Course Project

“Impact of Vehicle Routing on Operational Efficiency”

Freight Transportation Planning and Logistics

[CE 749]

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CHAPTER 1 : INTRODUCTION

In the rapidly evolving logistics and transportation industry, optimizing routes and fleet utilization is paramount for enhancing operational efficiencies and achieving substantial cost reductions. As globalization expands and consumer expectations rise, companies are under increasing pressure to deliver goods more quickly, reliably, and economically. To address these challenges, this report presents the results of a detailed simulation-based analysis, which evaluates the impact of integrating advanced Vehicle Routing (VR) technologies into logistics operations.

Vehicle Routing Technologies leverage complex algorithms to streamline the process of planning and executing delivery routes. This involves not just determining the shortest path between points but also considering variables such as traffic conditions, vehicle load capacities, delivery windows, and real-time adjustments for delays or emergencies. The strategic implementation of these technologies can lead to significant improvements in service levels and cost efficiencies by minimizing route redundancies, reducing fuel consumption, and optimizing driver hours.

This analysis aims to provide a comparative insight into the operational benefits and cost savings that can be achieved with VR, as opposed to traditional routing methods that do not utilize such advanced technologies. By simulating real-world logistics operations both with and without VR, the study seeks to highlight the tangible impacts of these technologies on a company's bottom line and operational efficiency. The findings are intended to guide logistics companies in making informed decisions about technology investments and strategic enhancements to their delivery systems.

CHAPTER 2 : DATA HANDLING AND PROCESSING

The simulation utilized a dataset (shipments data new) containing detailed information about shipments over a specified period, including dates, weights, and geographic coordinates (Latitude and longitude) of delivery points. The following steps were taken to handle and process the data:

- **Data Initialization**: Arrays were initialized to truck costs and truck counts for scenarios with Vehicle routing (VR) (truck_type_total_count_VR) and without VR (truck typetotal_count_noVR). In the data initialization step of simulation, arrays named truck_type_total_count_VR and truck_type_total_count_noVR are set up to monitor and compare key logistics metrics across different scenarios. These arrays serve as essential tools to organize and store data about the costs associated with each route and the number of trucks used, differentiated by whether vehicle routing (VR) technique is employed or not. Essentially, this setup allows for an effective and systematic comparison of operational efficiencies and costs in scenarios with and without the use of VR, providing a clear basis for analyzing how VR technique impacts logistical operations.
- **Time Frame Segmentation**: The "Time Frame Segmentation" step in our data handling process involves dividing the total number of days covered by the dataset (`no_of_days`) into smaller segments based on a defined planning horizon. This division into manageable batches is crucial for optimizing data processing tasks. By segmenting the data, the analysis can focus on shorter, specific periods, thereby enhancing computational efficiency and making the data easier to handle. This batch processing approach not only simplifies the management of large datasets but also improves the performance of the system by reducing the computational load during each cycle of the analysis. This method is particularly effective in scenarios where data volumes are large and continuous processing could strain system resources or complicate data management.
- **Daily Data Extraction**: For each batch, shipment data within the designated date range were extracted and processed to determine their geographic and weight attributes. This targeted extraction focuses on analyzing the shipments' geographical coordinates and their respective weights. By isolating data on a daily basis within each batch, the process ensures that only relevant entries are considered, which streamlines the handling and analysis of the data. This approach not only facilitates a more organized and manageable analysis of geographical routing and load distribution but also enhances the precision of

the logistical insights generated by focusing on detailed, temporal slices of the dataset. This method is essential for effectively determining optimal routing strategies and for efficient resource allocation in logistics operations.

CHAPTER 3 : METHODOLOGY

To assess the impact of Vehicle Routing (VR) on Operational Efficiency, our methodology involved a series of iterative cycles of route simulation and truck utilization analysis, each aligned with a specific batch of days within our planning horizon. Utilizing the Clarke-Wright (CW) truck assignment algorithm as a cornerstone of our approach, we were able to optimize the routing of trucks effectively. This optimization process was executed repetitively for each batch, allowing us to refine our analysis incrementally and observe the effects of VR on the logistics network over time. Through this methodical application of CW truck assignment, we aimed to identify and quantify the enhancements in routing efficiency and cost savings afforded by vehicle routing technology.

Route Simulation

- **Clarke-Wright Savings Algorithm**: This classical optimization technique, denoted as CW_truck_assignment, was used to assign shipments to trucks efficiently. The algorithm helps in creating routes that minimize total travel distance or cost by combining nearby locations into a single route.

  This algorithm is fundamental in logistics for reducing transportation costs and travel distances. It operates by identifying pairs of delivery points that, when combined into a single route rather than served separately, yield the greatest 'savings' in distance or cost. These savings are calculated based on the reduction in travel distance between two points compared to their individual distances from a depot. The algorithm iteratively merges the most economical pairs until no further cost-effective combinations can be found. This method not only streamlines the route planning process but also optimizes the use of vehicles by consolidating shipments that are geographically proximate, thus enhancing overall operational efficiency in transportation logistics.

- **VR vs. Non-VR Approaches**: The comparison between VR (Vehicle routing) and non-VR approaches is used to evaluate the practical benefits of using advanced visualization and planning tools in route optimization. By leveraging VR technology, the simulation can generate and assess routes that may offer more interactive and immersive planning experiences, potentially leading to more efficient routing decisions. This is compared against traditional routing approaches where such advanced tools are not utilized. The effectiveness of each method is measured by analyzing metrics such as cost, travel distance, and time, among others. This comparative analysis helps to determine whether VR tools can indeed enhance the route planning process by providing more detailed, realistic, and adaptable views of logistical scenarios, thus potentially improving the overall efficiency and effectiveness of transportation logistics.

Cost and Truck Utilization

- **Cost Calculation**: When assessing transportation costs for different route scenarios, it's essential to consider several factors that contribute to the overall expenses. Fuel consumption stands out as a significant cost consideration, influenced by factors such as distance, terrain, and traffic conditions. Each route's unique characteristics impact how much fuel is consumed per journey, affecting the total cost. Labor costs also play a pivotal role, encompassing wages for drivers and other personnel involved in transportation operations. Routes that require more labor hours due to longer distances or complex logistics can significantly increase overall labor costs. Additionally, maintenance expenses must be factored in, covering vehicle servicing and repairs. Routes with rough terrain or frequent stops may lead to higher wear and tear on trucks, necessitating more frequent maintenance and repair, thus adding to the overall cost. By meticulously calculating these expenses for each route scenario, businesses can make informed decisions to optimize their transportation operations and minimize costs effectively.

- **Truck Usage Analysis:** Evaluating truck utilization across different route scenarios provides valuable insights into fleet efficiency. High truck utilization rates indicate that trucks are effectively deployed, completing more deliveries or tasks within a given timeframe. This efficiency is crucial for maximizing the productivity of the fleet and minimizing idle time. Comparing truck usage across various routes helps identify which routes result in higher utilization rates, enabling businesses to optimize routing and scheduling accordingly. By deploying trucks where and when they are most needed, companies can ensure efficient resource allocation and avoid underutilization or overutilization of resources. Ultimately, truck usage analysis is instrumental in enhancing the efficiency and productivity of a transportation fleet, leading to cost savings and improved service quality.

CHAPTER 4 : DATA ANALYSIS

The analysis was conducted in a Jupyter Notebook environment that incorporates a suite of libraries. Essential libraries like numpy, math, pandas, and matplotlib were imported to facilitate the analysis process. The dataset includes a systematically arranged catalog of trucks, each specified by its unique name, capacity, and various operational metrics. The study considers four distinct categories of trucks—A_5, B_7, C_9, and D_16—with respective capacities of 5, 7, 9, and 16 tons, to underpin the logistical analysis. Here we identifies the maximum truck capacity from the given fleet; and 16 tonnes is the largest truck capacity. It represents the upper limit of what a single truck in the fleet can transport at one time. This capacity is crucial for planning, as it influences how shipments are allocated across the fleet, ensuring that each load is as close to the truck's full capacity as possible for efficiency. This value is then used as a benchmark in the logistics strategy to maximize the utilization of the fleet's carrying capabilities and to minimize the number of trips required, which can result in cost savings and improved operational efficiency. **Figure 1** representing the screenshot of Jupiter having code for above mentioned steps.

```
In [72]: import numpy as np
         import math
         import pandas as pd
         from datetime import datetime, timedelta, date
         from IPython.display import clear_output
         import matplotlib.pyplot as plt

In [73]: # [Truck Name, Truck capacity in Tonns, A , n]

         Truck_list = [["A_5_Tonns_truck", 5, 251.45, 0.315],
                       ["B_7_Tonns_truck", 7, 292.94, 0.316],
                       ["C_9_Tonns_truck", 9, 382.15, 0.343],
                       ["D_16_Tonns_truck", 16, 668.39, 0.38]]

         sorter_guide = []
         max_truck_capacity = 0
         for i in range(len(Truck_list)):
             sorter_guide.append([i,int(Truck_list[i][1])])
             if int(Truck_list[i][1])>=max_truck_capacity:
                 max_truck_capacity = int(Truck_list[i][1])
         sorter_guide = np.array(sorter_guide)
         sorter_guide = sorter_guide[sorter_guide[:,1].argsort()[::-1]]
         sorter_temp = []
         for i in range(len(sorter_guide)):
             sorter_temp.append(Truck_list[sorter_guide[i][0]])
         Truck_list = np.array(sorter_temp)

         print('\n',"max_truck_capacity =",max_truck_capacity,'\n')
         Truck_list

          max_truck_capacity = 16
```

Figure 1 Screenshot of Jupyter Notebook we implement a geodesic distance computation, which is essential for calculating the shortest path between two points on the Earth's surface, given their latitude and longitude coordinates. The Figure 2 represent the geodesic distance computation in Jupyter. Latitude and longitude inputs are converted from degrees to radians to align with the trigonometric functions used later in the Python math module, which necessitates angles in radians. Following this, the differences in latitude and longitude are determined, and these differences are utilized in conjunction with the cosine of the original latitudes to compute the haversine values, which are essential to the formula. An intermediate variable, a, encapsulates the core of the haversine calculation, combining the haversine of latitude differences with the product of cosines of latitudes and haversine of longitude differences. With a established, the angular distance c in radians is derived using the atan2 function, allowing for the calculation of the arc length. Multiplying this angular distance by the Earth's radius yields the distance between the two points. The resultant geodesic distance is crucial for logistics planning, providing accurate measures for route optimization and resource allocation within the simulation framework.

```
In [74]: from math import sin, cos, sqrt, atan2, radians

def Distance_calculator(lat1,lon1,lat2,lon2):
    # approximate radius of earth in km
    R = 6373.0

    lat1 = radians(lat1)
    lon1 = radians(lon1)
    lat2 = radians(lat2)
    lon2 = radians(lon2)

    dlon = lon2 - lon1
    dlat = lat2 - lat1

    a = sin(dlat / 2)**2 + cos(lat1) * cos(lat2) * sin(dlon / 2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))

    distance = R * c


    return distance
```

Figure 2 Geodesic Distance Computation in Jupyter

We elucidate the Clarke-Wright (CW) truck assignment algorithm, which we've executed to optimize logistics operations. The Figure 3 shows the algorithm for the same. Starting with a list of locations and corresponding weights, alongside a status indicator for the implementation of Vehicle Routing (VR), we set the stage for our CW truck assignment function. We first compute a distance matrix, calculating the distance between all pairs of locations using the previously defined Distance calculator function. Upon this matrix, we construct a savings matrix that captures the cost difference between direct and indirect routes. the assignment of shipments to trucks, ensuring that the combined weight of shipments does not exceed the maximum truck capacity. This process is meticulously documented, noting which shipments are combined and the total savings achieved with each truck assignment. A truck assignment matrix is then generated, assigning shipments to trucks while tallying the weights and savings associated with each vehicle.

we adjust for partially assigned shipments, accounting for those already assigned to a route while considering additional pairings that may fit within the weight capacity. Once all possible combinations are explored, we calculate the total weights for each assigned truck and the corresponding distances they will cover, adjusted for the savings identified.

In the final step, we correlate each truck's weight with the appropriate truck type from our predefined truck list. This correlation enables us to tally the types and number of trucks used, which serves as a fundamental indicator of the efficiency and effectiveness of the VR-enhanced routing process. The culmination of the algorithm is the computation of total costs, combining distances traveled with type-specific operational cost factors, resulting in a granular overview of the financial implications of our routing decisions.

```
In [75]: def CW_truck_assignment(locations_list,weights_list,vr_status):


    distance_matrix = [[Distance_calculator(locations_list[i][0],locations_list[i][1],locations_list[j][0],locations_list[i][1]) for i in range(len(locations_list))] for j
    distance_matrix = np.array(distance_matrix)


    cw_savings_matrix = [[(distance_matrix[0][i+1]+distance_matrix[0][j+1]-min(distance_matrix[0][i+1],distance_matrix[0][j+1])-distance_matrix[i+1][j+1]) for i in range(l
    if vr_status == True:
        savings_threshold = 0.42
    else:
        savings_threshold = 0.5

    cw_savings_percent_matrix = [[((distance_matrix[0][i+1]+distance_matrix[0][j+1]-min(distance_matrix[0][i+1],distance_matrix[0][j+1])-distance_matrix[i+1][j+1])/(distar

    cw_savings_matrix = np.array(cw_savings_matrix)
    for i in range(len(cw_savings_matrix)):
        cw_savings_matrix[i][i]=0

    for i in range(len(cw_savings_percent_matrix)):
        cw_savings_percent_matrix[i][i]=0

    cw_savings_list=[]

    for i in range(len(cw_savings_matrix)):
        j=0
        while j<i:
            if cw_savings_percent_matrix[i][j]>=savings_threshold:
                cw_savings_list.append([i+1,j+1,cw_savings_matrix[i][j]])
            j=j+1
    cw_savings_list=np.array(cw_savings_list)

    if(len(cw_savings_list)>0):
        cw_savings_list=cw_savings_list[cw_savings_list[:,2].argsort()[::-1]]
```

Figure 3 Clarke-Wright (CW) Truck Assignment Algorithm

CHAPTER 5 : RESULT

The dataset in question contains information regarding the geographic coordinates (latitude and longitude), date, location, and weight of each shipment. Figure 4 illustrates the distribution of shipment frequencies across a variety of weight classes, as derived from this dataset.

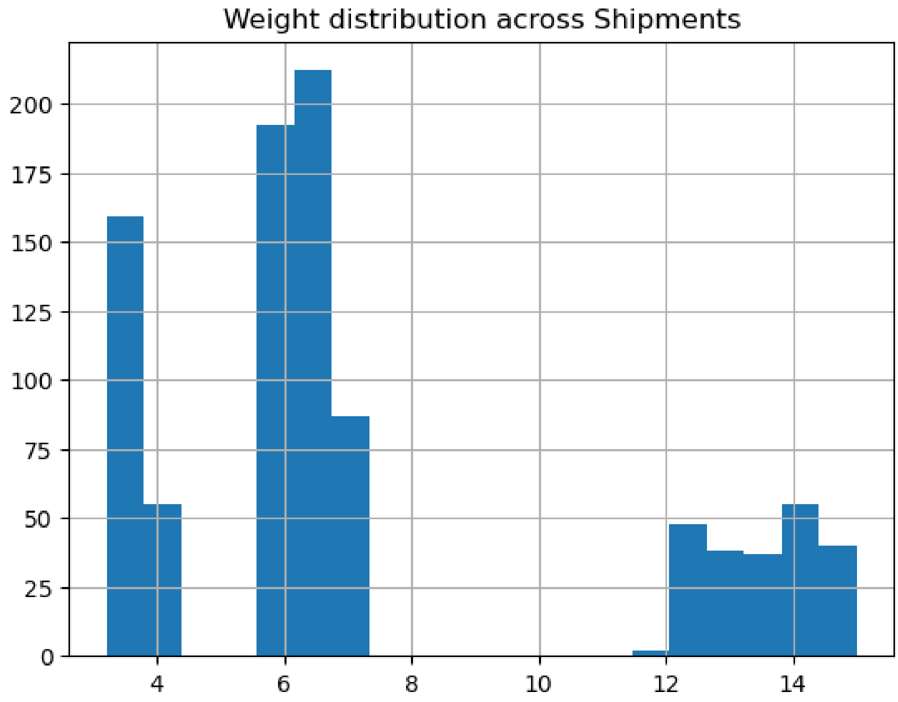

Figure 4 Weight Distribution Across Shipments

The weights are most frequently in the range of around 7 to 9 units (tons), as indicated by the tallest bars in the histogram. There are smaller peaks in the distribution, suggesting that there are other common shipment weights, but the central range dominates. This could indicate a standard shipment size or a common preference for shipments within this weight range due to cost, convenience, or other operational factors.

The Figure 5 presents the weight distribution across the top 10 cities. There's a steep decline in shipment weights from Delhi to Kolkata and a more gradual decline thereafter. Delhi, being at the far left, appears to have the highest total shipment weight, indicating it's a major hub for shipments in this dataset. The distribution shows how shipment weights are concentrated among the cities, with a significant drop after the first few, suggesting that a few cities may handle the majority of the goods transported in this network. This suggest that while there is a concentration of higher weights in specific cities and weight categories, there is also a diversity of shipment weights across the dataset.

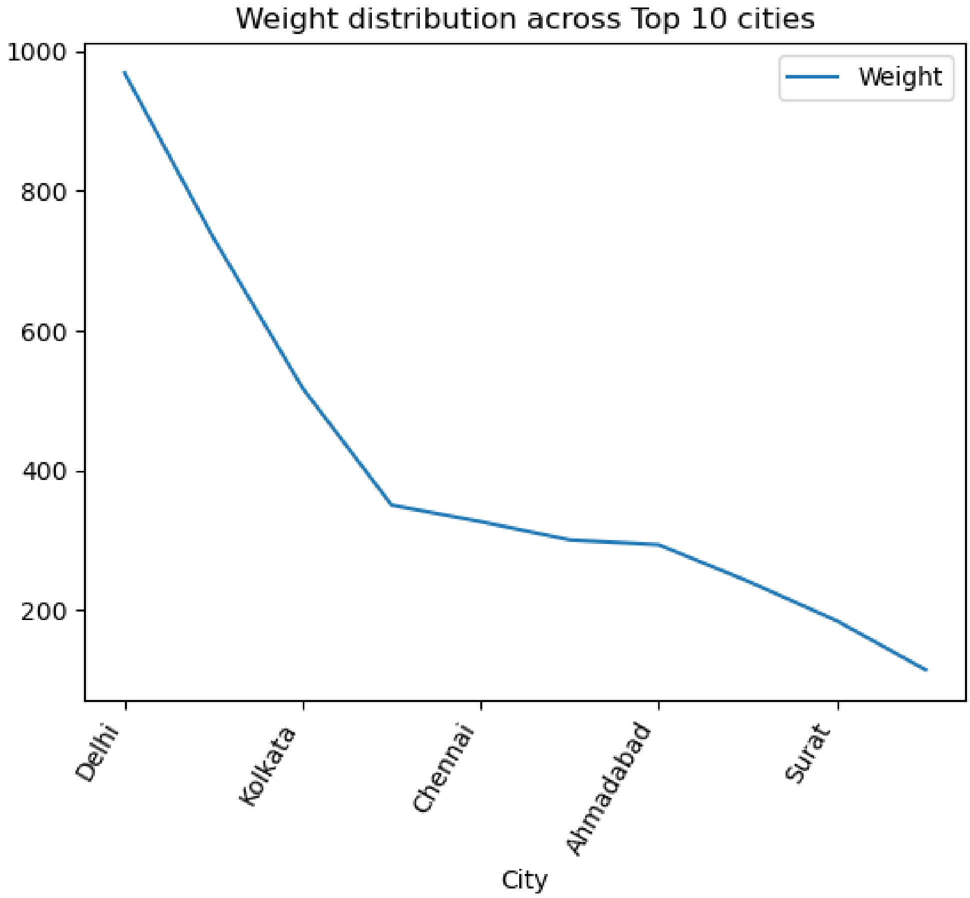

Figure 5 Weight Distribution Across Top 10 Cities

The line graph shown in Figure 6 ,compares the monthly transportation costs incurred with VR (Cost_with_VR) and without VR (Cost_with_no_VR) from November to November the following year. Both lines follow a similar trend throughout the year with costs peaking around June and October. Interestingly, the Cost_with_VR is consistently lower than the Cost_with_no_VR, suggesting that VR implementation is contributing to cost savings each month.

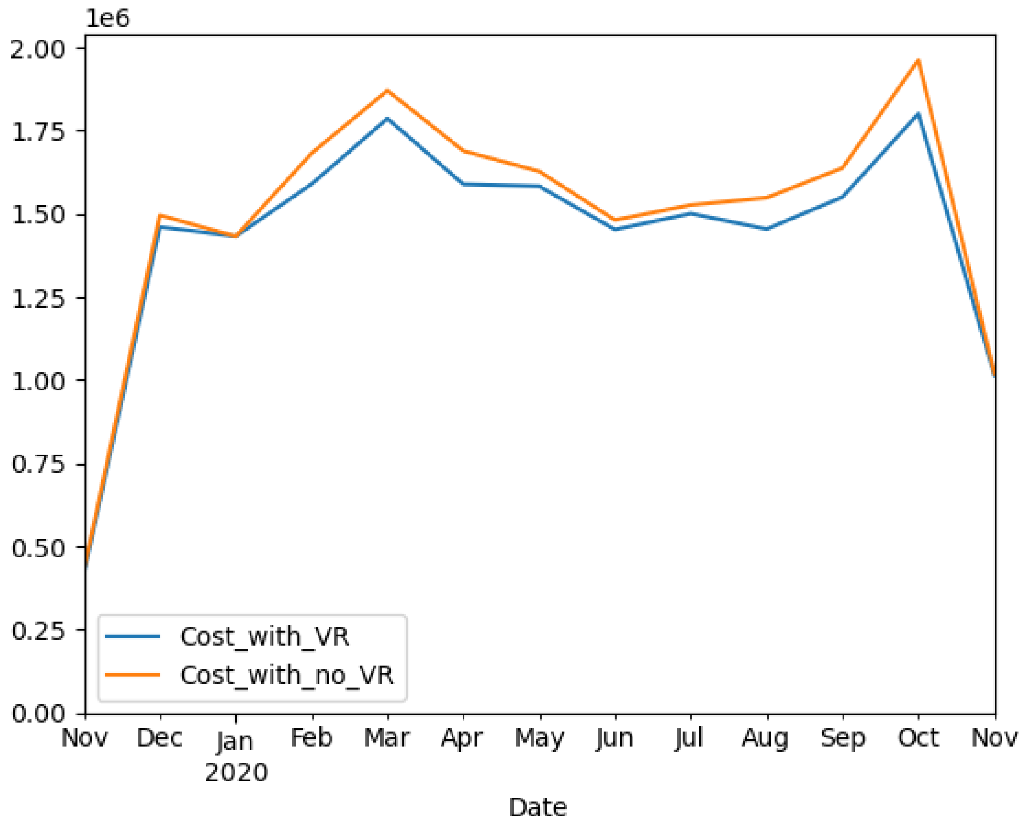

Figure 6 Compare Monthly Transportation Costs, with VR and with no VR.

The Figure 7 represent Truck Utilization by Capacity. The bar chart presents the count of trucks used categorized by their capacity in tonnes for scenarios with VR and without VR. It's evident that with VR, fewer trucks of each capacity are used compared to the scenario without VR, with the most significant difference seen in the 7-tonne category. This implies that VR not only reduces the number of trucks needed but is especially effective for medium-capacity vehicles.

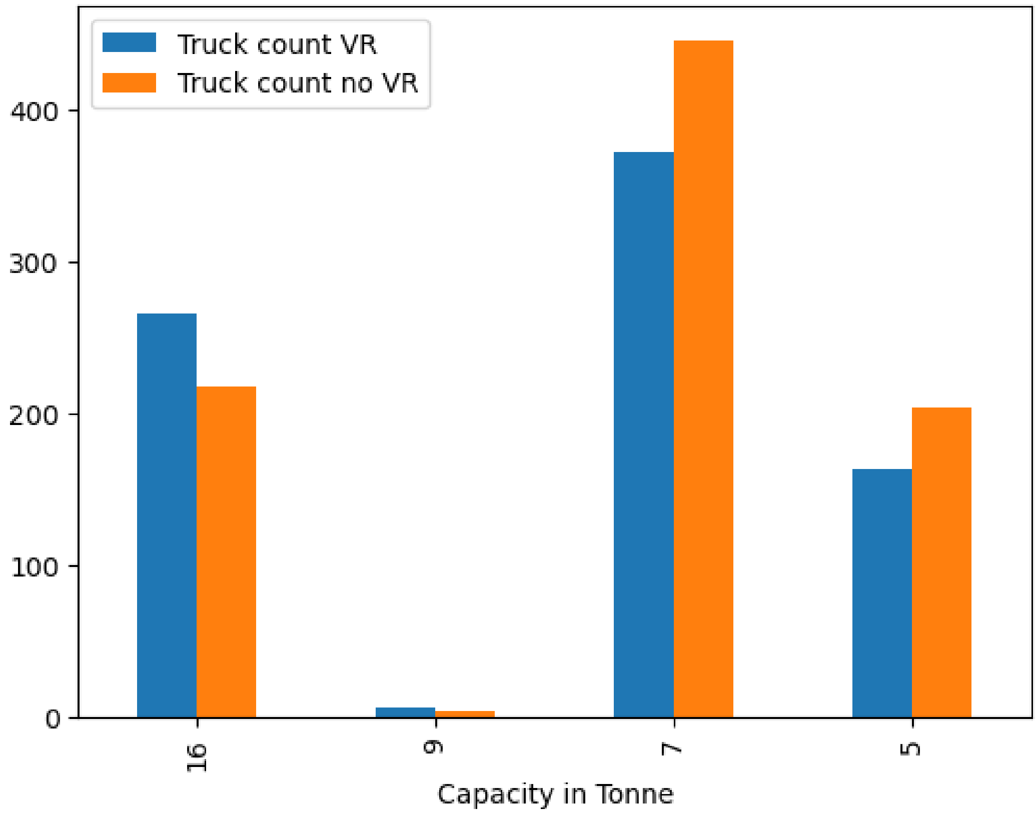

Figure 7 Truck Utilization by Capacity

The reported estimated costs show that using VR results in a total cost of 18,631,811, compared to 19,401,674 without VR, leading to a cost saving of 4%. In terms of truck numbers, VR has reduced the total count from 872 to 809 trucks.

The data clearly indicate the efficacy of Vehicle Routing technology in optimizing logistics operations. Over a span of a year, VR consistently delivered cost reductions each month, reflecting its robustness across varying seasonal demands and operational challenges. The truck utilization metrics underscore VR's role in enhancing fleet efficiency, particularly evidenced by a substantial reduction in the number of medium-capacity trucks required. An overall 4% cost saving, alongside a significant reduction in the number of trucks from 872 to 809, strongly suggests that VR is not merely a strategic enhancement but a crucial investment for achieving sustainable, cost-effective logistics operations. These findings advocate for the adoption of VR technologies as they bring forth quantifiable benefits, both financially and operationally, enhancing resource allocation and potentially reducing environmental impact through fewer vehicles on the road.

CHAPTER 6 : CONCLUSION

The study undertaken in this report, "Impact of Vehicle Routing on Operational Efficiency," provides a comprehensive analysis of the benefits derived from the integration of advanced Vehicle Routing (VR) technologies into logistics operations. Through rigorous simulation and methodical evaluation, it has been demonstrated that VR technologies are not only a viable but essential enhancement for optimizing route planning and fleet management in the freight transportation sector.

The adoption of VR technologies has shown significant improvements in operational efficiency, as evidenced by the reduction in fuel consumption, optimization of driver hours, and minimization of route redundancies. These enhancements contribute directly to cost savings, as the efficient use of resources leads to lower operational costs. Furthermore, the data-driven insights from the VR systems enable more informed decision-making, allowing logistics companies to adapt more dynamically to the complexities of transportation and delivery challenges.

Importantly, the comparative analysis between scenarios utilizing VR and those that do not underscores the tangible benefits of this technology. The consistent reduction in transportation costs and the optimized use of truck capacities highlight VR's role in not only improving economic efficiency but also in contributing to environmental sustainability by reducing the number of trucks required and, consequently, the emissions associated with them.

In conclusion, this report substantiates the argument that Vehicle Routing technologies are crucial for the modernization and enhancement of logistics operations. Companies that invest in these technologies are likely to see not only improved operational metrics but also enhanced competitive advantages in the logistics marketplace. As such, the strategic implementation of VR technologies is recommended as an integral component of future logistics and transportation strategies, promising both short-term gains and long-term sustainability.