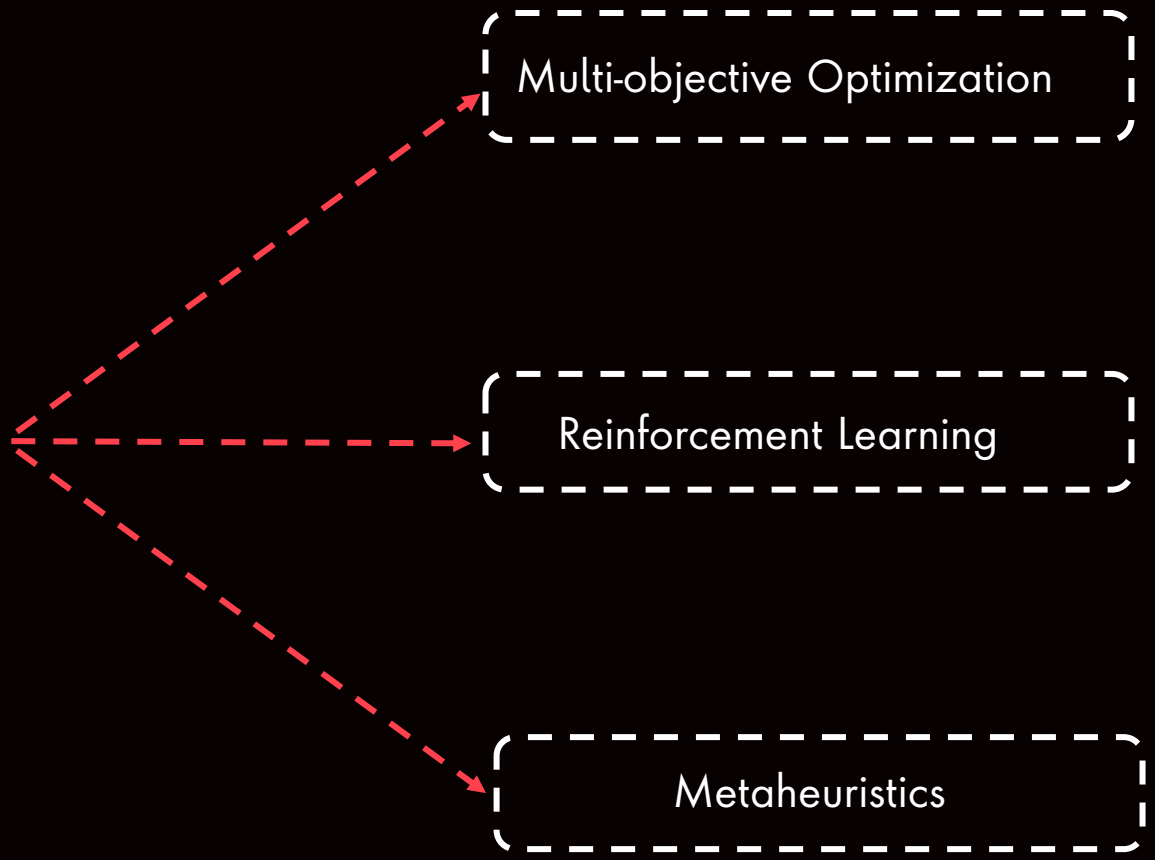
Time delay

Section 1

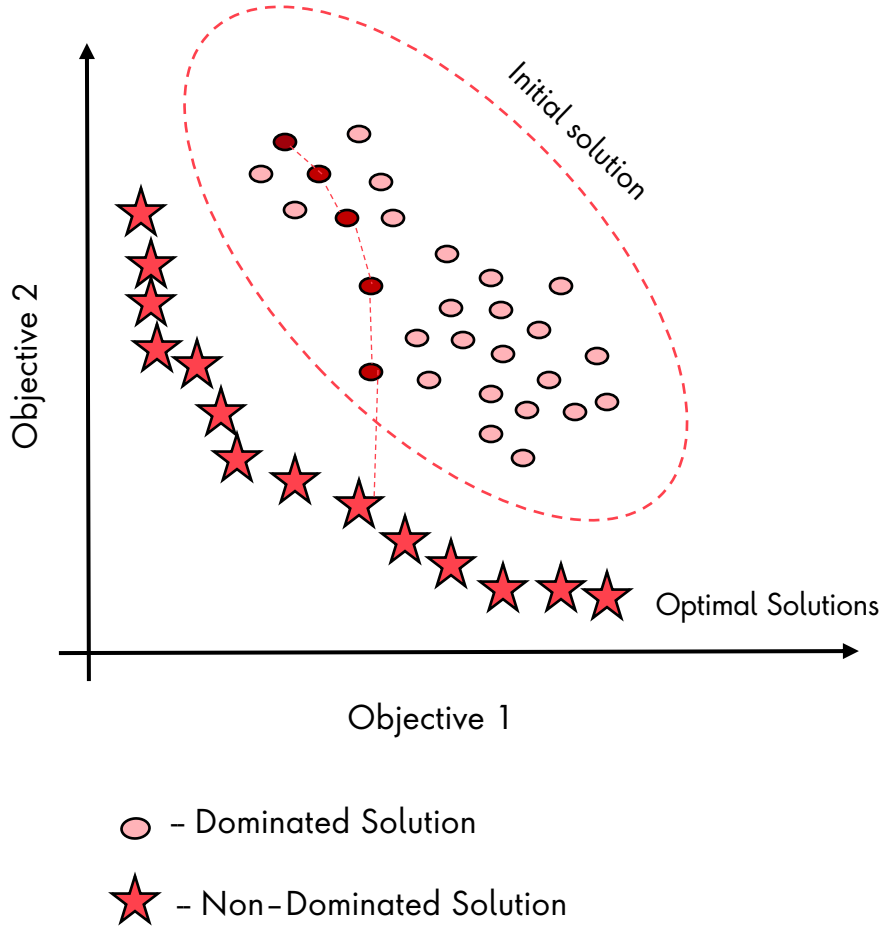
Route Optimizer Module - Demo

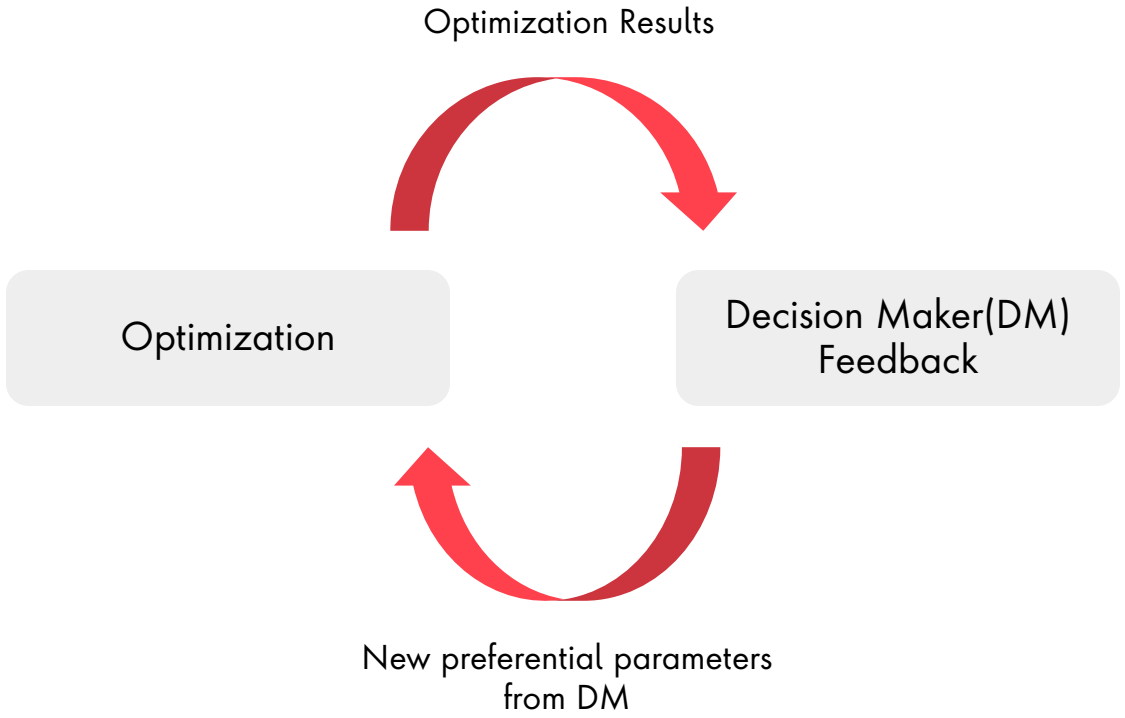
Section 3

Key Concepts

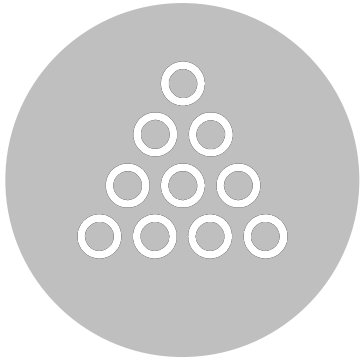


Introduction to multi-objective optimization



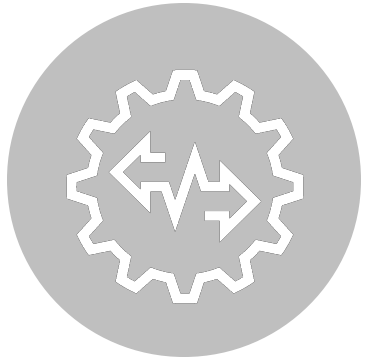


Why we require multi-objective optimization ?



More than one optimal solution

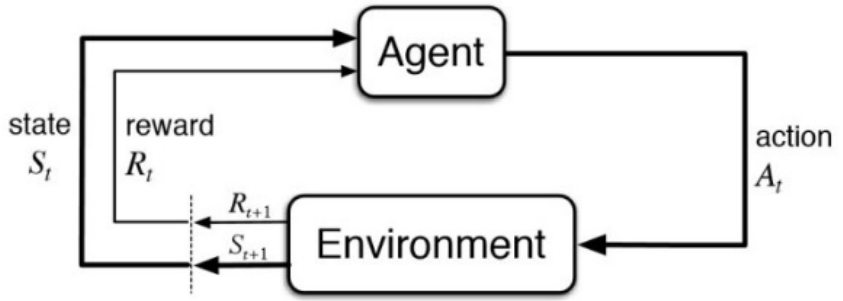
Real-World Engineering Problems



Conflicting Objectives

Introduction to Reinforcement Learning

Reinforcement Learning(RL) is a goal based learning, based on interaction from the environment. It is an approach to teach machines to interact with environments and receive rewards for performing the right actions until their goal is achieved.

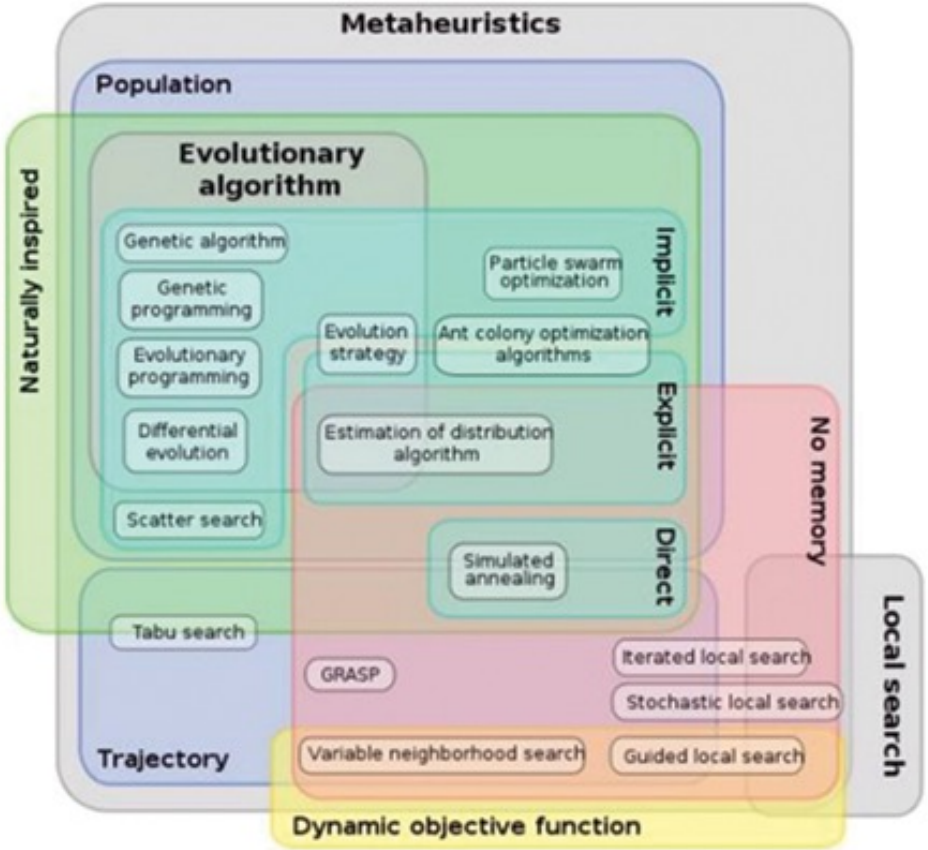


Some key terms describing the elements of a Reinforcement Learning Problem are:

- **Environment** : World in which the agent operates containing the depot, nodes, vehicles and rules governing there operation
- **State**: An immediate situation in which the agent finds itself in
- **Action**: It's the steps of choosing the next node recommended to a user to maximise rewards
- **Reward/Penalty**: The feedback which the agent gets hereby determined by negative of the total distance travelled
- **Policy**: Strategy employed by the agent to minimize the loss objective while satisfying the constraints of time and capacity

Introduction to metaheuristics

Derived from the ‘meta’ and ‘heuristic’, it’s a high-level methodology used for finding new strategies for solving a problem. These approaches can be distinguished into following types :



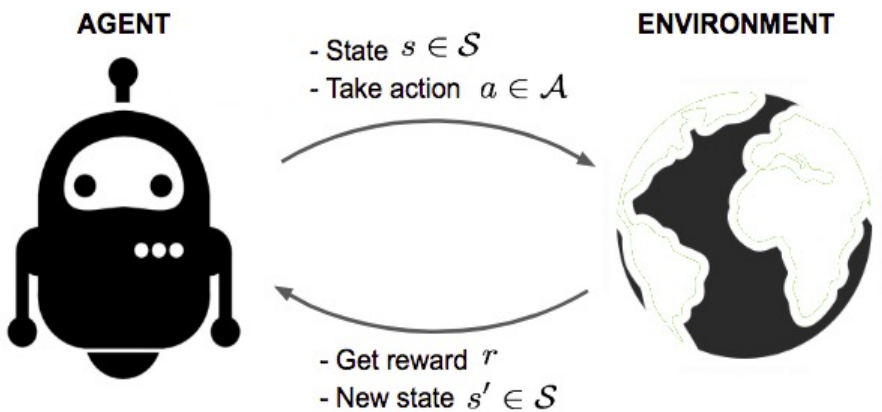
Here we will be looking into the Population based approaches namely :

- Genetic Algorithms
- Ant Colony Optimization

Section 4

Combination of RL and Metaheuristics

Details of the Model Building



$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} where \gamma \in [0, 1)$$

$$R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} ...$$

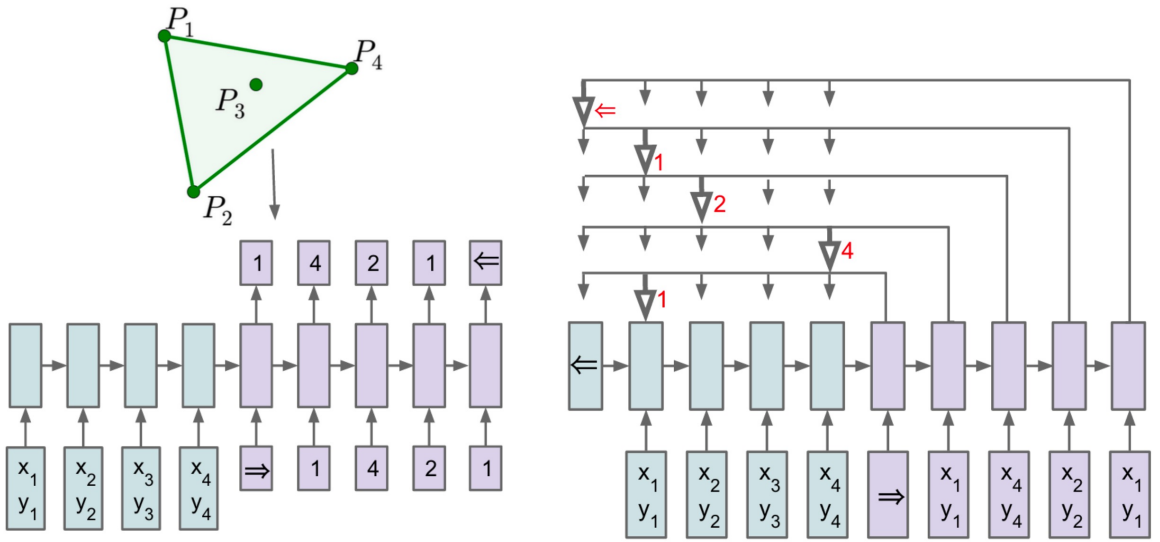
Algorithm 4 Asynchronous Advantage Actor-Critic (A3C)

initialize the actor network with random weights θ^0 and critic network with random weights ϕ^0 in the master thread.
initialize N thread-specific actor and critic networks with weights θ^n and ϕ^n associated with thread n.
repeat
  for each thread n **do**
    sample a instance problem from $\Phi_{\mathcal{M}}$ with initial state X_0^n
    initialize step counter $t^n \leftarrow 0$
    while episode not finished **do**
      choose y_{t+1}^n according to $P(y_{t+1}^n | Y_t^n, X_t^n; \theta^n)$
      observe new state X_{t+1}^n;
      observe one-step reward $R_t^n = R(Y_t^n, X_t^n)$
      let $A_t^n = \left(R_t^n + V(X_{t+1}^n; \phi) - V(X_t^n; \phi)\right)$
      $d\theta^0 \leftarrow d\theta^0 + \nabla_\theta A_t^n \log P(y_{t+1}^n | Y_t^n, X_t^n; \theta^n)$
      $d\phi^0 \leftarrow d\phi^0 + \nabla_\phi \left(A_t^n\right)^2$
      $t^n \leftarrow t^n + 1$
    end while
  end for
  periodically update θ^0 using $d\theta^0$ and ϕ^0 using $d\phi^0$
  $\theta^n \leftarrow \theta^0$, $\phi^n \leftarrow \phi^0$
  reset gradients: $d\theta^0 \leftarrow 0$, $d\phi^0 \leftarrow 0$
until training is finished

Why Pointer Networks instead of Sequence-to-Sequence ?
a modified form of the Pointer networks

1.The output of pointer networks is discrete and correspond to positions in the input sequence

2.the number of target classes in each step of the output depends on the length of the input, which is variable.

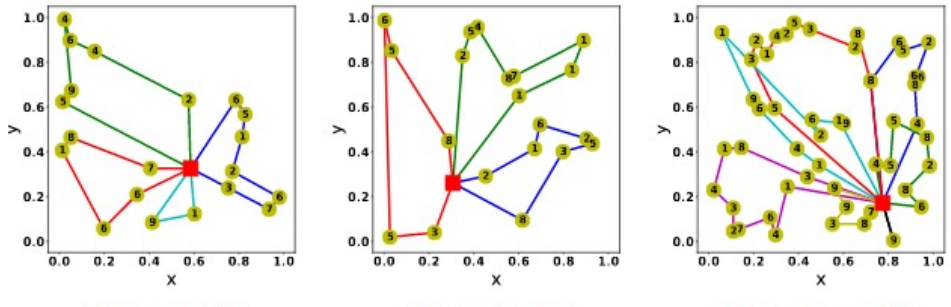


(a) Sequence-to-Sequence

(b) Ptr-Net

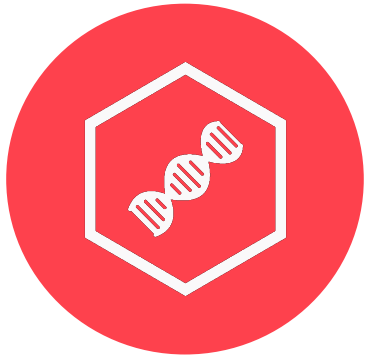
Training methodology and Results

Results



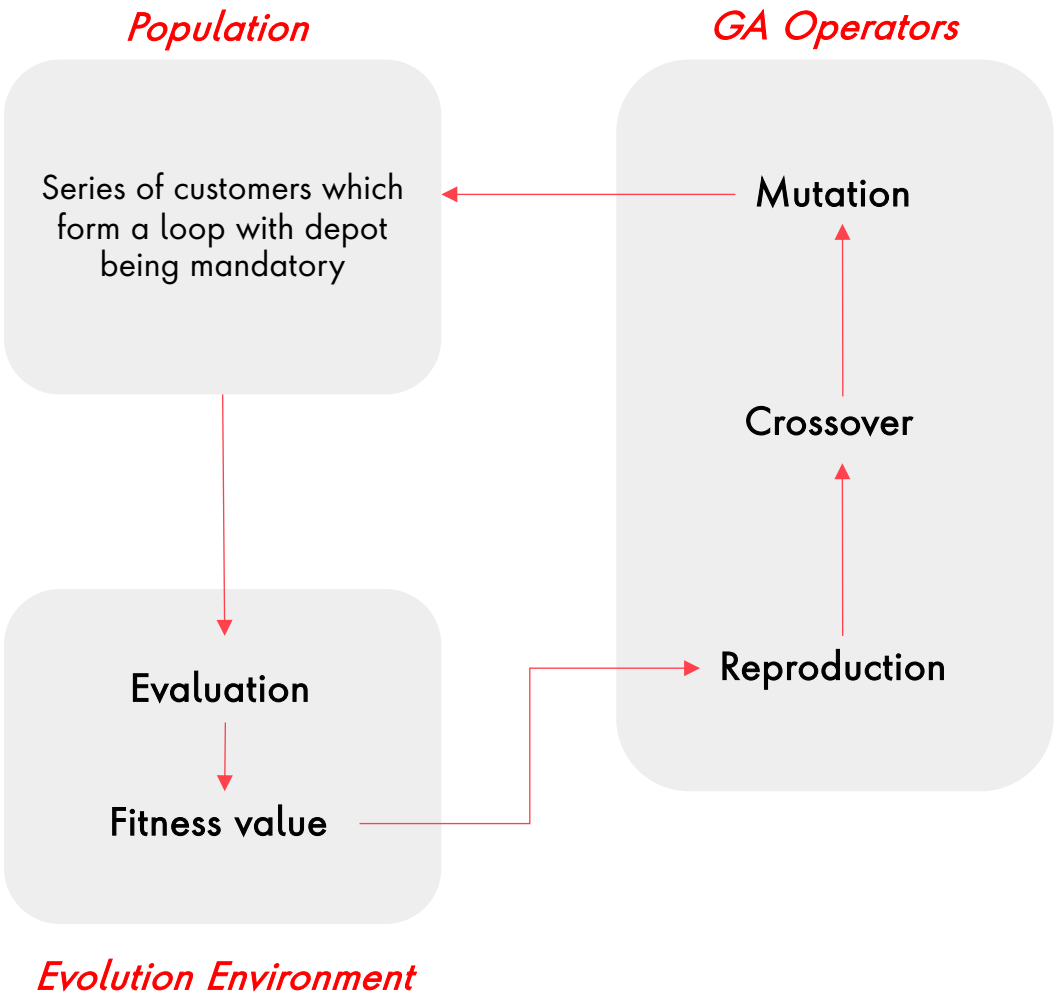
Here value written on each node is weight of the node

Combining with Metaheuristic Approaches - I



Genetic Algorithm

Based on Survival of the fittest
Steps involved are -
Initial Population, selection, crossover, mutation



Combining with Metaheuristic Approaches - II

Ant Colony Optimization

Ant go through food while laying down pheromone trails which attract other ants to follow same path.
Shortest path, more pheromone trail

The determining quantities of ACO:

- Ant Density
- Ant Quantity
- Any Cycle

Pheromones updated in each movement

Pheromones updated after all ants completed their tour

Conditions of Pheromone Update:

$$\tau_{xy} \leftarrow (1-\rho)\tau_{xy} + \sum_{k} \Delta\tau_{xy}^{k}$$

$$\Delta\tau_{xy}^{k} = \begin{cases} Q/L_k & \text{if ant } k \text{ uses curve } xy \text{ in its tour} \\ 0 & \text{otherwise} \end{cases}$$

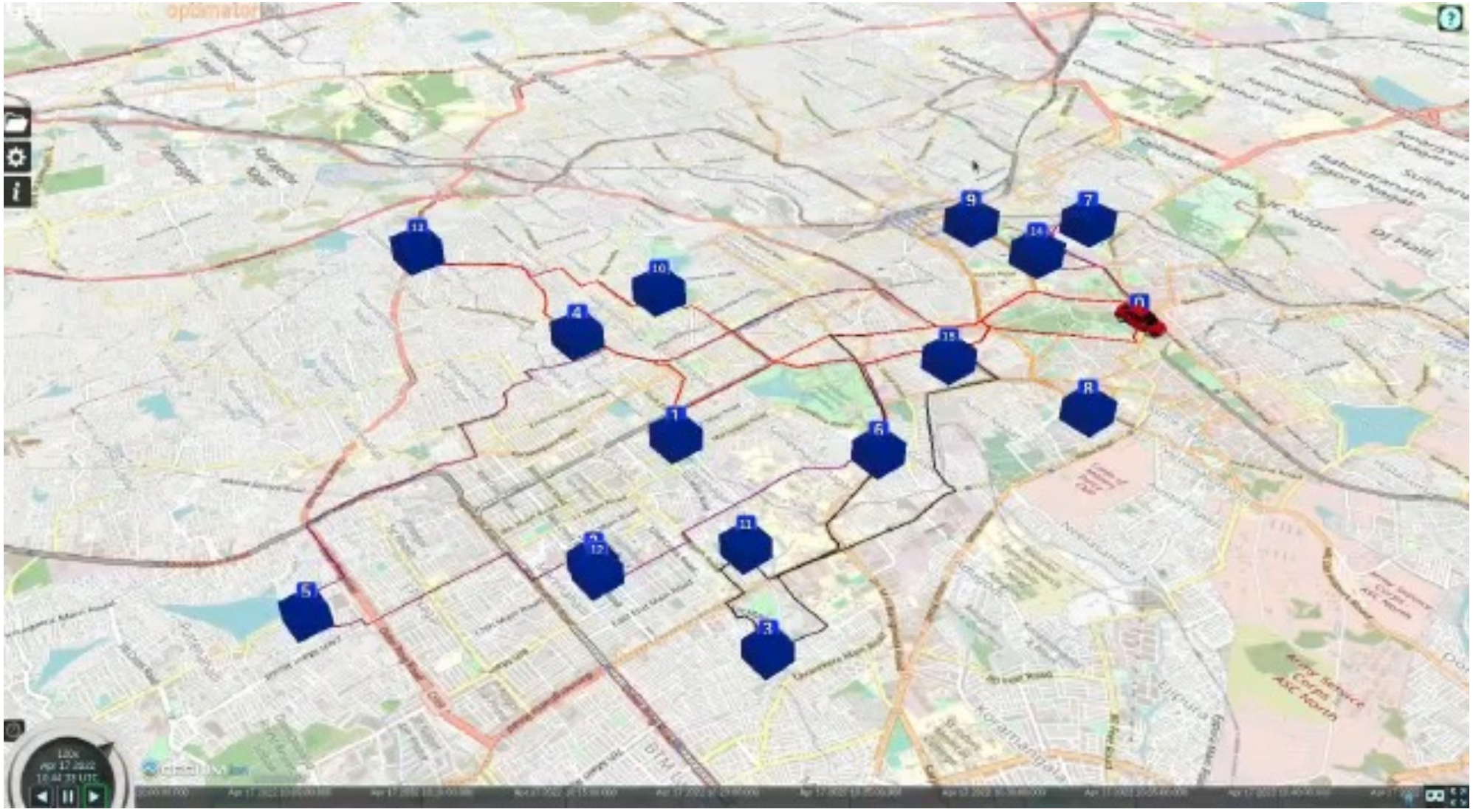
Section 4

Training and Result Discussion

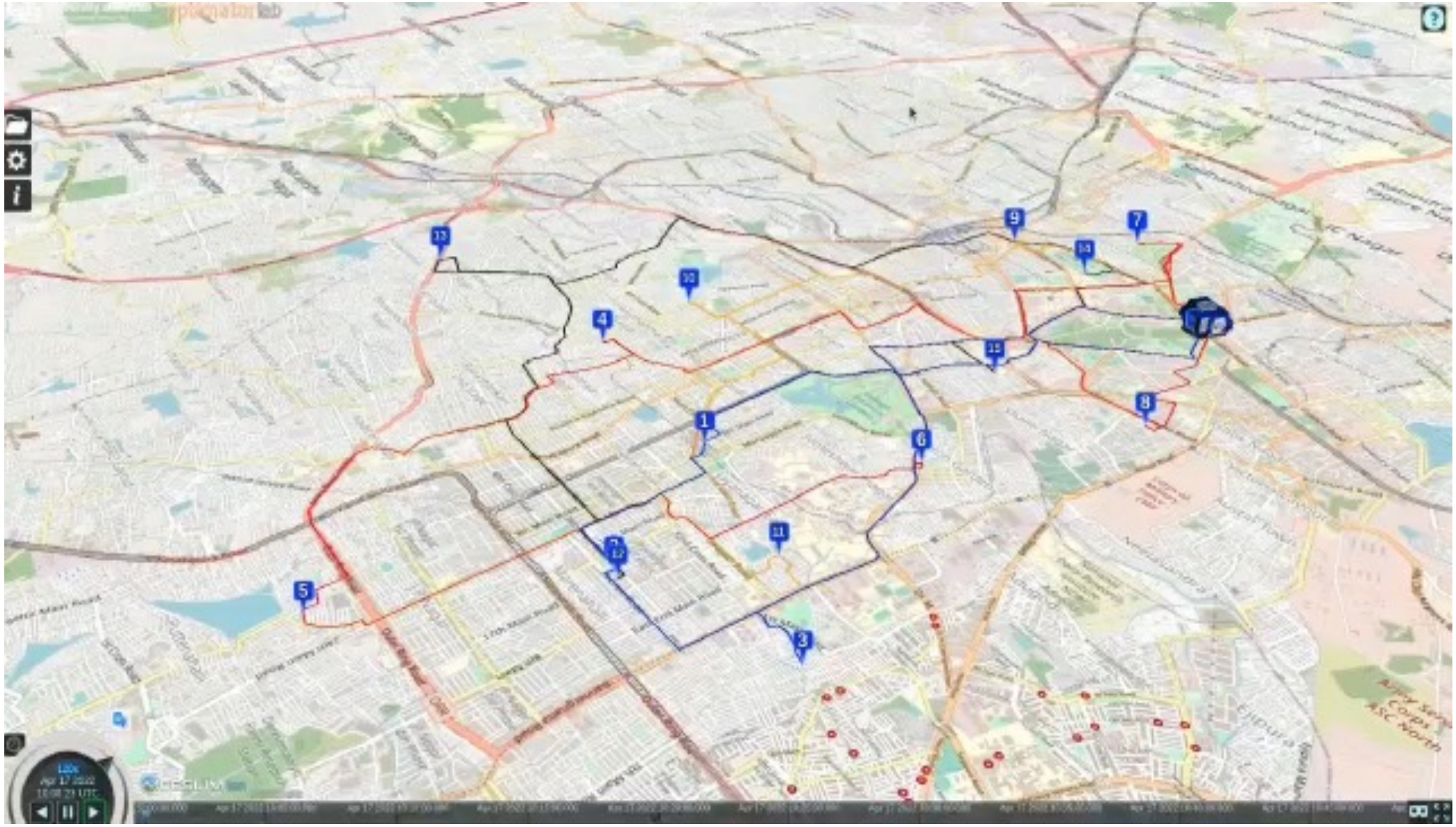
Comparison between the Base and Proposed Model...

	Genetic Algorithm	Baseline
Cost	₹ 1557	₹ 2882
Number of Trucks	3	4
Number of Cars	1	0
Distance	87 km	116km

Visualization of Route Optimization in Central Bangalore - Proposed



Visualization of Route Optimization in Central Bangalore - Baseline



Section 4

Future Works – Handling the Anomalies

How to deal with Weather Anomalies – using the weather API

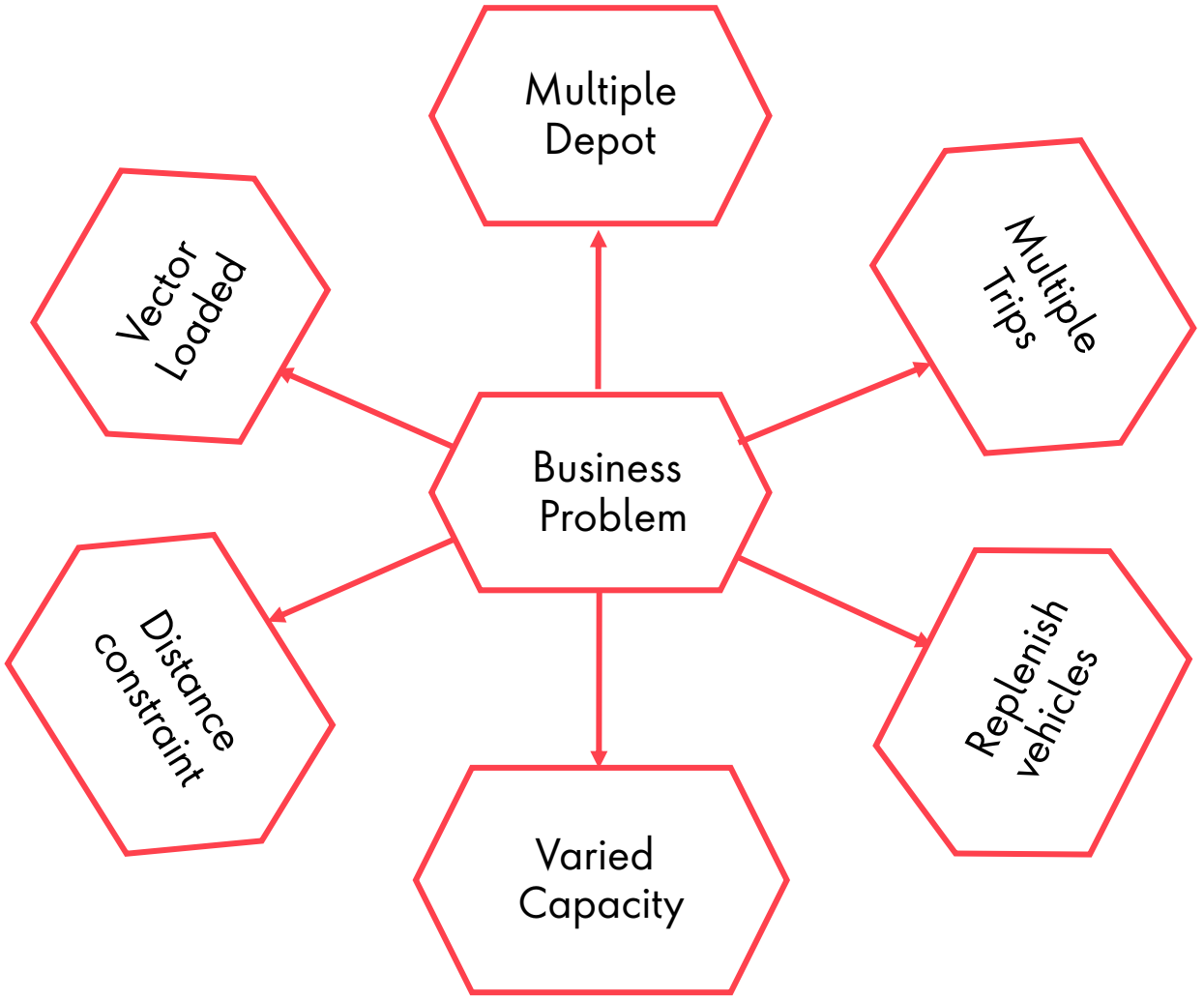
Bad weather at a location?

Increased wait cost

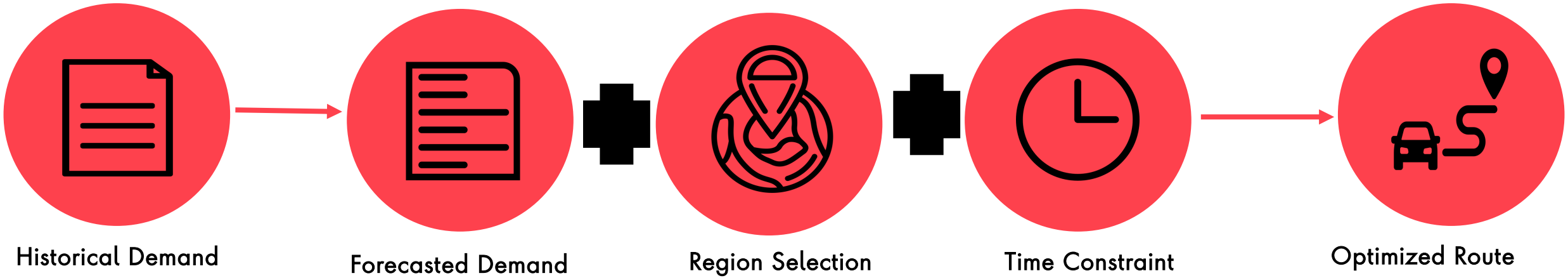
Increased service time

- Weather API delivers the information based on longitude , latitude of a location

Extensions to our business problem



Summary


Historical Demand
Forecasted Demand
Region Selection
Time Constraint
Optimized Route

thank you