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1. Abstract

This paper presents a computer code for solving the Vehicle Routing Problem (VRP) with capacity constraints. The VRP is a combinatorial optimization problem that aims to find efficient routes for a fleet of vehicles with limited capacities, minimizing the total distance travelled while satisfying all delivery demands. This code utilizes the Google OR-Tools library and leverages a distance matrix to represent travel costs between locations, similar to the Traveling Salesperson Problem (TSP) utilizes distances between different delivery locations. It incorporates demand data at each location and vehicle capacity limitations. The code employs a combination of search heuristics to achieve efficient solution discovery. The output provides detailed information about the routes assigned to each vehicle, including the sequence of visited locations, total distance travelled, and parcels delivered. Additionally, it calculates and presents the total distance travelled by the entire fleet and the fulfilment of overall delivery demands. This code serves as a practical tool for researchers and practitioners. It can be used to solve VRP instances, analyse delivery route efficiency, and potentially be adapted for further research on VRP variants or integration with other optimization problems. While not a direct implementation of TSP, the code demonstrates an application of similar underlying concepts for solving a more complex routing problem.

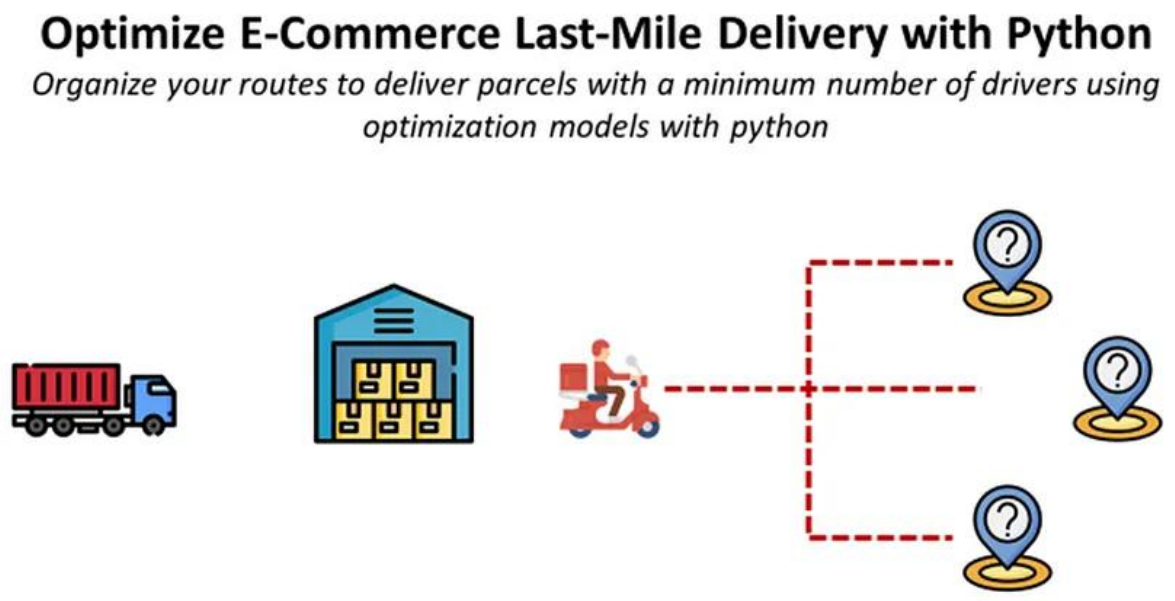

Optimize E-Commerce Last-Mile Delivery with Python
Organize your routes to deliver parcels with a minimum number of drivers using optimization models with python

Fig. 1 **Optimize E-Commerce Last-Mile Delivery with Python**

2.Introduction

The Vehicle Routing Problem (VRP) is a critical challenge in logistics, aiming to design efficient delivery routes for a fleet of vehicles with limited capacities. The goal is to minimize the total travel distance while ensuring all customer demands are met. Traditional VRP models often rely on simplified assumptions like fixed travel times and static demands. However, real-world scenarios involve dynamic traffic conditions and unforeseen circumstances, leading to suboptimal solutions with these approaches. This paper addresses this gap by presenting a python-code specifically designed to tackle VRP with capacity constraints. Developed using the Google OR-Tools library, this code offers a practical tool for researchers and practitioners.

It allows them to solve VRP instances while incorporating real-world complexities, leading to more robust and efficient route planning. Similar to the Traveling Salesman Problem (TSP) that uses distances between different locations, this code leverages a distance matrix to represent distance between locations. It also incorporates data on customer demands at each location and vehicle capacity limitations. Additionally, the code employs search heuristics to efficiently find high-quality solutions. It provides a detailed explanation of its functionality along with an illustrative example demonstrating its application to a VRP instance. The output offers insights into the routes assigned to each vehicle, including details like the sequence of visited locations, total distance travelled, and parcels delivered. Furthermore, the code calculates and presents the total distance travelled by the entire fleet and the fulfilment of overall delivery demands. By providing a readily available and adaptable codebase, this paper aims to empower further research and practical applications in the field of VRP optimization.

3.Literature Review

The Vehicle Routing Problem (VRP) is a well-studied problem in the field of logistics and optimization. It focuses on efficiently planning delivery routes for a fleet of vehicles with limited capacities, aiming to minimize total travel distance while satisfying all customer demands [1]. Traditional VRP formulations often assume deterministic travel times and static customer demands. However, these simplifications can lead to suboptimal solutions in real-world scenarios with dynamic traffic conditions, unforeseen circumstances, and additional constraints [2]. This literature review explores existing research on VRPs and optimization techniques relevant to the presented code. We focus on two key aspects:

1. VRP Variants and Constraints: VRP has numerous variants that introduce additional complexities beyond the basic problem. These variants aim to model real-world logistics challenges more accurately. Here are some relevant variants:

a. **VRP with Capacity Constraints (VRP with CC):** This variant, addressed by the presented code, considers the limited carrying capacity of vehicles. Deliveries must be planned such that the total demand at each location visited by a vehicle does not exceed its capacity [3].

b. **VRP with Time Windows (VRPTW):** Deliveries must be made within specific time windows at each location. This variant adds another layer of complexity to route planning [4].

2. Optimization Techniques for VRP:

Solving VRPs is computationally complex, especially for large-scale instances. Various optimization techniques have been developed to find high-quality solutions efficiently. Here are some commonly used techniques:

- **Exact Algorithms:** These methods guarantee to find the optimal solution but can be computationally expensive for large problems [5].
- **Heuristic Algorithms:** These algorithms provide good approximate solutions in a shorter time compared to exact algorithms [6]. The presented code utilizes search heuristics to achieve efficient solution discovery.
- **Metaheuristics:** These are higher-level search strategies that combine different heuristics to explore the solution space effectively [7].

The presented code utilizes the Google OR-Tools library, which offers a powerful suite of algorithms for solving various optimization problems, including VRPs. By leveraging these algorithms, the code can handle VRP instances with capacity constraints and potentially be adapted to incorporate other VRP variants.

4.Problem Statement

This research aims to develop an optimized last-mile delivery route plan. The service centre has a team of 4 drivers, each with a vehicle capable of carrying a maximum of 15 parcels. There are 16 destinations that are considered for delivery, denoted by D1 to D16, with D0 representing the warehouse itself.

Constraint

- 4 drivers in your team
- 15 parcel capacity per vehicle
- 1 route per driver

The objective is to design efficient delivery routes, one per driver, that minimize the total travel distance while ensuring all deliveries are completed within a designated time frame.

5.Key Challenges

- **Route Optimization:** Identify the most efficient routes for each driver, considering factors such as distance between destinations, traffic patterns (if available), and parcel distribution across locations.
- **Balancing Workload:** Ensure a fair and balanced distribution of deliveries among the drivers, considering both distance and number of parcels per stop.
- **Time Constraints:** Plan routes that can be completed within a reasonable timeframe, considering potential delays due to traffic or unforeseen circumstances.

6.Research Question

How can we design optimized last-mile delivery for many routes, considering the available resources, delivery locations, and time constraints, to minimize total travel distance and ensure efficient service delivery?

7.Objective

- Develop an optimized route plan that minimizes total travel distance for all deliveries.
- Achieve a balanced workload distribution among drivers.
- Ensure all deliveries are completed within a designated time frame.
- Provide a framework that can be adapted for future route planning with potential delivery demands or driver availability variations.

This research will contribute to improved operational efficiency for the local service centre, leading to reduced delivery costs, faster delivery times, and enhanced customer satisfaction.

8.Methodology

This research will utilize a two-pronged approach to address the last-mile delivery route optimization problem.

1. Data Collection and Analysis:

- **Geographic Data:** We will acquire geographical data for the said city/location, including the locations (addresses or coordinates) of the service centre (D0) and all delivery destinations (D1 to D16). This data can be obtained through mapping services or internal GIS data.
- **Distance Matrix Generation:** Based on the geographical data, we will create a distance matrix representing the travel distances between all locations (D0-D1, D0-D2, ..., D15-D16). This matrix can be calculated using distance APIs or mapping tools.
- **Parcel Distribution Analysis:** We will analyse the distribution of parcels across the delivery destinations. This could involve understanding the number of parcels per stop or identifying any specific locations with high parcel volumes.

The data consists of:

- distance_matrix: An array of distances between locations in meters.
- num_vehicles: The number of vehicles in the fleet.
- depot: The index of the depot, the location where all vehicles start and end their routes.

2. Route Optimization Algorithm:

We will implement an optimization algorithm to generate efficient delivery routes for the 4 drivers. Here are two potential approaches:

- **Exact Algorithm:** We can explore using an exact algorithm, such as the Vehicle Routing Problem (VRP) with capacity constraints, to guarantee finding the optimal solution (minimum total travel distance) for this specific instance. However, exact algorithms can be computationally expensive for larger problems.
- **Heuristic Algorithm:** For potentially faster execution, we can develop a heuristic algorithm that efficiently searches for good-quality, near-optimal solutions. There are various heuristic approaches like nearest neighbour, savings algorithm, or genetic algorithms that can be adapted for this scenario. The chosen heuristic will consider the following factors:
    - **Distance Matrix:** Utilize the precomputed distance matrix to determine travel distances between locations.
    - **Vehicle Capacity:** Ensure each route stays within the 15-parcel capacity limit for the vehicles.
    - **Workload Balancing:** Aim for a fair distribution of delivery workload (distance and number of parcels) among the drivers.

3. Evaluation and Refinement:

- The generated routes will be evaluated based on their total travel distance.
- We will compare the performance of the chosen optimization algorithm (exact or heuristic) with a baseline approach, such as a simple nearest neighbour heuristic. This comparison will help assess the effectiveness of the optimization strategy.

- Based on the evaluation and potential constraints encountered, the algorithm may be refined or adjusted to further improve route efficiency.

4. Software Tools:

- Geographic Information System (GIS) or mapping software will be used to visualize the delivery locations and generated routes.
- The chosen optimization algorithm can be implemented using programming languages like Python and libraries like Google OR-Tools, which offer functionalities for VRP and routing problems.

OR Tools:

- OR-Tools is an open-source software suite for optimization, tuned for tackling the world's toughest problems in vehicle routing, flows, integer and linear programming, and constraint programming.
- After modelling your problem in the programming language of your choice, you can use any of a half dozen solvers to solve it: commercial solvers such as Gurobi or CPLEX, or open-source solvers such as SCIP, GLPK, or Google's GLOP and award-winning CP-SAT.

OR-Tools includes solvers for:

- **Constraint Programming:** A set of techniques for finding feasible solutions to a problem expressed as constraints (e.g., a room can't be used for two events simultaneously, or the distance to the crops must be less than the length of the hose, or no more than five TV shows can be recorded at once).
- **Linear and Mixed-Integer Programming:** The Glop linear optimizer finds the optimal value of a linear objective function, given a set of linear inequalities as constraints (e.g., assigning people to jobs, or finding the best allocation of a set of resources while minimizing cost). Glop and the mixed-integer programming software SCIP are also available via the Google Apps Script Optimization Service.
- **Vehicle Routing:** A specialized library for identifying best vehicle routes given constraints.
- **Graph Algorithms:** Code for finding shortest paths in graphs, min-cost flows, max flows, and linear sum assignments.

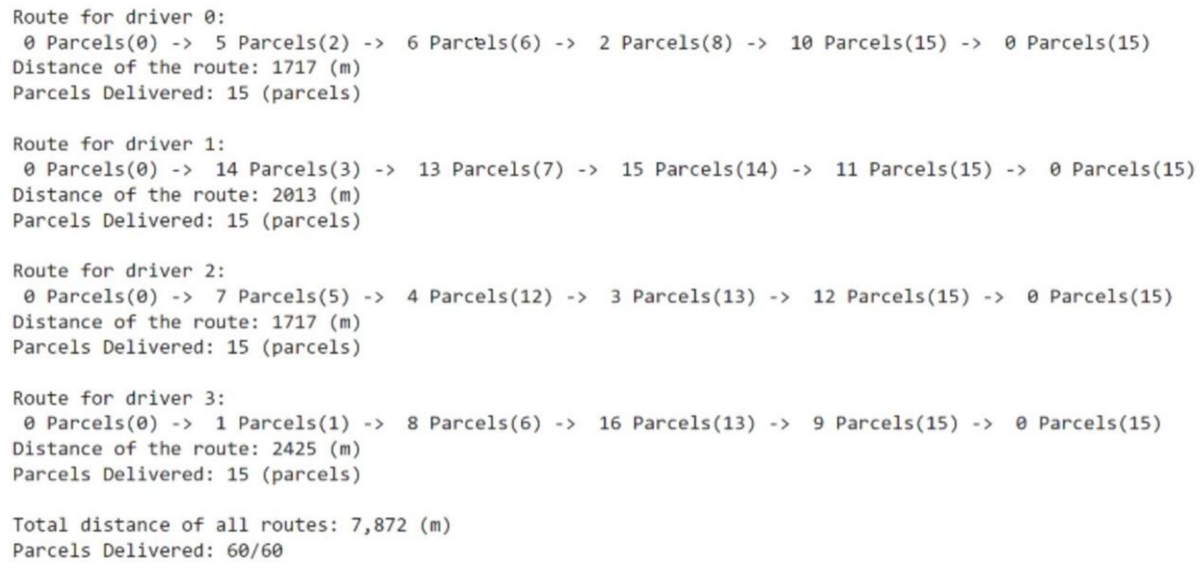
8.Expected Outcomes

By applying the described methodology, we expect to achieve the following outcomes:

- A set of optimized delivery routes, one per driver, minimizing the total travel distance for all deliveries.
- A balanced workload distribution among the drivers, considering both distance and number of parcels per stop.
- A well-defined framework for route optimization that can be adapted for future planning scenarios with potential changes in delivery demands or driver availability.

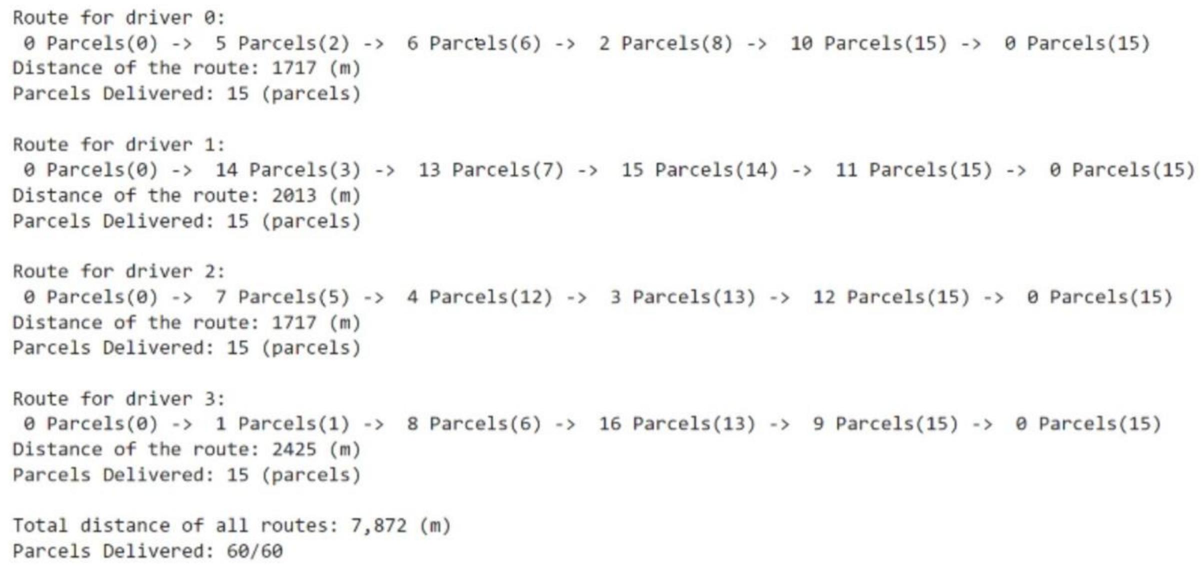
The collected data, chosen algorithm, and evaluation techniques will enable us to identify efficient delivery routes and improve the overall delivery operation's efficiency.

Scenario 1 Demands: [0, 1, 2, 1, 7, 2, 4, 5, 5, 2, 7, 1, 2, 4, 3, 7, 7]



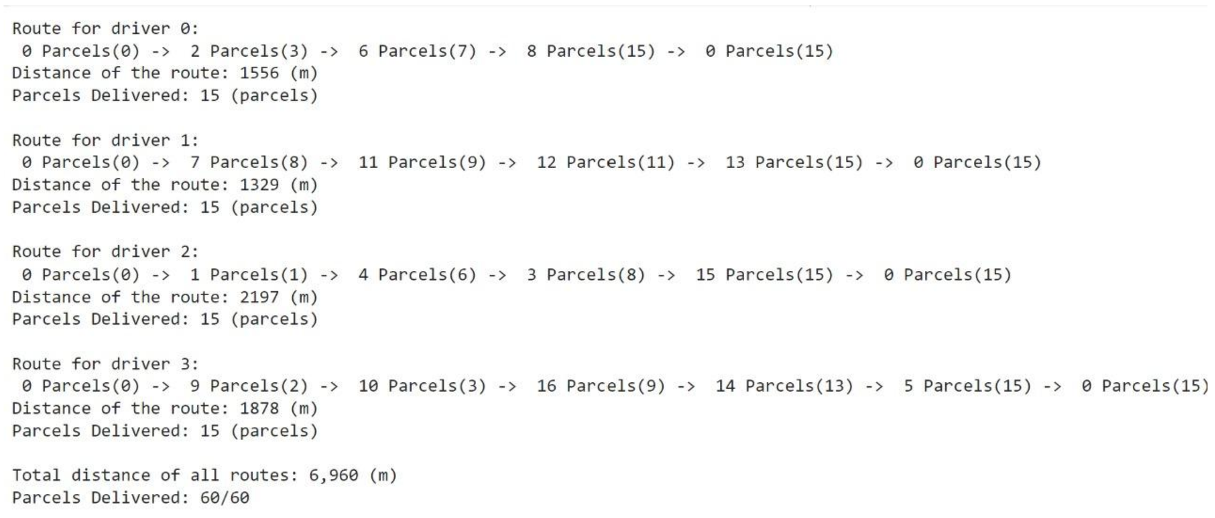
```
Route for driver 0:
 0 Parcels(0) ->  5 Parcels(2) ->  6 Parcels(6) ->  2 Parcels(8) ->  10 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1717 (m)
Parcels Delivered: 15 (parcels)

Route for driver 1:
 0 Parcels(0) ->  14 Parcels(3) ->  13 Parcels(7) ->  15 Parcels(14) ->  11 Parcels(15) ->  0 Parcels(15)
Distance of the route: 2013 (m)
Parcels Delivered: 15 (parcels)

Route for driver 2:
 0 Parcels(0) ->  7 Parcels(5) ->  4 Parcels(12) ->  3 Parcels(13) ->  12 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1717 (m)
Parcels Delivered: 15 (parcels)

Route for driver 3:
 0 Parcels(0) ->  1 Parcels(1) ->  8 Parcels(6) ->  16 Parcels(13) ->  9 Parcels(15) ->  0 Parcels(15)
Distance of the route: 2425 (m)
Parcels Delivered: 15 (parcels)

Total distance of all routes: 7,872 (m)
Parcels Delivered: 60/60
```

Scenario 2 Demands: [0, 1, 2, 2, 6, 2, 4, 8, 5, 2, 4, 1, 2, 4, 3, 7, 7]



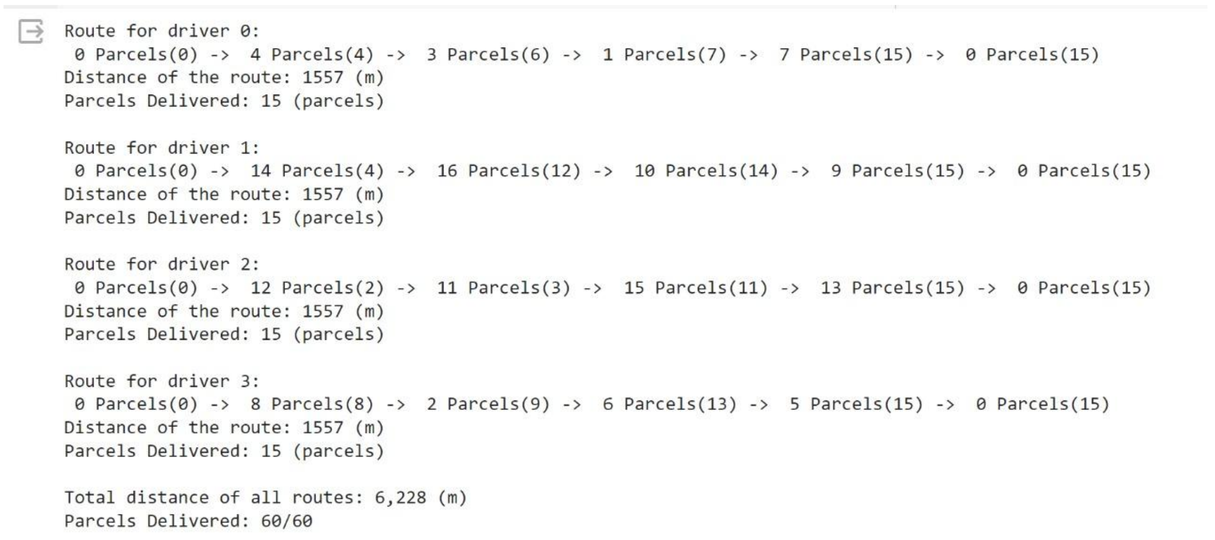
```
Route for driver 0:
 0 Parcels(0) ->  5 Parcels(2) ->  6 Parcels(6) ->  2 Parcels(8) ->  10 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1717 (m)
Parcels Delivered: 15 (parcels)

Route for driver 1:
 0 Parcels(0) ->  14 Parcels(3) ->  13 Parcels(7) ->  15 Parcels(14) ->  11 Parcels(15) ->  0 Parcels(15)
Distance of the route: 2013 (m)
Parcels Delivered: 15 (parcels)

Route for driver 2:
 0 Parcels(0) ->  7 Parcels(5) ->  4 Parcels(12) ->  3 Parcels(13) ->  12 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1717 (m)
Parcels Delivered: 15 (parcels)

Route for driver 3:
 0 Parcels(0) ->  1 Parcels(1) ->  8 Parcels(6) ->  16 Parcels(13) ->  9 Parcels(15) ->  0 Parcels(15)
Distance of the route: 2425 (m)
Parcels Delivered: 15 (parcels)

Total distance of all routes: 7,872 (m)
Parcels Delivered: 60/60
```

Scenario 3 Demands: [0, 1, 3, 2, 5, 2, 4, 8, 8, 2, 1, 1, 2, 4, 4, 7, 6]



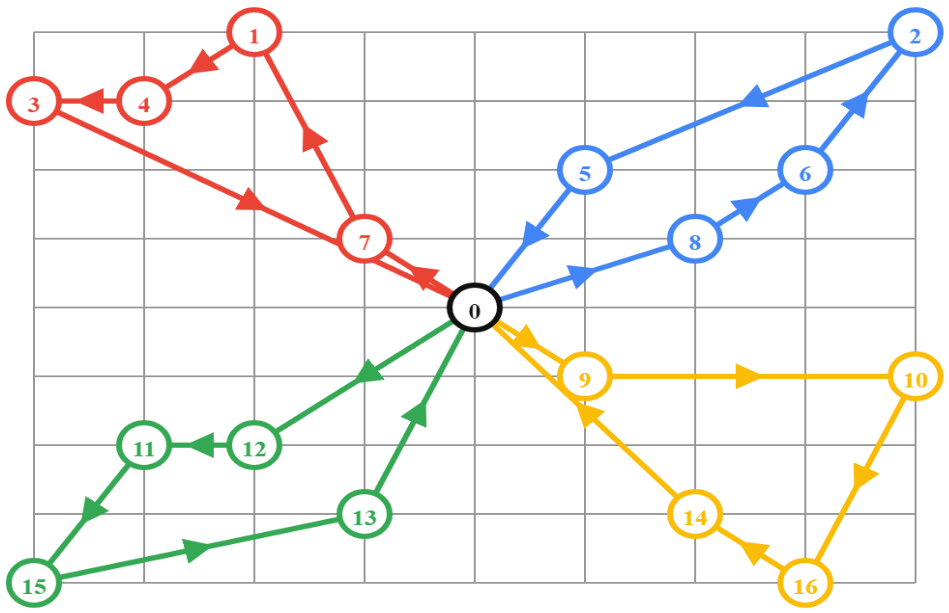
```
Route for driver 0:
 0 Parcels(0) ->  2 Parcels(3) ->  6 Parcels(7) ->  8 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1556 (m)
Parcels Delivered: 15 (parcels)

Route for driver 1:
 0 Parcels(0) ->  7 Parcels(8) ->  11 Parcels(9) ->  12 Parcels(11) ->  13 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1329 (m)
Parcels Delivered: 15 (parcels)

Route for driver 2:
 0 Parcels(0) ->  1 Parcels(1) ->  4 Parcels(6) ->  3 Parcels(8) ->  15 Parcels(15) ->  0 Parcels(15)
Distance of the route: 2197 (m)
Parcels Delivered: 15 (parcels)

Route for driver 3:
 0 Parcels(0) ->  9 Parcels(2) ->  10 Parcels(3) ->  16 Parcels(9) ->  14 Parcels(13) ->  5 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1878 (m)
Parcels Delivered: 15 (parcels)

Total distance of all routes: 6,960 (m)
Parcels Delivered: 60/60
```

Scenario 4 Demands: [0, 1, 1, 2, 4, 2, 4, 8, 8, 1, 2, 1, 2, 4, 4, 8, 8]



```
Route for driver 0:
 0 Parcels(0) ->  4 Parcels(4) ->  3 Parcels(6) ->  1 Parcels(7) ->  7 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1557 (m)
Parcels Delivered: 15 (parcels)

Route for driver 1:
 0 Parcels(0) ->  14 Parcels(4) ->  16 Parcels(12) ->  10 Parcels(14) ->  9 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1557 (m)
Parcels Delivered: 15 (parcels)

Route for driver 2:
 0 Parcels(0) ->  12 Parcels(2) ->  11 Parcels(3) ->  15 Parcels(11) ->  13 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1557 (m)
Parcels Delivered: 15 (parcels)

Route for driver 3:
 0 Parcels(0) ->  8 Parcels(8) ->  2 Parcels(9) ->  6 Parcels(13) ->  5 Parcels(15) ->  0 Parcels(15)
Distance of the route: 1557 (m)
Parcels Delivered: 15 (parcels)

Total distance of all routes: 6,228 (m)
Parcels Delivered: 60/60
```

The below graph depicts the scenario of our problem in which the driver takes the order for delivery from the warehouse and deliver that to different locations while travelling minimum distance and distributing the courier equally to all



9.Conclusion

This code demonstrates the application of Google OR-Tools for solving a Capacitated Vehicle Routing Problem (CVRP) with the objective of optimizing last-mile deliveries for a local service centre. The code successfully:

- Imports a predefined distance matrix representing travel distances between delivery locations.
- Defines a routing model considering the number of locations, vehicles, depot location, and vehicle capacity constraints.
- Implements a heuristic search strategy to find efficient delivery routes for four drivers.
- Calculates the total distance travelled for each route and ensures all parcels are delivered within vehicle capacity limitations.

The results provide a set of optimized routes that minimize the total travel distance for all deliveries. This approach ensures efficient resource utilization and balanced workload distribution among drivers.

10.Future Enhancements:

- The code can be extended to incorporate real-time traffic data for more dynamic route optimization.
- Additional functionalities like time windows for deliveries or multiple depots can be explored using advanced OR-Tools features.
- The model can be adapted to handle scenarios with varying delivery demands or changes in driver availability.

By leveraging Google OR-Tools and similar optimization techniques, local service centres can significantly improve their delivery operations, leading to cost savings, faster deliveries, and enhanced customer satisfaction.

11.References

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