Optimization of Inventory and distribution routing planning for a multi-product supply chain network model for spare parts in Automobile company

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in

Mechanical Engineering

by

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Spring Semester, 2023-24

April 27 , 2024

DECLARATION

I hereby declare that the thesis entitled "Statistical Modeling of Psychosis Data" submitted by me for the completion of the Bachelor's Thesis Project 1 for the degree of Bachelor of Technology in Mechanical Engineering to IIT Kharagpur is a record of bonafide work carried out by me under the supervision of Prof. D.K. Pratihar. I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the completion of any other project for any degree or diploma in this institute or any other institute or university.

Date: April 27, 2024	(Mohammed Raafid M V)
Place: Kharagpur	(20MF3IM33)

DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR

KHARAGPUR - 721302, INDIA

CERTIFICATE

This is to certify that the project report entitled " **Optimization of Inventory and distribution routing planning for a multi-product supply chain network model for spare parts in Automobile company**" submitted by **Mohammed Raafid M V** (Roll No. 20MF3IM33) to Indian Institute of Technology Kharagpur towards partial fulfilment of requirements for the award of degree of Bachelor of Technology in Mechanical Engineering is a record of bona fide work carried out by him under my supervision and guidance during Spring Semester, 2023-24.

Date: April 27, 2024

Place: Kharagpur

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Abstract

Name of the student: **Mohammed Raafid M V** Roll No: **20MF3IM33**

Degree for which submitted: **Bachelor of Technology**

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Thesis supervisor: **Dr. Biswajit Mahanty**

Month and year of thesis submission: **April 27 , 2024**

The company seeks to enhance its daily operations concerning production, inventory management, and spare parts distribution. The optimization process involves a multi-product, multi-term distribution system encompassing manufacturing plants and distribution centers. Transporting parts involves different transporters with varying charges based on product type and distance traveled. Distribution centers have distinct maximum storage capacities and are situated along different routes from the automobile company. An effective heuristic routing algorithm is employed to solve the delivery consolidation problem, treating it as a capacitated transportation problem with additional constraints. The proposed methodology aims to streamline the inventory and distribution process, ultimately improving overall supply chain efficiency and customer satisfaction.

Acknowledgements

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Introduction

Inventory management is the linchpin of supply chain efficiency, ensuring products move seamlessly from production to warehousing to point of sale. The core aim is crucial to have the right products available at the right place and time. Achieving this necessitates inventory visibility, knowing precisely when, where, and how much stock to store. Transportation, as a key driver in the supply chain, heavily influences expenses. Recent emphasis on integrating various supply chain functions acknowledges the interconnectedness of cost minimization efforts and the potential for unintended cost escalation in other areas.

Picture a bustling manufacturing plant, churning out a multitude of automobile parts destined for assembly lines. These parts, ranging from intricate components to essential assemblies, form the backbone of a complex supply chain. Transporting these parts from production floors to multiple distribution centers sprawled across regions and continents is no small feat. Weekly logistics operations orchestrate a symphony of movement, with trucks and carriers navigating intricate transportation networks with precision. Beyond mere delivery, this task entails strategic route optimization to ensure timely and cost-effective transportation, shaping the operational landscape of manufacturing plants and logistics operations alike.

The report embark on an exploration of vehicle routing optimization within the context of automobile parts manufacturing. We navigate through theoretical frameworks, algorithmic approaches, and real-world insights, unraveling the complexities of this logistical puzzle. From understanding routing challenges to examining optimization methodologies and algorithms, we shed light on strategies for enhancing efficiency, reducing costs, and maximizing operational potential. Our journey spans diverse industries, showcasing how vehicle routing optimization principles resonate across urban landscapes and rural terrains alike. As we delve into the quest for operational excellence amidst the intricacies of modern transportation and logistics, we envision a future where each mile traveled brings us closer to efficiency and innovation.

Background of the problem:

In the automobile company of focus, Domestic Spare parts business takes place in the following way. The distribution centers place order based on the sales or assumption of upcoming sales an online portal. This information is received to the manufacturing plant to work order is released as per the demand level and after confirmation of money transaction. Then based on the work order the parts picked, packed, and then stored in respective areas of dispatch, organized based on the state/location in India. Transporters are then allocated to the accumulated Work order based on the cost charged /kg /km based on the region and based on the serviceability level. Based on observing the process the scope of making this decision-making process more optimized by either incorporating Inventory routing problem method or the Production, Inventory, Distribution and Routing problem method is implemented.

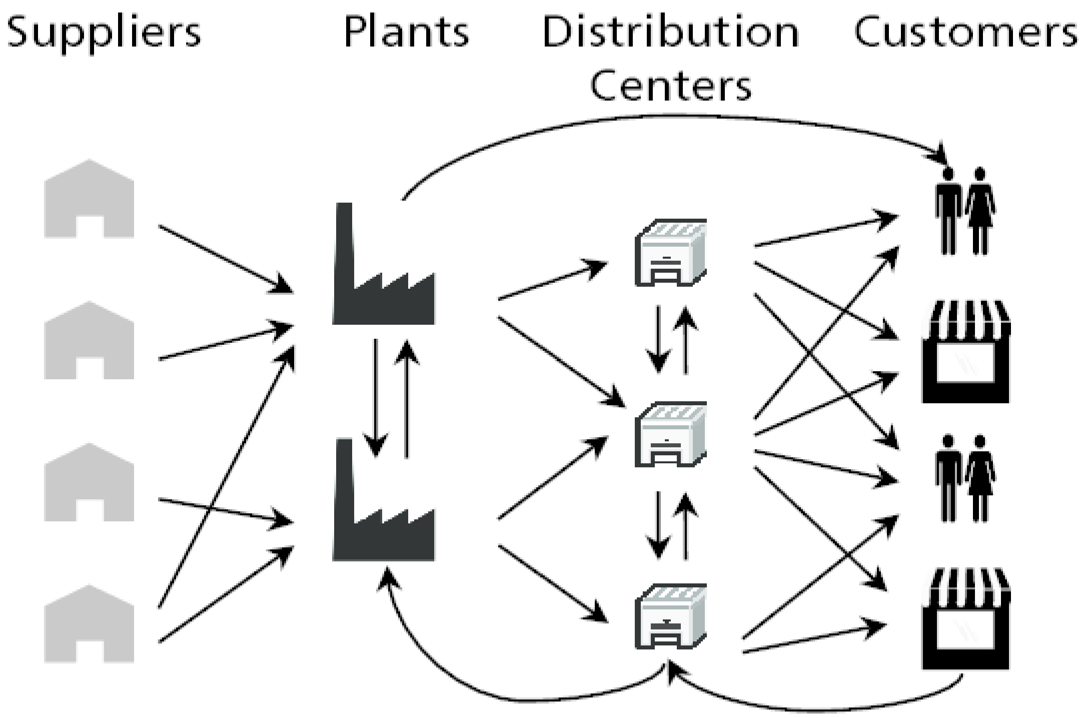

Figure 1: Example of a supply chain network

Literature Review

The literature on spare parts distribution reveals various approaches to tackle the challenges of multi-level supply chains and stochastic demand. Achamrah et al. (2022) address these complexities by proposing a mixed-integer linear programming model for the inventory routing problem. Their model considers transshipment and substitution under stochastic demands, aiming to minimize costs related to inventory holding, transportation, transshipment, substitution, and lost sales.

Early research in vehicle routing optimization primarily focused on developing heuristic and exact algorithms to solve different variants of the vehicle routing problem (VRP). Classic algorithms such as the Clarke-Wright savings algorithm, the nearest neighbor algorithm, and the branch-and-bound method have been extensively studied and applied in various real-world scenarios (Clarke & Wright, 1964; Fisher & Jaikumar, 1981; Laporte, 1992).

In response to the limitations of traditional approaches, researchers have explored advanced optimization techniques such as metaheuristics, genetic algorithms, simulated annealing, and ant colony optimization (Toth & Vigo, 2002; Golden et al., 2008). These techniques offer robust solutions for complex VRP variants, including capacitated VRP, time-dependent VRP, and VRP with time windows. Metaheuristic algorithms, in particular, have gained prominence due to their ability to effectively explore large solution spaces and adapt to diverse problem instances (Osman & Laporte, 1996; Colorni et al., 1991).

Campbell et al. (1997) propose a two-phase approach to the inventory routing problem, focusing on optimal customer service scheduling, product allocation, and route selection. Their methodology involves using integer programming to determine delivery quantities and timings in the first phase, followed by route optimization in the second phase. By identifying customer clusters, they streamline route planning, enabling cost-effective delivery solutions.

Vehicle routing optimization has been a subject of extensive research in the fields of logistics, transportation, and operations management. Over the years, numerous studies have explored various algorithms, methodologies, and technologies aimed at optimizing vehicle routes to improve efficiency, reduce costs, and enhance overall logistics performance. Additionally, the integration of modern technologies such as the Google Maps API has opened up new avenues for route optimization, allowing for real-time data integration and dynamic decision-making.

Recent advancements in technology have revolutionized the field of vehicle routing optimization, enabling the integration of real-time data sources and geospatial information systems (GIS) into route planning and decision-making processes. The emergence of the Google Maps API has facilitated seamless access to dynamic traffic data, distance matrices, and geolocation services, empowering organizations to optimize routes based on current traffic conditions, road closures, and other external factors.

Several studies have demonstrated the effectiveness of integrating the Google Maps API into vehicle routing optimization frameworks. For example, Li et al. (2017) proposed a hybrid genetic algorithm integrated with Google Maps API for optimizing urban logistics operations, achieving significant improvements in route efficiency and cost reduction. Similarly, Zhang et al. (2020) developed a real-time vehicle routing system leveraging Google Maps API to dynamically adjust routes based on traffic congestion and delivery priorities, resulting in enhanced delivery performance and customer satisfaction.

While the integration of Google Maps API offers immense potential for enhancing route optimization, several challenges remain to be addressed. These include data privacy concerns, accuracy of real-time traffic information, and the scalability of optimization algorithms for large-scale applications. Furthermore, as autonomous vehicles and drones emerge as viable modes of transportation, there is a growing need to incorporate these technologies into vehicle routing optimization frameworks, opening up new avenues for research and development (Bektas & Laporte, 2011; Garcia & Vidal, 2016).

Vehicle routing optimization represents a critical aspect of logistics and transportation management, with the integration of technologies such as the Google Maps API offering new opportunities for improving route efficiency and responsiveness to dynamic operational conditions. As research in this field continues to evolve, addressing the challenges and leveraging emerging technologies will be key to unlocking the full potential of vehicle routing optimization in the era of digital transformation.

Research Gap

While all the papers dealt with the two-phase methodology or the three phase methodology for approaching the problem of optimizing both the inventory levels at manufacturing plant and the distribution centers where in the inventory distribution and routing alone is taken care or production, inventory , distribution and routing are taken care of , most of the papers did not consider having to distribute multi-product distribution where in the cost of distributing each product varies and the amount that can be sent in a single truck varies.

While choosing the delivery route, either the variable cost for choosing the particular cost is being considered and the time frame available for making the delivery is considered because the constraints are such that the demand must be fulfilled at the right time. And also, while considering the distance matrix, only Euclidean distances were considered, which is not so practical. Considering a more accurate measure of calculating the real-way distance using either **Google Maps API** or Python libraries would give more practical solutions to the problem. These are all the research gaps that will be focused while approaching the problem.

Figure 2: Flow of supply chain

Problem Statement

Retailers place orders for stocks via an online portal, forecasting their demand for the upcoming period. Upon payment completion, the manufacturing plant acknowledges receipt of the order and transmits it via an ERP system to the production lines. Subsequently, an automatic work order is generated based on the ERP data, linked to the payment ID, and communicated to the production lines.

Manual prioritization occurs considering factors like order size, raw material availability, and transporter availability. Work orders are then displayed on screens at workstations, where personnel engage in picking, packing, and grouping items for specific orders. Once completed, the work orders are transferred to the shipment area and sorted by destination region.

When shipments near a Full Truck Load for specific regions, transporters are manually allocated based on cost per kilogram per kilometer charges, which vary depending on the product type.
In the context of our scenario, the capacitated vehicle routing problem arises as a critical logistical challenge. We envision a scenario where multiple vehicles are tasked with transporting various products from a central manufacturing plant to eight distribution centers. Each vehicle is capable of carrying multiple products, and each product has a specific weight associated with it. Additionally, the vehicles have a maximum capacity constraint, limiting the total weight of products they can carry at any given time. Moreover, the manufacturing plant maintains a certain level of inventory for each product, with a minimum safety inventory requirement enforced to ensure uninterrupted supply chain operations.

Furthermore, the demand for products at the distribution centers fluctuates over time, necessitating dynamic adjustments to transportation schedules and routes. As such, the primary objective of VRP optimization in this scenario is to minimize transportation costs while ensuring the timely delivery of products to meet demand at the distribution centers. Additionally, another key objective is to balance the loads of the vehicles to optimize resource utilization and minimize the risk of underutilization or overloading.

Current Process:

While analyzing the sales data according to the states, Tamil Nadu stands at the top consistently in both billing quantity and the revenue amount generated. In TN, there will be in one manufacturing location and 8 Distribution Centre considered for the 233 parts mentioned for implementation.

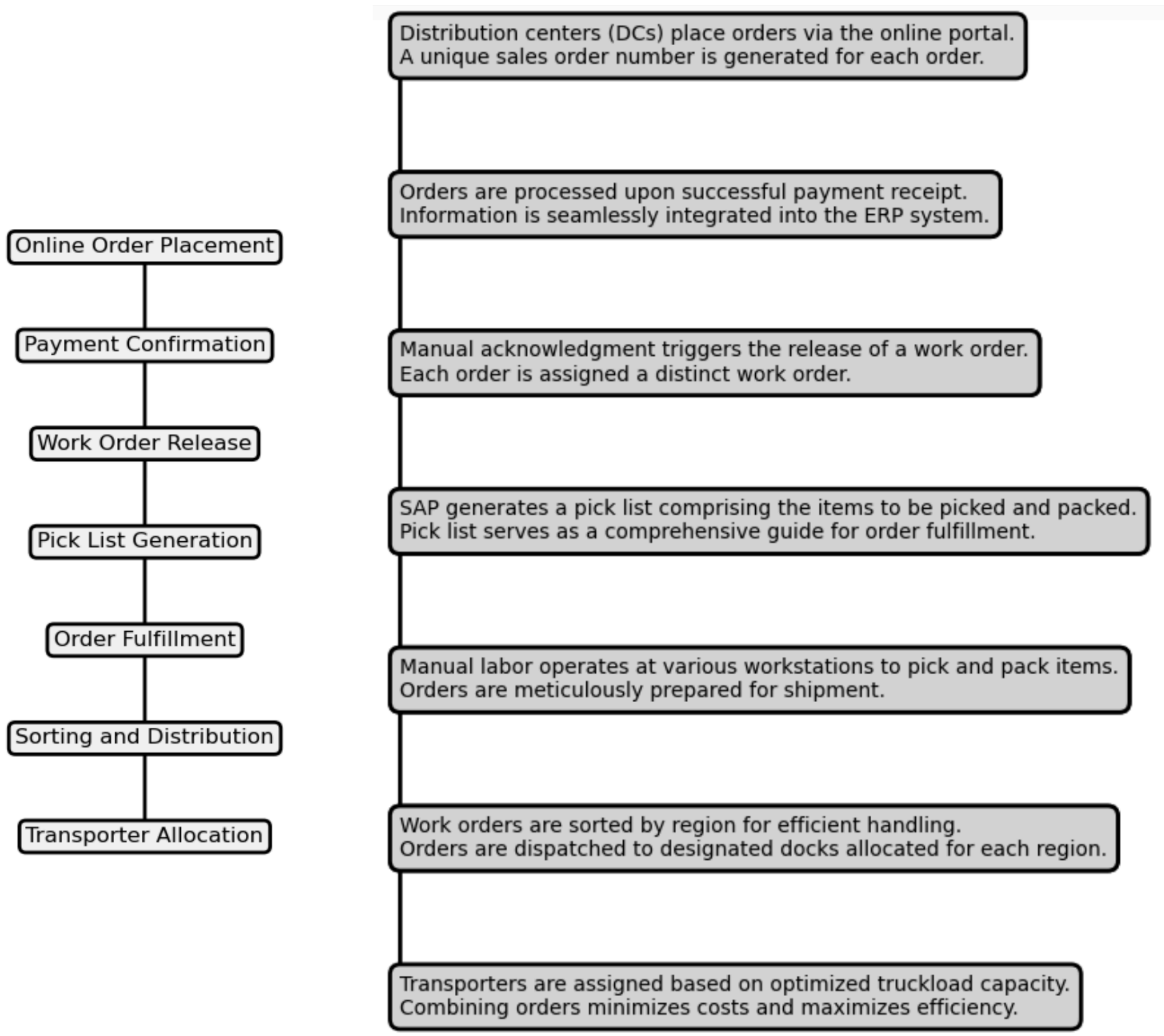

Figure 3 Current process flow chart

Solving Model

After the collection of the data, we are moving on to the modelling the problem as a Mixed Integer Problem. The model is coded and solved in Python using the library PuLP is an Linear Programming modeler and solved for pilot data which included **1 manufacturing plant**, **1 Distribution Centers**, **5 Products** and **4 time periods**. For the pilot data the distance matrix and the travel time are procured directly from the Google maps and then calculated. For the real data, this would be automatically taken by providing the co-ordinates of the location and getting real distance.

Data Collection

There are **8 Distributors** in the focus state of **Tamil Nadu**, each located varying from a distance of **175** kilometers to almost **1100** kilometers from the Manufacturing plant located at Hosur, Tamil Nadu. To be able to deliver the required parts during the right time as of not to miss any sales or keep the end customers waiting for too long, the order data has to reach the manufacturer on time. For this purpose, the ordering is enabled online via a Dealership Management System, where in the Distributors aka Dealerships will place the order online and make payments via the same portal. Data from the Distributor falls into many categories, their location, Inventory holding capacities, Inventory holding costs.

- Location of the Distributor

S.NO	NAME	CITY	LATITUDE	LONGITUDE
1	POPULAR PRIVATE LIMITED (*DC1*)	CHENNAI	*13.06486*	*80.26754*
2	TBF AUTO SOLUTIONS (*DC2*)	SALEM	*11.6489*	*78.1591*
3	POPULAR AUTO DISTRIBUTORS (*DC3*)	MADURAI	*9.8784*	*78.1149*
4	RKS AUTO AGENCIES (*DC4*)	ERODE	*11.3323*	*77.7037*
5	MVR AUTO SOLUTIONS (*DC5*)	TRICHY	*10.8606*	*78.7121*

6	XMR ENTERPRISES (*DC6*)	TIRUNELVELI	*8.7555*	*77.6883*
7	SPH ENTERPRISES LLP (*DC7*)	VILLUPURAM	*11.925*	*79.4836*
8	ADR ENTERPRISES (*DC8*)	COIMBATORE	*10.998*	*76.99*

Table 1: Distribution centers location details in Tamil Nadu

- Demand Data for 5 Parts from 8 Distributors during 4 time periods(weeks)

Distributor 1	Week 1	Week 2	Week 3	Week 4	Total
Part 1	16	16	15	15	62
Part 2	249	263	248	300	1060
Part 3	226	246	226	290	988
Part 4	376	418	350	459	1603
Part 5	28	28	23	25	104

Table 2: Demand data for parts for Distributor 1 during 4 weeks

- Inventory capacity at Different distributor locations

DC1	Inventory Capacity
Part 1	967
Part 2	725
Part 3	258
Part 4	645
Part 5	226

Table 3: Inventory capacity at Distributor center 1 during all time periods

- Inventory holding costs at Different locations.

	Part 1	Part 2	Part 3	Part 4	Part 5
DC1	91	84	6	41	7
DC2	92	85	6	42	7
DC3	82	76	5	37	6
DC4	78	73	5	35	6
DC5	83	77	5	38	6
DC6	88	82	5	40	7
DC7	86	80	5	39	7
DC8	81	76	5	37	6

Table 4: Inventory holding costs in Rs at different distributor locations.

- ❖ Truck capacity - 7 Tonne truck is used by all the vehicles from different transporters.
- ❖ Shipping charges based on destination location

	Part 1	Part 2	Part 3	Part 4	Part 5
Transporter 1	19.67	18.2	2.19	7.1	2.06
Transporter 2	17.18	15.89	1.91	6.2	1.8
Transporter 3	19.13	17.7	2.13	6.9	2.01
Transporter 4	9.89	9.15	1.1	3.57	1.04
Transporter 5	38.63	35.73	4.31	13.94	4.05

Table 5: Shipping charges based on destination to distributor center 1

- ❖ Number of trucks available for service Number of trucks available for service

Transporter	Number of trucks available
Transporter 1	2
Transporter 2	5

Table 6: Number of trucks available

❖ Part Details

Part	Part weight (in grams)	Part cost (Rs)
Part 1	2575	720.56
Part 2	682	671.48
Part 3	287	41.05
Part 4	929	324.72
Part 5	510	51.01

Table 7: Part details

❖ Inventory carrying costs, carrying capacity inventory levels allowed for each part

Part	Inventory carrying cost (Rs)	Inventory carrying capacity (Nos)	Production cost (Rs)	Production capacity / week (Nos)
Part 1	86	3600	1.295	4934
Part 2	80	2700	1.295	4934
Part 3	4	1800	1.39	1149
Part 4	38	2400	0.229	6990
Part 5	6	840	0.133	11983

Table 8: Inventory carrying costs, capacity, production cost and capacity of parts

Methodology

1. **Observation**: Thoroughly understanding the current business model, its objectives, and its relevance to recent industrial practices and trends is essential. This involves examining both the existing process and the proposed mode in detail.

2. Preliminary **data collection**: Gathering preliminary data is crucial, including inventory holding costs for different products, transportation charges from various transporters, transportation times from manufacturing plants to retailers, retailer inventory levels, and demand forecasts. This data will be used for calculations and fed into the model.

3. **Distance matrix procurement**: Utilizing tools such as the Google API or Python modules, an exact distance matrix must be collected to accurately calculate transportation distances between various locations.

4. **OR Model development**: Developing the Operations Research (OR) model involves capturing the objectives and converting operational conditions into constraints effectively. This results in a model capable of providing practical and optimal solutions.

5. Pilot area **testing**: Critical parameters are identified and tested using pilot data to compare against actual costs incurred during normal operations. This comparison allows for validation of the mathematical model's optimized cost predictions.

6. Full-scale implementation: Once the model has been validated and accepted at the management level, it is implemented considering all relevant Stock Keeping Units (SKUs) and all eight distribution centers within the focus region.

7. Conclusion and future scope: Finally, the insights gained from the model, its implementation, and any fine-tuning efforts are summarized. Areas for future expansion or refinement of the model are identified and communicated for consideration, should the automobile company wish to extend the scope of the project to include a wider area or additional product lines.

Objective function and Decision variable

transport_vars[(i, 'plant', k, t, w)]: This term represents a decision variable that denotes the quantity of part k transported from the manufacturing plant to distribution center i, belonging to company t, in week w.

```
# Defining objective function

prob += lpSum(transport_vars[(i, 'plant', k, t, w)] * (cost_price[(k, t)] )+(inventory_dist[(i, k, w)] * (inventory_holding_cost1[k])\
                                                          +prod_plant['plant',k,w]*prod_price[(k)]\
                                                          +(inventory_dist2[('plant', k, w)] * (inventory_holding_cost[k])))\
                                                  for i in distribution_centers
                                                  for k in parts
                                                  for t in companies
                                                  for w in weeks)
```

Figure 4: Objective function

transport_vars: Decision variables representing the transportation of parts.

inventory_dist: Decision variables representing the inventory of parts at distribution centers.

inventory_dist2: Decision variables representing the inventory of parts at the plant.

prod_plant: Decision variables representing the production of parts at the manufacturing plant.

cost_price: Parameter representing the cost of transportation of parts.

inventory_holding_cost1: Parameter representing the inventory holding cost at distribution centers.

prod_price: Parameter representing the price of production of parts.

inventory_holding_cost: Parameter representing the inventory holding cost at the manufacturing plant.

```
# Defining decision variables
transport_vars = LpVariable.dicts("Transport", [(i, j, k, t, w) for i in distribution_centers
                                                  for j in ['plant']
                                                  for k in parts
                                                  for t in companies
                                                  for w in weeks], lowBound=0, cat='Integer')
```

```
# Defining the number of parts stored in each distribution center for each part type and each week
inventory_dist = pulp.LpVariable.dicts("Inventory", ((i, j, k) for i in distribution_centers for j in parts for k in weeks), lowBound=0, cat='ir

inventory_dist2 = pulp.LpVariable.dicts("Inventory", (('plant', j, k)  for j in parts for k in weeks), lowBound=0, cat='integer')

prod_plant = LpVariable.dicts("production", [(i, j, w)
                                              for i in ['plant']
                                              for j in parts

                                              for w in weeks], lowBound=0, cat='Integer')
```

Figure 5: Decision variables

Constraints

Demand constraints: Ensure the demand for each part at each distribution center is met. Production capacity constraints: Ensure the production capacity for each part at the manufacturing plant is not exceeded.

```
# Defining demand constraints
for i in distribution_centers:
    for k in range(len(parts)):
        for w in range(len(weeks)):
            prob += lpSum(transport_vars[(i, 'plant', parts[k], t,weeks[w])] for t in companies) >= demand[('center_'+str(i), parts[k],weeks[w])
```

Figure 6: Constraints

Inventory update constraints: Update the inventory level for each part at each distribution center based on: Previous week's inventory, Current week's demand, Goods transported from the manufacturing plant.

```
for i in distribution_centers:
    for j in range(len(parts)):
        for w in range(len(weeks)):
            if w == 0:
                prob += inventory_dist[(i, parts[j], weeks[w])] == initial_inventory[parts[j]]
            else:
# Update the inventory level for the current part at the current distribution center based on various factors
# Previous week's inventory, current week's demand, and goods transported from the manufacturing plant
                prob += inventory_dist[(i, parts[j], weeks[w])] == \
                            inventory_dist[(i, parts[j], weeks[w - 1])] \
                            - demand[('center_' + str(i), parts[j], weeks[w])] \
                            + lpSum(transport_vars[(i, 'plant', parts[j], t, weeks[w])] for t in companies)
            prob += inventory_dist[(i, parts[j], weeks[w])] >= 0
```

Fig: Constraints

Transportation constraints: Ensure the total weight of goods transported from the manufacturing plant to each distribution center does not exceed the transportation capacity for each route.

Inventory capacity constraints: Total inventory for each part at each distribution center is within the specified inventory capacity.

```
#Total inventory should be less than or equal to the specified inventory capacity for distribution center

for k in parts:
    prob += lpSum(inventory_dist[(i, k, w)] for i in distribution_centers
                                            for w in weeks) <= inventory_capacity[k]

#Total inventory should be greater than or equal to the minimum inventory capacity for plant

for k in parts:
    prob += lpSum(inventory_dist2[('plant', k, w)]
                                            for w in weeks) <= inventory_capacity2[k]
```

Minimum inventory capacity constraints: Total inventory for each part at the manufacturing plant is greater than or equal to the minimum inventory capacity.

Production capacity constraints: Ensure the total amount of each part transported from the manufacturing plant to each distribution center does not exceed the production capacity for that part.

```
# Defining transportation capacity constraints

# Total weight of goods transported for that company should be less than or equal...
#  ...to the product of its transport capacity and the truck capacity

for t in companies:
    prob += lpSum(transport_vars[(i, 'plant', k, t, w)] * weight_per_unit[k] for i in distribution_centers
                                                                              for k in parts
                                                                              for w in weeks) <= transport_capacity[t] * truck_capacity

# Defining production capacity constraints

# Ensure that the total amount of each part transported from the manufacturing plant
# does not exceed the production capacity for that part

for k in parts:
    prob += lpSum(transport_vars[(i, 'plant', k, t, w)] for i in distribution_centers
                                                         for t in companies
                                                         for w in weeks) <= production_capacity[k]
```

Fig: Constraints

Objectives of Vehicle Routing:

Minimizing Transportation Costs: By optimizing routes and vehicle assignments, transportation costs can be significantly reduced, leading to improved profitability and cost-efficiency for the manufacturing operation.

Meeting Demand Requirements: Dynamically adjusting routes and schedules based on demand forecasts and inventory levels, VRP optimization helps prevent stockouts and backorders, thereby enhancing customer satisfaction and maintaining service level agreements.

Balancing Vehicle Loads: Distributing the workload evenly among vehicles, the risk of underutilization or overloading is minimized, leading to optimal resource allocation and improved fleet performance.

Optimizing Inventory Carrying Costs: Optimizing delivery schedules and inventory replenishment strategies, VRP optimization helps minimize inventory holding costs while ensuring adequate stock levels to meet demand variability and supply chain uncertainties.

Ensuring Regulatory Compliance: Compliance with regulatory requirements, such as weight restrictions, driving hour limitations, and environmental regulations, is paramount in transportation operations. By incorporating regulatory compliance into route planning, the risk of fines, penalties, and reputational damage is mitigated, enhancing the overall sustainability and legality of transportation operations.

Improving Operational Efficiency: Beyond cost reduction and customer satisfaction, VRP optimization aims to improve the overall operational efficiency of the transportation network. By optimizing routes and schedules, minimizing empty miles, and reducing idle time, VRP optimization maximizes the utilization of transportation resources and minimizes non-value-added activities.

Capacitated vehicle routing problem with multiple vehicles and products involves balancing various objectives, including minimizing transportation costs, meeting demand requirements, balancing vehicle loads, optimizing inventory carrying costs, ensuring regulatory compliance, enhancing environmental sustainability, and improving operational efficiency. By addressing these objectives holistically through effective route planning, vehicle assignment, and scheduling strategies, VRP optimization enables manufacturing plants to achieve cost savings, enhance customer satisfaction, and maintain a competitive edge in today's dynamic business environment.

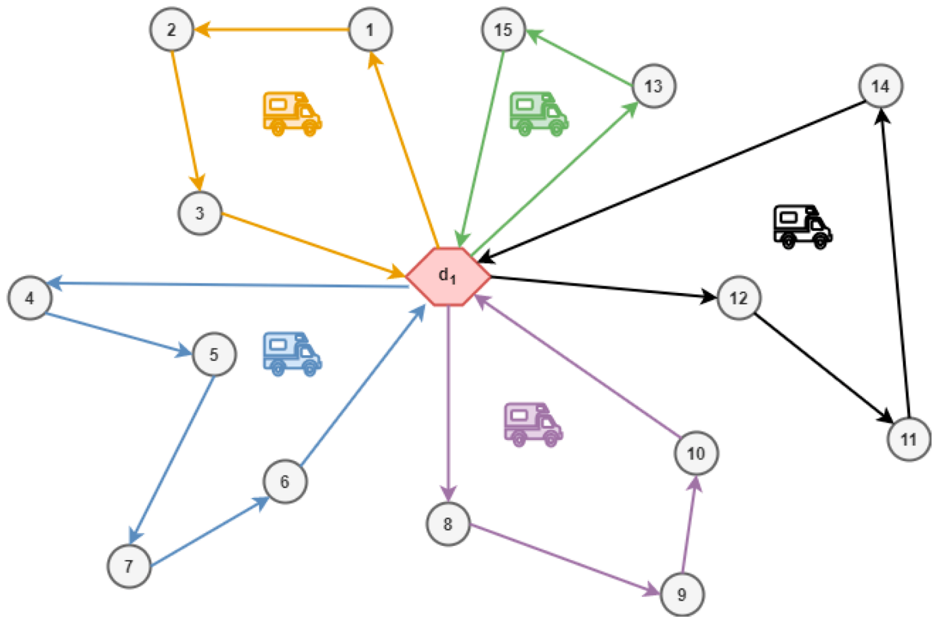

Figure 7: Example of Vehicle Routing

Google Maps employs a sophisticated combination of algorithms, including Dijkstra's algorithm, A* search algorithm, and real-time traffic data analysis, to deliver optimized routes for users. These algorithms enable Google Maps to efficiently calculate the shortest paths between locations while considering factors such as traffic congestion, road closures, and accidents. By leveraging real-time traffic data and machine learning techniques, Google Maps dynamically adjusts routes to provide users with the fastest and most efficient navigation options, even in dynamic and unpredictable environments.

Capacitated Vehicle Routing

The Capacitated Vehicle Routing Problem entails optimizing the routes of a fleet of vehicles originating from a single depot to serve a set of customer locations. The primary goal is to minimize the total distance traveled by all vehicles while ensuring that each customer is visited exactly once and that the total demand served by each vehicle does not exceed its capacity. This optimization not only enhances operational efficiency but also offers several advantages. Firstly, it ensures resource utilization by balancing vehicle loads and minimizing empty trips, thereby leading to cost savings in fuel, maintenance, and labor.

It improves customer satisfaction by guaranteeing timely deliveries and reducing delivery lead times. The environmental impact is mitigated through reduced fuel consumption and emissions. CVRP finds extensive applications across various sectors, including logistics and distribution, waste collection, field service management, public transportation, and e-commerce delivery. A comprehensive report on CVRP would cover its formulation, solution algorithms, real-world applications, advantages, challenges, and future research directions, providing insights into its significance in optimizing transportation and logistics operations.

Figure 8: Process chart for CVRP

- D be the set of distribution centers, where $|D| = 8$.
- C be the set of vehicles available at the depot.
- Q be the maximum capacity of each vehicle.
- q_i be the demand of distribution center i for i in D.
- d_{ij} be the distance between distribution centers i and j for i, j in D.
- x_{ijk} be a binary decision variable that is equal to 1 if vehicle k travels directly from distribution center i to distribution center j, and 0 otherwise.
- u_{ik} be a decision variable representing the cumulative demand served by vehicle k when it leaves distribution center i.

The objective is to minimize the total distance traveled by all vehicles:

$$\text{Minimize:} \quad \sum_{i \in D} \sum_{j \in D} \sum_{k \in C} d_{ij} \cdot x_{ijk}$$

Subject to:

1. Each distribution center must be visited exactly once by one vehicle:

$$\sum_{k \in C} x_{ijk} = 1 \quad \forall i \in D$$

2. Each vehicle must start and end its route at the depot:

$$\sum_{i \in D} x_{0i0} = 1 \quad \text{(Departure from depot)}$$

$$\sum_{i \in D} x_{i00} = 1 \quad \text{(Return to depot)}$$

3. Vehicle capacity constraint:

$$\sum_{i \in D} q_i \cdot x_{i0k} \leq Q \quad \forall k \in C$$

$$u_{ik} - u_{jk} + q_i \cdot x_{ijk} \leq Q \quad \forall i, j \in D, i \neq j, k \in C$$

$$0 \leq u_{ik} \leq Q \quad \forall i \in D, k \in C$$

4. Binary constraint on decision variables:

$$x_{ijk} \in \{0, 1\} \quad \forall i, j \in D, k \in C$$

Result

The estimated total cost the all processes for inventory storage, production of parts, and transportation is **Rs 1,70,000**. After the mathematical modeling using Mixed Integer Linear Programming, the total cost was reduced to **Rs 158,395**. There is an increase of **6.83%** profit.

❖ Inventory stored in Distribution Center 1

The inventory transported to the distribution center serves as safety stock, ensuring that any excess demand can be met promptly. Additionally, an initial inventory is included to ensure that there is a sufficient quantity available from the outset, thereby allowing for smooth operations from week 1 onwards.

	Week 2	Week 3	Week 4
Part1	40	40	40
Part2	33	33	34
Part3	16	17	17
Part4	30	30	30
Part5	66	67	67

Table 9: Number of quantity stored in Inventory of Distribution Center 1

❖ Number of parts transported for Distribution Center 1

It is the amount where the number of parts being distributed from the Hosur Main plant to center 1 Chennai.

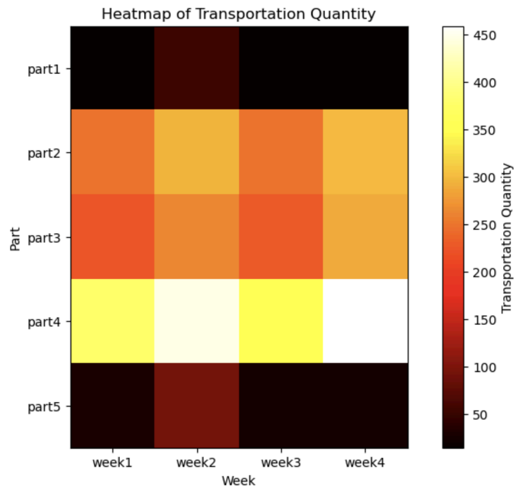

Figure 9: Heat map of the table 10

	Week 1	Week 2	Week 3	Week 4
Part1	16	56	15	15
Part2	249	296	248	301
Part3	226	262	227	290
Part4	376	448	350	459
Part5	28	94	24	25

Table 10: Number of parts transported for Distribution Center 1

❖ Coordinates marked in Maps

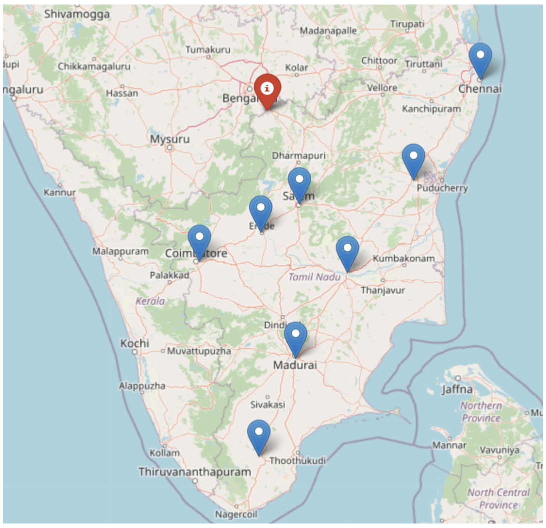

Figure 10: Coordinates of Manufacturing Plant and Distribution Center in real map

❖ Shadow price, also known as dual value or marginal value, is a concept used in optimization and sensitivity analysis, particularly in linear programming and mathematical optimization problems with constraints. In linear programming, the shadow price represents the rate of change in the objective function value with respect to a unit change in the right-hand side of a constraint. In other words, it indicates the increase or decrease in the optimal objective function value for each additional unit of a constrained resource.

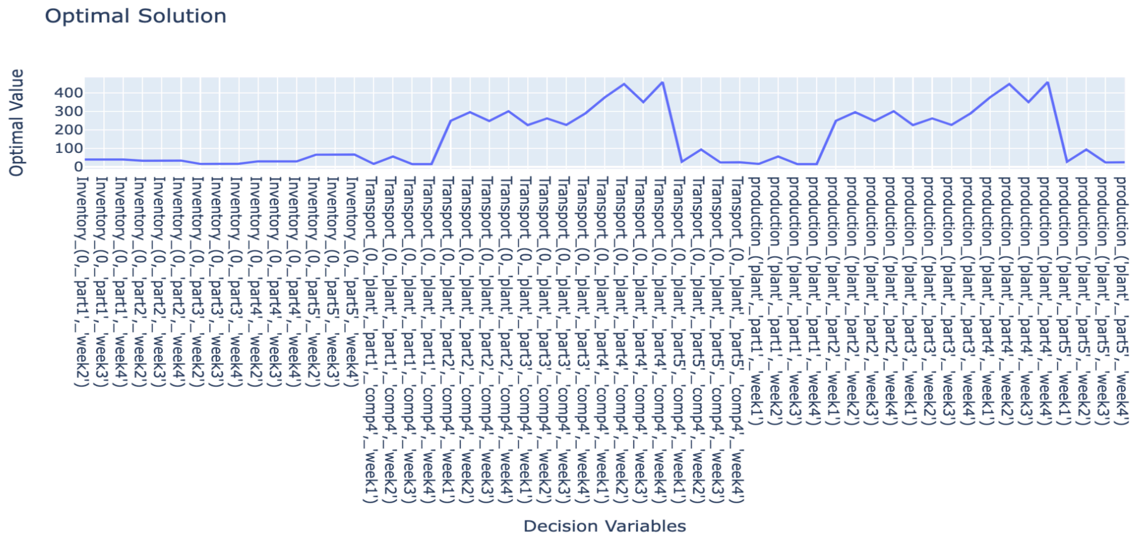

Figure 11: Number of parts in inventory, transported, produced

The **slack value** for a constraint is calculated as the difference between the actual value of the constraint and its upper lower bound. It represents the amount by which the constraint can be relaxed if it is positive slack or tightened if it is negative slack without affecting the optimality of the solution

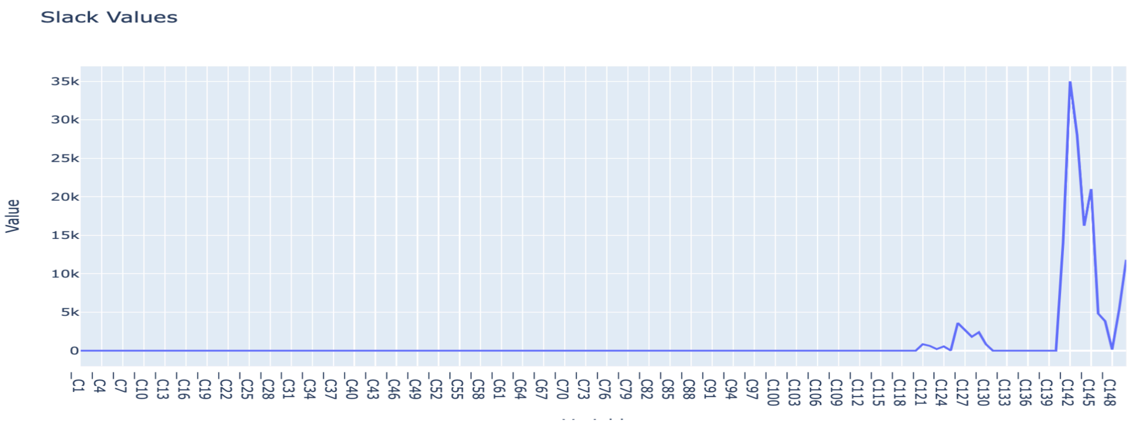

Figure 12: Slack values with constraints

In **sensitivity analysis**, shadow prices are used to assess the sensitivity of the optimal solution to changes in the constraints or resource availability. By examining how the **shadow prices** change as constraints are relaxed or tightened, analysts can identify critical constraints and prioritize resource allocation to achieve the desired objectives.

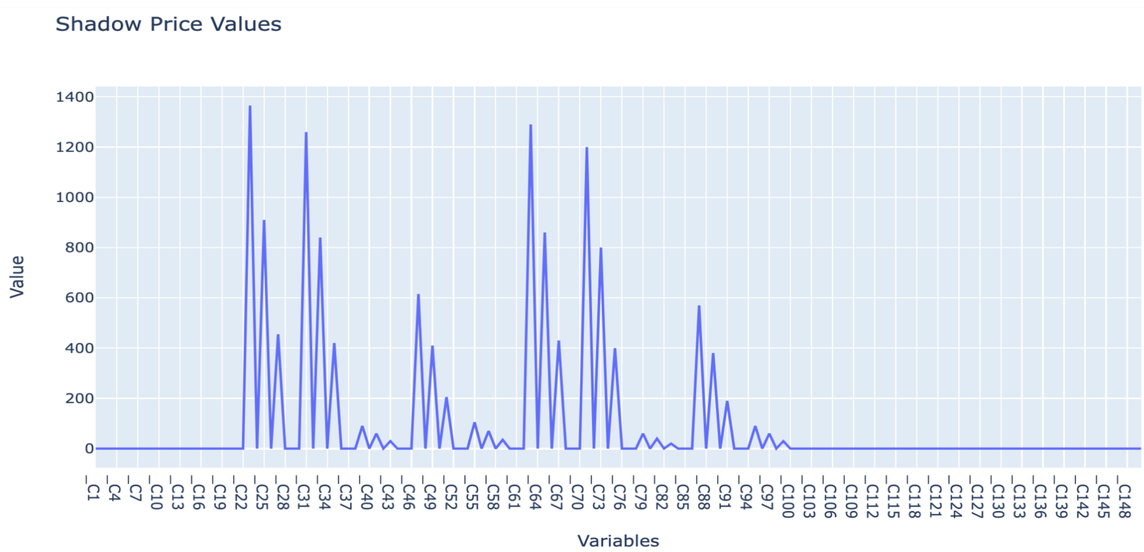

Figure 13: Shadow Price values with constraints

Among the **160 constraints** only **29 constraints** are slack variables exhibited values greater than zero, For shadow price out of 160 constraints count of **30 constraints** displayed shadow prices exceeding zero. This comparison underscores the dynamic interplay between constraints and objective function values, shedding light on the intricacies of our optimization framework.

❖ The output route followed by the truck:

```
Route for vehicle 0:
 0 Load(0) ->  7 Load(2300) ->  1 Load(4600) ->  0 Load(4600)
Distance of the route: 718050m
Load of the route: 4600

Route for vehicle 1:
 0 Load(0) ->  5 Load(2300) ->  3 Load(4600) ->  6 Load(6900) ->  0 Load(6900)
Distance of the route: 1130661m
Load of the route: 6900

Route for vehicle 2:
 0 Load(0) ->  2 Load(2300) ->  4 Load(4600) ->  8 Load(6900) ->  0 Load(6900)
Distance of the route: 645695m
Load of the route: 6900

Total distance of all routes: 2494406m
Total load of all routes: 18400
```

Figure 14: Route of vehicle and capacity to load in the plants

- **Route 1** travels from **Hosur to Villupuram**, then **to Chennai**, and finally **back to Hosur**.
- **Route 2** goes from **Hosur to Trichy**, then **to Madurai**, then **to Tirunelveli**, then **to Hosur**
- **Route 3** from **Hosur to Salem**, then **to Erode**, then **to Coimbatore back to Hosur**

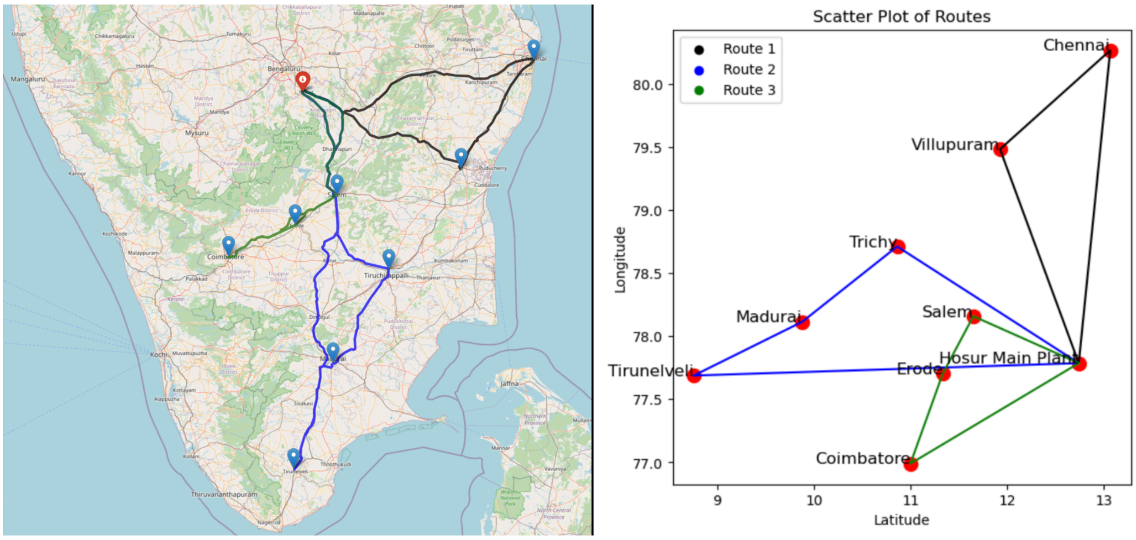

Figure 15: Map view of route followed by the 3 trucks

❖ Total distance traveled was **estimated 2052.22 km**, calculated through Euclidean distance without utilizing Google Maps. However, in practical scenarios, relying solely on Euclidean distances for route planning is unrealistic as it does not consider actual road networks and geographical features. After integrating with Google Maps, which employs the shortest path algorithm for real-time distance calculations, the actual total distance traveled was found to be **actual 2497.408 km**. This substantial difference between the estimated and actual distances underscores the limitations of Euclidean distance-based calculations. The error percentage in the distance estimation was approximately **17.79%**, highlighting the disparity between estimated and actual distances.

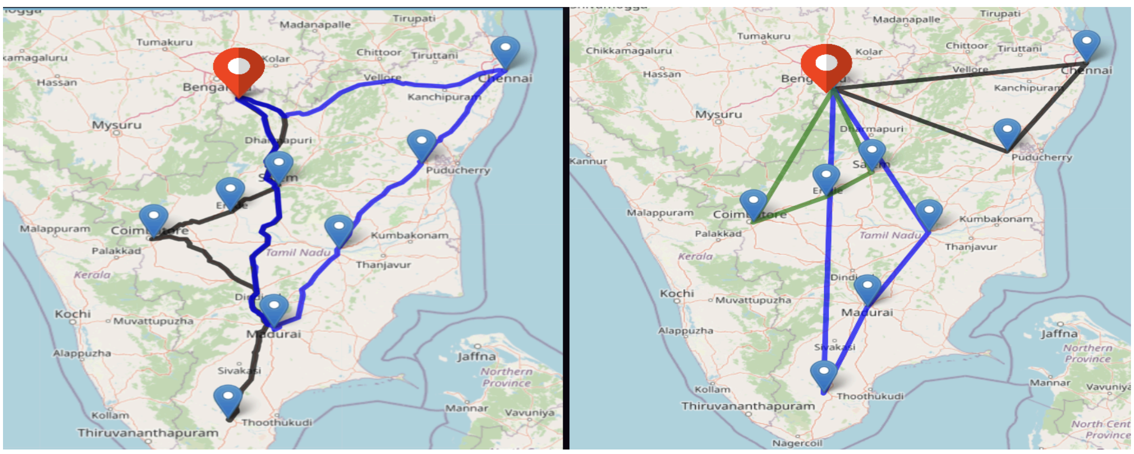

Figure 16: i. The route follows before optimizing the route
ii. Route is shown as the distances between locations

❖ Distance between each of the Distribution centers in kilometers

	Hosur	Chennai	Salem	Madurai	Erode	Trichy	Tirunelveli	Villupuram	Coimbatore
Hosur	0	316	172	413	235	301	546	237	331
Chennai	316	0	339	463	404	317	615	165	500
Salem	151	338	0	241	67	129	374	174	163
Madurai	387	463	236	0	199	146	156	299	208
Erode	214	406	69	205	0	140	338	242	95
Trichy	281	317	130	146	140	0	299	153	209
Tirunelveli	525	615	374	156	338	299	0	451	346
Villupuram	239	165	174	299	240	152	451	0	336
Coimbatore	310	502	165	217	98	208	351	338	0

Table 11: Distance between the locations in km

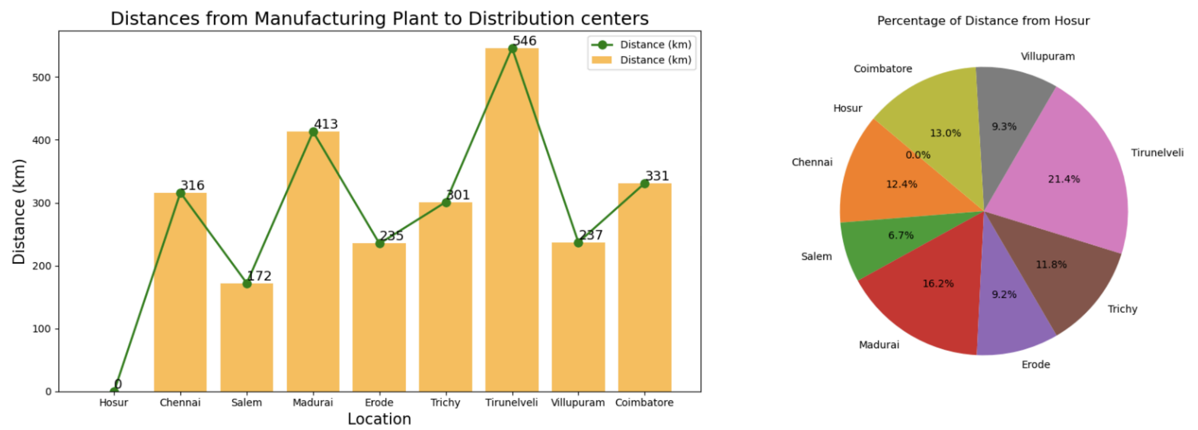

Figure 17: Barplot and a pie chart of the distances of centers from plant Hosur

By leveraging the matrix identify the most efficient distribution routes, minimizing transportation costs and lead times. This optimized approach not only results in cost savings but also enhances customer service through faster delivery times and improved product availability. Moving forward, investments in distribution network expansion, transportation infrastructure, and technology solutions will further strengthen supply chain resilience and competitive advantage.

❖ Time taken to reach the locations in hours (hours: minutes)

	Hosur	Chennai	Salem	Madurai	Erode	Trichy	Tirunelveli	Villupuram	Coimbatore
Hosur	0:0	05:58	3:5	06:53	04:22	05:35	08:41	04:21	05:50
Chennai	6:2	0:0	06:17	8:6	07:39	05:43	10:25	03:21	9:8
Salem	03:10	06:11	0:0	03:59	01:35	02:40	05:46	02:57	3:4
Madurai	06:59	8:4	4:0	0:0	4:6	02:25	02:31	04:50	04:16
Erode	04:28	07:37	01:39	4:5	0:0	03:15	05:53	04:23	01:55
Trichy	05:42	05:43	02:43	02:25	03:15	0:0	04:44	02:28	4:9
Tirunelveli	08:45	10:23	05:46	02:30	05:52	04:44	0:0	7:9	6:2
Villupuram	04:32	03:26	03:00	04:49	04:21	02:26	7:7	0:0	05:50
Coimbatore	05:53	9:3	3:4	04:13	01:53	4:8	6:0	05:48	0:0

Table 12: Time taken to travel in every routes in hours

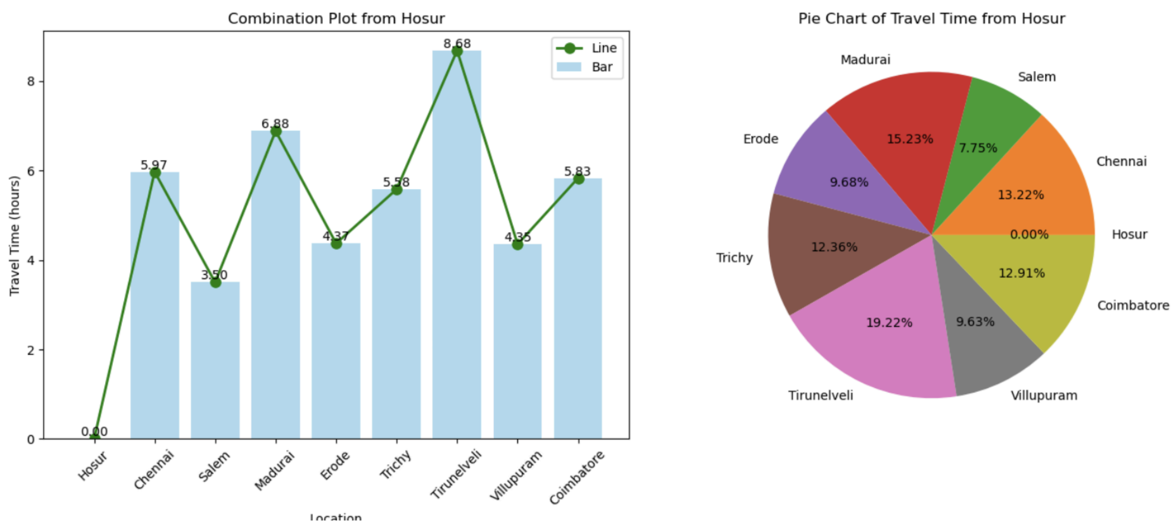

Figure 18: Barplot and a pie chart of the time taken of centers from plant Hosur

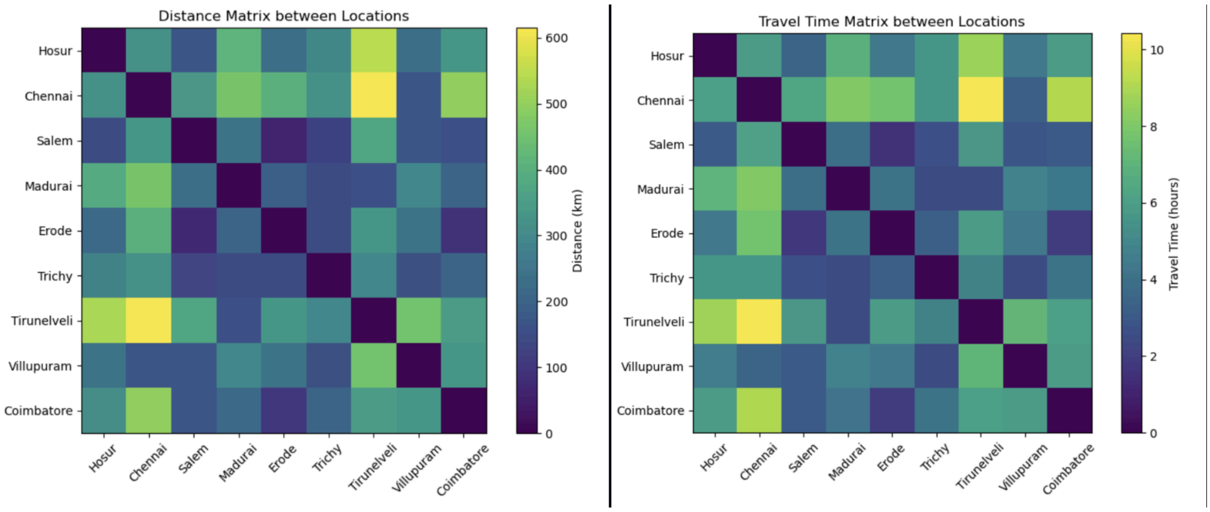

Figure 19: Heat map of distance matrix and time matrix

❖ Distance traveled in 3 routes and the total distance traveled in km

```
Total distance for Route 1: 718.057 kilometers
Total distance for Route 2: 1130.664 kilometers
Total distance for Route 3: 648.687 kilometers
Sum of all distances: 2497.408 kilometers
```

Following vehicle route optimization, the total distance traveled significantly decreased from **3554.0** kilometers to **2497.4** kilometers, representing a reduction of **1056.6 kilometers**, or distance **reduce by 29.73%** in relative terms. This optimization, achieved by consolidating routes and utilizing three trucks instead of following the fixed route to the distribution center, resulted in a notable increase in efficiency. Additionally, the cost savings associated with this reduction in distance traveled are substantial and contribute to enhanced operational efficiency and cost-effectiveness in spare parts distribution.

Future Research

Future research and development efforts in vehicle routing optimization can focus on addressing these challenges and advancing, Machine learning algorithms that that can learn from historical data and real-time observations to make informed decisions and adapt to changing conditions. Integrating optimization techniques with emerging transportation technologies, such as autonomous vehicles, drones, and smart infrastructure, to create innovative solutions for next-generation transportation and logistics systems.

One potential avenue for expansion involves optimizing the bin and packing of parts in trucks using a combination of primary and secondary boxes. By introducing secondary boxes for smaller parts, the packing efficiency can be improved, leading to better space utilization within the trucks. Additionally, the inclusion of loading and unloading time windows can further refine the optimization process, ensuring that deliveries are synchronized with operational constraints and minimizing idle time at distribution centers.

Moreover, extending the project to incorporate routing problems, such as the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW), can offer a comprehensive solution for transportation logistics. The CVRPTW considers not only vehicle capacity constraints but also time windows for customer visits, enabling efficient scheduling of deliveries within specified time frames. Furthermore, integrating real-time traffic data and road condition information into the routing optimization algorithms can enhance route planning by adapting to dynamic environmental factors. By accounting for traffic congestion and road conditions, the optimized routes can minimize travel time and improve overall delivery efficiency.

In conclusion, the future scope of the project involves expanding the optimization framework to address additional complexities in logistics and transportation, including enhanced packing strategies, incorporation of time windows, and integration of routing algorithms considering traffic and road conditions. These enhancements aim to provide a more robust and adaptive solution for optimizing transportation operations, ultimately leading to cost savings, improved delivery performance, and enhanced customer satisfaction.

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