

Optimal solution techniques to the vehicle routing problem arising in Lion Beer distribution in Sri Lanka

D.G.N.D. Jayarathna *, M. A. Hoque **, G. H. J. Lanel ***

* Department of Scientific Computing, Faculty of Computing, University of Sri Jayewardenepura, Gangodawila, Nugegoda, Sri Lanka
nuwand@sjp.ac.lk

** BRAC Business School, BRAC University, Dhaka, Bangladesh
abdul.hoque@bracu.ac.bd

*** Department of Mathematics, University of Sri Jayewardenepura, Nugegoda, Sri Lanka
ghjlanel@sjp.ac.lk



Article history:

Received: January 14, 2025
1st Revision: May 29, 2025
Accepted: September 06, 2025

DOI:

[10.14254/jsdtl.2025.10-2.2](https://doi.org/10.14254/jsdtl.2025.10-2.2)

Abstract: The problem investigated in this paper originated from the distribution of beers by a Colombo-based company, Lion Brewery (Ceylon) PLC, in Sri Lanka. Currently, this company's outbound logistics consist of a decentralized distribution model and a redistribution process for its beer bottles and cans in the Colombo region. Extra routing costs due to unreasonable consumption of additional distance have been noticed in the current decentralized redistribution process. Here, the problem is modeled as a variant of the vehicle routing problem with a heterogeneous fleet. Our objective is to minimize the routing costs by imposing constraints on the volume of company vehicles. Centralized heuristic and genetic algorithm solution procedures for the problem are presented. The superior performance of the proposed heuristic is demonstrated relative to existing heuristics through a beer distribution instance and 10 additional small-scale real-world application instances. The computational investigation highlights the cost savings that the proposed heuristic can accrue. The cost savings can be as significant as 19.84% compared to a company's existing decentralized method, 4.34% compared to the genetic algorithm, and 6.73% and 2.47% compared to the two recent methods. This cost-saving has a practical impact on supplying customers with a necessary drink, beer, at a reduced price.

Keywords: vehicle routing problem, heterogeneous vehicle fleet, beer distribution, heuristic algorithms

Sustainable Development Goals (SDGs): **SDG 8:** Decent Work and Economic Growth; **SDG 9:** Industry, Innovation, and

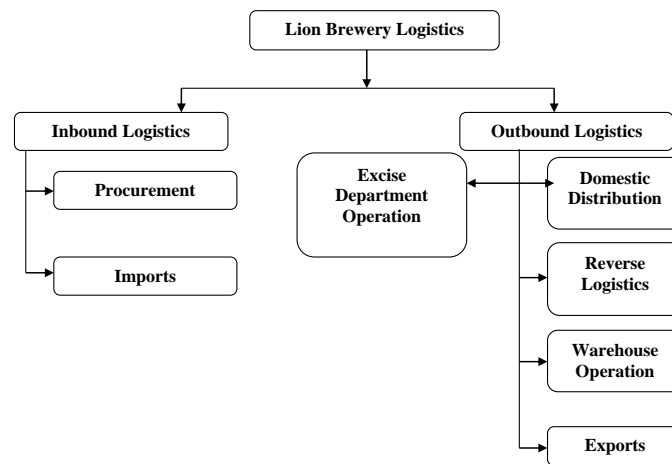


Infrastructure; **SDG 12:** Responsible Consumption and Production; **SDG 13:** Climate Action

1. Introduction

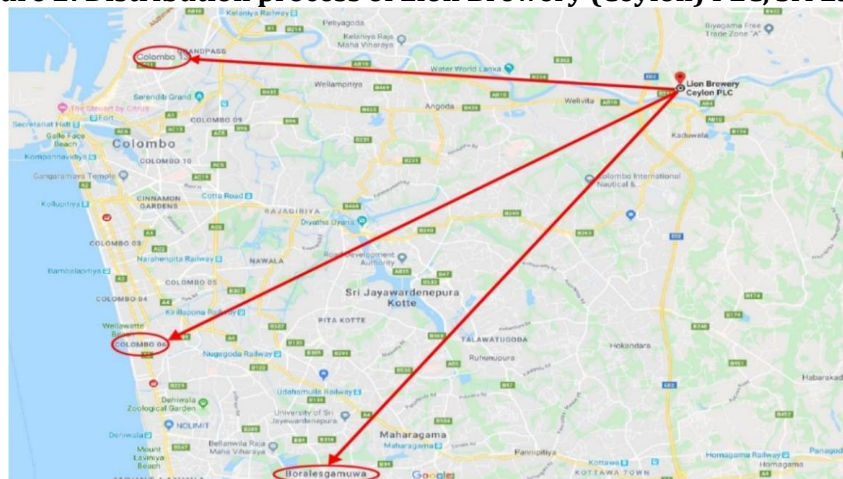
The beer brewing industry is a subcategory of the alcoholic beverage brewing industry, as beer contains less than 10 percent alcohol. Beer is one of the most popular drinks in Sri Lanka and a vital item in the country’s drink supply chain. The availability of beers at reasonable prices, along with better service, is crucial in people’s lives there. However, beer demand in the Sri Lankan market is volatile, and volatility has been increasing steadily due to the influence of social, cultural, seasonal, and environmental factors. Demand patterns vary from provision to provision. The highest demand is found in the Colombo region. The volume of beer sold has been increasing rapidly for the last four years. The average monthly sales have increased from 440,000 to 1.2 million bottles and cans. Three beer companies have been producing beer in Sri Lanka to meet this volatile demand, and Lion Brewery Ceylon PLC is the market leader in terms of popularity. This company manufactures and distributes beer to both the domestic and international markets. The inbound and outbound logistics systems of its beer distribution are depicted in Figure 1.

Figure 1: Lion Brewery logistics process



In Sri Lanka, there are approximately 3100 outlets maintained by 18 consignment agents. All beer products (bottles and cans) are delivered from the production plant to the agents, who then redistribute them. There are three consignment agents in the Colombo region responsible for redistributing bottles and cans to 491 outlets around the city. Figure 2 below shows a map of the delivery route for all products from the Biyagama plant to three agent locations: Colombo 06, Colombo 13, and Boralasgamuwa.

Figure 2: Distribution process of Lion Brewery (Ceylon) PLC, Sri Lanka



Maintaining a high service level is essential to achieving a competitive advantage in the industrial beer market. Some companies faced obstacles in doing so due to difficulties in the outbound beer distribution and redistribution supply chain. They outsourced their outbound process to third-party logistics providers to minimize transport costs, capital expenditures, and risk. However, the current challenges a company faces are rapid fluctuations in fuel pricing, driver shortages, expansion among 3PL and 4PL providers, commoditization of carrier pricing, the increased use of technological tools, and growing government regulations. Additionally, due to several cost factors and a highly competitive business plan, Lion Brewery Ceylon PLC has been struggling to compete with market prices for beer. So, proper management of this drink supply chain is essential to efficiently handling the challenges and complexities it faces. The Lion Brewery Ceylon PLC has allocated a significant portion of its budget for the proper management of its logistics system for beer distribution. Over the last few years, the redistribution of bottles and cans has been handled using the same process as for vehicles. Disappointed with the current redistribution system, the company's management has decided to outsource several services. The purpose is to fulfill the company's requirements with the minimum possible expenses.

During our study, we identified additional routing costs in the company's current decentralized redistribution process. Additional costs have been identified as inventory and storage handling, operations, and general administrative expenses. In a central warehouse, when small or medium-sized problems (i.e., several customers of 100) were handled, storage costs were low, whereas they were comparatively high for large-sized problems (i.e., several customers of 100 or more). Therefore, if there are fewer customers to satisfy, the central warehouse system is found to be more effective. However, when there are more customers to satisfy, the decentralized warehouse system is found to be more effective. Concepts of "distribution" and "redistribution" are compelling in outbound supply chain management. Proper redistribution highlights a company's image and helps create market stability; hence, the redistribution process should be given priority. However, it should be carried out under the effective control of a system to maintain the standard service level.

Allocating trucks in this system is rigid, and it affects business profits. Therefore, a robust truck allocation method is necessary to maximize truck utilization, minimize total transportation costs, and maintain standard service levels. Thus, the company requires a robust and efficient distribution and redistribution system to avail the competitive advantage of the brewery industry. Therefore, to achieve a cost-benefit by maintaining a standard service level, we have constructed a centralized distribution system to pinpoint the precise sites for redistributing beers in the Colombo region and a master plan for doing so. Usually, this centralized distribution strategy dominates the decentralized distribution in

- determining an ideal central warehouse location
- reducing safety stock
- smoothening the redistribution route plan
- redistribution of the Lorry with minimum cost

Additionally, to be a market leader, the company needs to attract customers by offering standard-quality products and services at competitive prices. Therefore, unnecessary costs in key business areas should be avoided. Moreover, to synchronize the production chain, more attention needs to be given to the operations management of beer production. In this regard, the supply chain and logistics management process are critical in the beer production and distribution system. Additionally, instead of managing a decentralized system, the corporation is seeking a centralized one. The company chose to investigate a centralized operations system to streamline the Colombo delivery process and increase income. Therefore, we aim to develop an innovative, centralized approach to distributing beer products in the Colombo region, leveraging vehicle redistribution to minimize total fuel and maintenance costs. The goal is to create an effective beer supply chain that can meet customers' anticipated demand for this daily essential beverage in a timely and affordable manner.

For this research, secondary data from the SAP ERP (System Application & Product Enterprise Resource Planning) system has been used, and additional required data has been collected from the agent-based database operation system, such as monthly target demand, monthly actual demand, daily demand, and all the charges of each distributor etc. This research has considered a two-month daily demand because the agent database is maintained by recording only the previous two months' outlet daily demand.

The outline of the paper is as follows: Section 2 provides a summary of related works. Assumptions and notations are presented in Section 3. Section 4 describes the problem statements and model formulation. A new heuristic method is proposed alongside the existing method, and its shortcomings are highlighted in Section 5. Comparative assessments are performed in Section 6. Finally, the conclusion and future research scope for the topic are presented in Section 7.

2. Related work

In the existing setup of Lion Brewery Ceylon PLC, products are delivered from production plants to agents, who then redistribute them to the other 491 agents, a type of vehicle routing problem (VRP). VRP can be described as the process of obtaining the minimal-cost delivery paths from a depot to a set of geographically dispersed clients, with a focus on crosswise constraints. VRP is used for product and service distribution in logistics and supply chain management. This is essential in distribution management, and therefore, transporters regularly deal with the problem. There are some modifications to the original VRP that are based on the nature of the goods being transported, the value of the service, and the characteristics of the clients and vehicles. Modern solutions focus on machine learning and algorithmic enhancements for faster and more accurate route planning (Desaulniers, Desrosiers, & Spoorendonk, 2011)

The Capacitated Vehicle Routing Problem (CVRP) accounts for vehicle capacity when servicing clients. The Multi-Depot VRP (MDVRP) has been developed to manage logistics systems with multiple depots, enabling better fleet utilization and reduced costs. The CVRP and MDVRP are widely applicable to companies like Lion Brewery, which require optimized routes across diverse client locations (Montané et al., 2002; Goeke & Schneider, 2015; Jayarathna & Jayewardene, 2019). Contributions were made towards reformulating this issue as a linear advanced optimization problem, which commonly arises in the domains of supply chain and operational management. This can be further explained as the way of servicing a group of clients, geographically scattered from the central warehouse, by utilizing the fleet of trucks with different capacities, which becomes VRP, which is one of the most widely used phenomena in the field of advanced line programming.

The enhancement of some forms of VRPs was found to be accompanied by strategies for determining the shortest route. Goetschalckx (2011) and Urquhart & Viera (2002) defined the VRP as the problem of determining the shortest route for a vehicle that departs from a depot to serve various customer needs at multiple destinations. Every vehicle with a specific capacity begins at a depot and returns to the same depot after visiting each client only once. Moreover, Sitek and Wikarek (2019) introduced the Capacitated Vehicle Routing Problem (CVRP), a new variant of VRP with Pickups and Alternative Delivery (CVRPPAD), and they proposed a hybrid approach for its solution. However, since CVRP is NP-hard, solving it by exact methods is quite time-consuming. Heuristic and meta-heuristic approaches are usually the preferred options for solving practical-sized problems. Additionally, VRP offers a range of heuristics and meta-heuristics (Laporte, 2009; Gendreau, 2002; Cordeau, 2005; Hosny, 2011). Thus, VRP is broadly taken into account due to its familiar use and significance in designing effective modes for minimizing transportation costs in distribution systems (Jayarathna & Jayasooriya, 2018; Das & Borthakur, 2006; Jayarathna et al., 2019; Jayarathna et al., 2021a; Jayarathna et al., 2022; Jayarathna, 2024; Jayarathna et al., 2020; Jayarathna et al., 2021b; Jayarathna et al., 2021c).

The Vehicle Routing Problem with Pickups and Deliveries (VRPPD) extends the classical Vehicle Routing Problem (VRP) to scenarios where customers may both receive and send goods. Unlike traditional VRPPD approaches, which assume that pickups occur only after all deliveries, this method integrates pickups and deliveries simultaneously. It solves the original VRP and subsequently adjusts it to meet the specific requirements of the VRPPD, achieving feasibility without relying on insertion techniques (Goeke & Schneider, 2015; Jayarathna et al., 2021d). Gábor Nagy and Sad Salhi (2005) introduced heuristic algorithms for single- and multiple-depot truck routing problems, including pickup and delivery operations. Rousseau et al. (2004) employed a constraint-programming-based column-generation technique to solve the Vehicle Routing Problem with Time Windows (VRPTW). De Silva (2001) used the column generation approach to combine constraint programming and linear programming in a real-world bus driver scheduling application.

Koç et al. (2020) comprehensively reviewed the literature on the vehicle routing problem with simultaneous pickup and delivery (VRPSPD), including mathematical formulations, algorithms,

variants, case studies, and industrial applications. Vidal et al. (2020) presented an overview of existing and emerging variants of the vehicle routing problem. Arnold et al. (2019) proposed a local search heuristic for solving very large-scale routing challenges. Privé et al. (2006) proposed three construction heuristics and an improvement technique to address a vehicle routing issue in soft drink delivery.

Thus, VRP plays a vital role in obtaining a minimum-cost solution to the problem of distributing and redistributing products from plants to agents, and then from agents to customers. We need to address a VRP-type problem involving the distribution and redistribution of beer bottles and cans from plants to agents and then from agents to customers, aiming to minimize the total cost. Solving it using exact methods would be quite time-consuming; therefore, a VRP-based heuristic is preferred for solving this real-world problem. Note that senior management can apply the same rationale to distribute their products evenly across the country. As a result, the purpose of this study is to provide a heuristic approach for achieving a high-quality solution within a limited time frame while also addressing the real-world problems faced by large vehicle fleets. Our objective here is to achieve a viable solution to the mentioned problem by positively influencing logistics and distribution tactics. For this reason, we created a novel heuristic method and used the genetic algorithm to solve the aforementioned VRP problem.

Then, we demonstrate the superiority of our heuristic compared with the Genetic algorithm and the two recently developed methods through comparative studies on real-life problem instances.

3. Assumptions and notation

The underpinning assumptions and notations of the model are as follows:

3.1. Assumptions

- 1) Due to intricate daily demand and redistribution of routes, this research is limited to the Colombo region only.
- 2) Google Maps is used to find the distance between two demand points in the Colombo region.
- 3) Theoretically, the shortest distance between two points is given by a straight line between the two points. However, since the consideration of such a shortest distance is impractical, it is not considered here. Instead, only the Google distance value is considered.
- 4) Time factor, driver's behaviour, individual condition of a vehicle, unavoidable circumstances like accidents and weather conditions, which may affect the redistribution process, are not considered.
- 5) Distance between outlets in a sub-cluster is not considered.
- 6) Rapid change in demand is not allowed.
- 7) Empty bottles are equivalent to delivered filled bottles, and reverse logistics does not influence this research.
- 8) There is no barrier to delivering goods.
- 9) Allocated a truck in a cluster to deliver goods within the cluster only. None of the trucks travels between two distinct clusters.
- 10) The total capacity of all vehicles in a cluster is greater than or equal to the total demand of the relevant cluster.

3.2. Notation

The notation associated with the development of our model is listed as follows:

Decision variables

D = total number of clusters arranged;

n_i = number of clients in the i^{th} cluster, $i \in \{1, 2, 3, \dots, D\}$;

$n = \sum_{i=1}^D n_i$, total number of clients in the distribution;

Other parameters

$G = (V, E)$, a graph of a logistics distribution network;

$V = \{V_i / i \in \{0, 1, 2, \dots, n + 1\}\}$, a set of nodes/vertices, where node V_0 represents the central depot, $n + 1$ represents the distribution depot, and the remaining nodes represent clients;

- $E = \{(i, j) | i, j \notin V, i \neq j\}$: set of arcs in which (i, j) denotes the arc between node i and j ;
 Q_i = vehicle capacity of the i^{th} cluster;
 q_j^i = weight (demand) associated with the j^{th} client at the i^{th} cluster;
 $d_{V_j V_k}^i$ = distance traveled from client V_j to client V_k in the i^{th} Cluster; (Here $d_{V_j V_k}^i = d_{V_k V_j}^i$)
 TC_i = Total transportation cost for the i^{th} cluster;
 TF_i = Total fuel cost for the i^{th} cluster;
 TM_i = Total maintenance cost for the i^{th} cluster;
 X_i = Minimum distance from n_i^{th} client to $(n_i + 1)^{\text{th}}$ client in the i^{th} cluster ;
 d_i = Total distance traveled in the i^{th} cluster
 VC_i = Original vehicle cost for assigning in the i^{th} cluster;
 r_i = Depreciation factor ratio for vehicle assigned in i^{th} cluster, where

$$r_i = \frac{\text{Annual depreciation value of a vehicle of the respective year assigned in the } i^{\text{th}} \text{ cluster}}{\text{Value of this vehicle at the beginning of the respective year}}$$

 t_i = Number of years a vehicle is used in the i^{th} cluster;
 R_i = Unit distance maintenance cost coefficient ratio for a vehicle used in the i^{th} cluster,

$$R_i = \frac{\text{Maintenance cost of a vehicle of the respective tour engaged in the } i^{\text{th}} \text{ cluster}}{\text{Corresponding distance of the respective tour in the } i^{\text{th}} \text{ cluster}}$$

 F_i = Unit distance fuel cost coefficient ratio for a vehicle used in the i^{th} cluster, where

$$F_i = \frac{\text{Fuel cost of the vehicle of the respective tour in the } i^{\text{th}} \text{ cluster}}{\text{Corresponding distance of the respective tour of the } i^{\text{th}} \text{ cluster}}$$

After excluding the central depot, the remaining nodes represent geographically spread customers. Each customer $i \in V - \{V_0\}$ has a certain positive demand such that $\sum_{j=1}^{n_i} (q_j^i) \leq Q_i$.

4. Problem statement and the model formulation

4.1. Problem statement

The distribution of the highly sought-after Lion beer brand in Colombo and its suburbs by Lion Brewery (Ceylon) PLC, with a focus on minimizing total transportation costs, is the primary objective of this study. It has been found that Lion Brewery's outbound logistics system is decentralized, with a redistribution process in the Colombo region. However, the company incurs additional transportation costs in this system due to redundant distances resulting from improper utilization. Ganepola et al. (2018) and Jayarathna et al. (2022) employed centralized warehouse methods to address this issue. However, the company still believes that these solution methods are insufficient to achieve the expected level of reduction in transportation costs, particularly in the Colombo city region. Therefore, the company's senior management wishes to conduct a further investigation to minimize the additional transportation costs incurred in the city area. We propose a new heuristic method and use the genetic algorithm to solve this VRP, anticipating superior results compared to current methods.

4.2. Identification of a new warehouse location by using the Gravity model

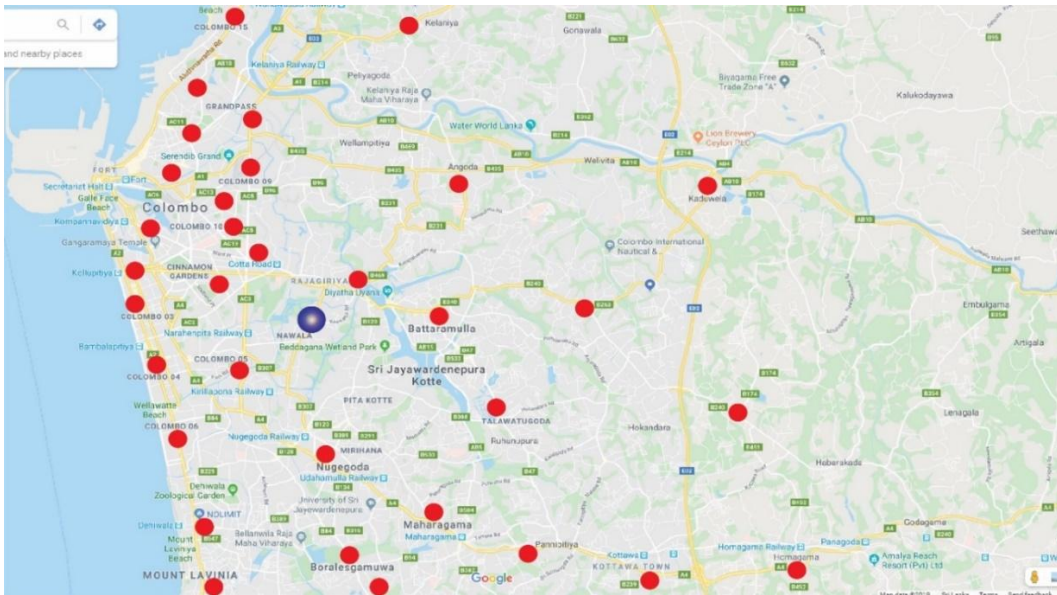
We use the gravity model as given below from (Andersson, 1979) to identify the exact location of the central warehouse:

$$X = \frac{\sum_i^n d_i \times x_i}{\sum_i^n d_i}, \quad Y = \frac{\sum_i^n d_i \times y_i}{\sum_i^n d_i},$$

where n is the number of demand points $(1, 2, 3, \dots, n)$, (x_i, y_i) is the given location coordinates with the i^{th} demand point (latitude, longitude), d_i is the demand associated with the i^{th} demand point, and (X, Y) is the unknown location coordinate of the new warehouse facility.

In our study, 491 subclients in the Colombo region were clustered into 35 main demand points. Figure 3 shows the distribution of the demand points for Lion Brewery products in the Colombo region.

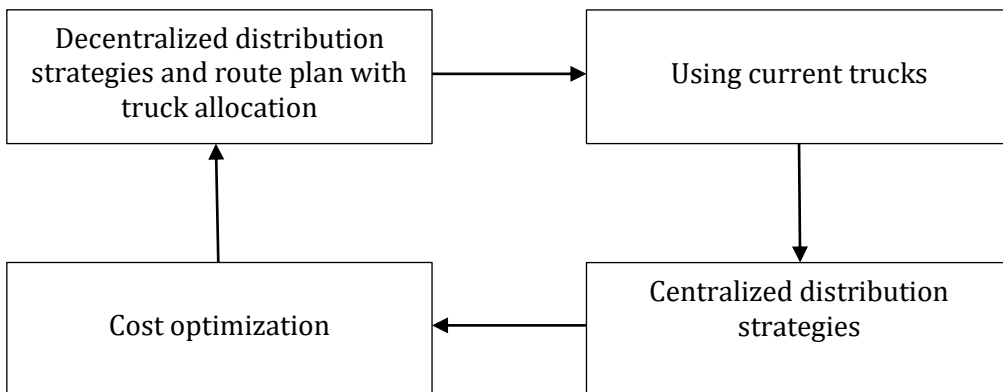
Figure 3: Distribution of demand points of Lion Brewery Products in the Colombo Region



Source: Geographical Map of Sri Lanka

This research is based on the existing Decentralized distribution Strategy and proposes new Centralized distribution Strategies. Figure 4 below shows the company’s main delivery plan.

Figure 4: Conceptual framework



We illustrate the gravity model with an example problem of demand and location coordinates (latitude & longitude) of the main clients of Lion Brewery PLC in the Combo region, as shown in Table 1.

Table 1: Daily demands of Lion Brewery (Ceylon) PLC in the Colombo region

Index	Colombo region demand points	Demand (d_i)	Latitude (x)	Longitude (y)	d_i*y	d_i*x
1	Colombo 1	103	6.93197	79.85775	8225.348	713.9929
2	Colombo 9	368	6.93197	79.85775	29387.65	2550.965
3	Colombo 11	633	6.93197	79.85775	50549.96	4387.937
4	Colombo 12	212	6.93197	79.85775	16929.84	1469.578
5	Colombo 13	357	6.93197	79.85775	28509.22	2474.713
6	Colombo 14	211	6.93197	79.85775	16849.99	1462.646
7	Colombo 15	220	6.93197	79.85775	17568.71	1525.033
8	Colombo 2	289	6.93197	79.85775	23078.89	2003.339
9	Colombo 3	249	6.93197	79.85775	19884.58	1726.061
10	Colombo 4	71	6.93197	79.85775	5669.9	492.1699
11	Colombo 5	301	6.93197	79.85775	24037.18	2086.523
12	Colombo 7	58	6.93197	79.85775	4631.75	402.0543
13	Colombo 8	160	6.93197	79.85775	12777.24	1109.115
14	Colombo 10	170	6.93197	79.85775	13575.82	1178.435
15	Battaranulla	225	6.897994	79.92229	17982.51	1552.049
16	Thalawathugoda	139	6.88867	79.93082	11110.38	957.5251
17	Malabe	167	6.906079	79.96963	13354.93	1153.315
18	Kaduwela	103	6.93083	79.98422	8238.374	713.8755
19	Athurugiriya	185	6.877246	79.98993	14798.14	1272.291
20	Gothatuwa	291	6.929658	79.90606	23252.66	2016.53
21	Rajagiriya	208	6.909504	79.89622	16618.41	1437.177
22	Kottawa	61	6.841165	79.96543	4877.891	417.3111
23	Pannipitiya	235	6.84332	79.9553	18789.5	1608.18
24	Maharagama	245	6.847278	79.92661	19582.02	1677.583
25	Nugegoda	244	6.864908	79.89968	19495.52	1675.038
26	Homagama	169	6.841273	80.00306	13520.52	1156.175
27	Padukka	76	6.83997	80.08955	6086.805	519.8377
28	Hanwella	210	6.93197	79.85775	16770.13	1455.714
29	Boralasgamuwa	124	6.841166	79.90248	9907.908	848.3046
30	Dehiwala	361	6.83967	79.87597	28835.22	2469.121
31	Mt. Lavinia	122	6.93197	79.85775	9742.646	845.7003
32	Rathmalana	110	6.93197	79.85775	8784.353	762.5167
33	Moratuwa	463	6.79326	79.88065	36984.74	3145.279
34	Piliyandala	339	6.93197	79.85775	27071.78	2349.938
35	Colombo 6	277	6.93197	79.85775	22120.6	1920.156

Using the gravity model, the exact location of the central warehouse is at latitude 6.90255 and longitude 79.88668, situated on the western side of Navala.

4.3. The model formulation

This section considers a transportation system for distributing brewery products from a central depot using a group of vehicles. The distribution depot organizes each vehicle according to a transportation plan and a corresponding routing. A vehicle starts its route from the distribution depot and returns to it after fulfilling the requirements. Assume that the number of vehicles needed for the said task is large enough to satisfy all the transportation demands. This is a reasonable assumption, as it is common knowledge in training that the main distribution depot can reassign its vehicles to meet transportation demand. Each vehicle has a load capacity limit and will incur fuel consumption and usage costs while completing its tasks. Thus, the central depot has to arrange transportation routes to minimize the total transportation cost of the whole system by accounting for those costs. Thus, our proposed VRP model in this paper, compared with existing VRP models, is new in that we include fuel consumption and usage costs, which are essential to transportation practice from the perspective of achieving economic efficiency through coordination among relevant partners. Here, the fuel consumption cost mainly comprises oil costs and usage costs (measured by time consumed and primarily including depreciation costs, operator salaries, insurance expenses, etc.).

Calculation of the fuel cost and the maintenance cost

One can easily obtain the following:

$$[VC_i - r_i * t_i * VC_i] = \text{vehicle value which used } t \text{ years in } i^{\text{th}} \text{ cluster vehicle};$$

$$\sum_{j=0, j \neq k}^{n_i} \min(d_{V_j V_k}^i) = \text{total distance traveled in the } i^{\text{th}} \text{ cluster vehicle};$$

Thus, the fuel cost and the maintenance cost are given by

$$TF_i = [VC_i - r_i * t_i * VC_i] * R_i \sum_{j=0, j \neq k}^{n_i} \min(d_{V_j V_k}^i), \text{ where } j, k \in \{0, 1, 2, 3 \dots \dots n_i\}$$

$$TM_i = [VC_i - r_i * t_i * VC_i] * F_i \sum_{j=0, j \neq k}^{n_i} \min(d_{V_j V_k}^i), \text{ where } j, k \in \{0, 1, 2, \dots, n_i\} \text{ respectively.}$$

If TC_i denotes the total transportation cost of the i^{th} cluster, then $TC_i = TF_i + TM_i$

Hence, the total cost over the clusters, along with the constraints, can be formulated as

$$TC = \sum_{i=0}^D TC_i = \sum_{i=0}^D \{VC_i [1 - r_i * t_i]\} * \{R_i + F_i\} \sum_{j=0, j \neq k}^{n_i} \min(d_{V_j V_k}^i), \{0, 1, 2, \dots, n_i\},$$

$$\text{where } i \in \{1, 2, 3, \dots, D\},$$

$$d = \sum_{i=1}^D (d_i), \quad d_i \in \{d_1, d_2, d_3 \dots \dots d_D\}$$

$$d_i = \sum_{j=0, j \neq k}^{n_i} \min(d_{V_j V_k}^i), i \in \{1, 2, 3, \dots, D\}, \quad j, k \in \{0, 1, 2, \dots, n_{i+1}\}, V_0^i = V_{n_{i+1}}^i$$

$$\sum_{j=1}^{n_i} (q_j^i) \leq Q_i, \quad i \in \{1, 2, 3, \dots, D\}$$

$$n = \sum_{i=1}^D (n_i)$$

The capacity constraint ensures that the total demand generated by the above method does not exceed the vehicle's capacity.

$$d_{V_j V_k}^i + d_{V_k V_l}^i \geq d_{V_j V_l}^i \text{ for all } j, k, l \in \{0, 1, 2, \dots, n_i\}$$

The distance matrix is symmetric, i.e.

$$d_{V_j V_k}^i = d_{V_k V_j}^i \text{ for all } j, k \in \{0, 1, 2, \dots, n_i\}, i \in \{1, 2, 3 \dots, D\}, i \neq j$$

To serve customers, we have to design routes for a fleet with D vehicles distributed from a single depot. Each route must start at the depot, visit a subset of customers, and then return to the depot. All customers must be visited exactly once.

Finding an optimal solution to this model is a computationally intensive task (Andersson 1979). However, this type of model has economic value, particularly when integrated with a supply chain management system. As a result, many logistics solution providers have emerged to cater to this rising demand, and companies are willing to pay a premium for these custom-made solutions. At the same time, software has also been developed to facilitate accurate solutions to these mathematical models. However, the solution to a problem can be obtained faster and without errors by coding the objective function and all constraints in a specific programming language.

5. Analysis of the research

5.1. Route analysis - Hamiltonian cycle and deficiency of the existing method

Here, we introduce an approach proposed by Ganepola et al. (2018) (given in Appendix A) to calculate transportation costs for a given distribution of clients, which requires client clustering. They divided vehicle routes into several sub-routes, each constructed based on vehicle capacity. The total client demand was calculated by summing the demands of all sub-routes. Following this method, 35 main demand points in the Colombo region are identified. These demand points are divided into five main clusters based on their geographic locations. The method is illustrated with the optimal solution to the problem given in Table 2. Here we have taken the average demand. For the Colombo region, daily sales data from the SAP ERP system and agent-based operational data, which show variation within a small range, are collected. In total, 18 distributors operate in Sri Lanka, with three located in the

Colombo region. Average daily sales of Colombo 6, Colombo 13, and Boralasgamuwa distributors are shown in Table 2.

Table 2: Average sales of the Colombo region

Distributor	Average Daily Demand (Dozens)	Daily Total Average Demand (Dozens)
Colombo 06	1788	7753
Colombo 13	2571	
Boralasgamuwa	3394	

Source: Constructed by the author based on SAP data

Following the method of Ganepola et al. (2018), an optimal route is found using LINGO (a software for finding optimal solutions to linear and nonlinear programming problems). The total distance traveled in each cluster, in kilometers, obtained for this problem using the mentioned method, is shown in Table 3.

Table 3: Daily distances travelled in the clusters by Ganepola et. al. (2018)'s approach and with a smaller number of clusters

Ganepola et. al. (2018)		With a smaller number of clusters	
Cluster	Daily distance travelled (km)	Cluster	Daily distance travelled (km)
1	38	1	149.9
2	27		
3	51	2	55.3
4	66		
5	38		
Total distances traveled	220		205.2

Note that the time taken by each route is not taken into consideration. We have sought a path that would reduce the total distance traversed from the central storage to all clusters. In the calculations in Table 3, we have considered the capacity of each vehicle in each cluster and assumed that the total capacity of all vehicles in each cluster is greater than or equal to the total demand of that cluster. However, this solution method is found to be incapable of achieving the expected level of reduction in transportation costs, particularly in the Colombo city region. Therefore, it highlights the need to develop an alternative, better solution to address the problem.

5.2. Calculation of transportation cost–single depot cluster analysis by vehicle routing methods

We have used Jayarathna et. al. (2022)'s method, developed a new method (proposed heuristic), and a Genetic algorithm to solve the capacitated vehicle routing problem. In the heuristic, we first form client clusters based on their vehicle capacity and demand. Then, the optimal number of clusters and the corresponding clients are determined using this heuristic. Finally, the total transportation cost is calculated by summing up the transportation costs of each sub-cluster. The algorithm for the proposed heuristic method is given below.

Proposed heuristic algorithm

Initially, following the gravity model formulae proposed by Andersson (1979), find the optimal location for the central depot (V_0). Then, from the pool of clients (or n demand points), identify the nearby client (V_1) to the central depot. This can be done by taking the minimum distance from the central depot to each client in the distribution. Thereafter, from the remaining $n-1$ number of clients, identify the next nearby client (V_2) to V_1 . This can also be done by taking the minimal value of the distances from V_1 to each of the remaining $n-1$ number of clients in the distribution. In order to see whether V_2 belongs to the same cluster as V_1 belongs, compare the distances of V_2 from both V_0 and V_1 denoted

mathematically as $d_{V_0V_2}$ and $d_{V_1V_2}$ respectively. If $d_{V_0V_2} \geq d_{V_1V_2}$, then choose the vertex V_2 as the element of the first cluster. If $d_{V_0V_2} < d_{V_1V_2}$ then V_1 and V_2 do not belong to the same cluster, that is, V_2 belongs to the second cluster. If V_2 belongs to the second cluster, then from the remaining $n-2$ number of clients, identify the next nearby client V_3 from V_2 or V_1 . If $d_{V_0V_3} \geq d_{V_1V_3}$ and $d_{V_2V_3} \geq d_{V_1V_3}$, then the vertex V_3 belongs to the first cluster. If $d_{V_1V_3} \geq d_{V_2V_3}$ and $d_{V_0V_3} \geq d_{V_2V_3}$, then the vertex V_3 belongs to the second cluster. If $d_{V_0V_3} < d_{V_1V_3}$, $d_{V_0V_3} < d_{V_2V_3}$, then we filter the vertex V_3 into a new cluster (the third cluster).

Thus, first identify the nearest of the demand points to V_0 and form the first cluster including this demand point, V_1 (say). Then identify the nearest of the remaining demand points to V_1 as V_2 . If V_2 is nearest to V_1 in contrast to its distance from V_0 , include it in the first cluster. Next, identify the nearest of the remaining demand points (excluding the chosen V_1 and V_2) to the chosen demand point V_2 as V_3 . If V_3 is nearest to V_1 in contrast to its distances from V_0 and V_2 , include it in the first cluster. Again, identify the nearest of the remaining demand points (excluding the chosen V_1 , V_2 and V_3) to the chosen demand point V_3 as V_4 . If V_4 is nearest to V_1 in contrast to its distances from V_0 , V_2 and V_3 , include it in the first cluster. In this way, continue to include a demand point in the first cluster until no further demand points remain to be considered for inclusion. Thereafter, consider the set of all demand points excluding those of the first cluster, and form the second cluster by repeating the process used to form the first cluster. After that, consider the set of all demand points excluding the points of the first and second clusters, and form the third cluster using the same process as for the first and second clusters. Thus, continue forming the next cluster until no demand point is available to form one. Then, by using the cost formulae (1), calculate the total fuel and the total maintenance cost for each of the clusters, and hence the total cost of all clusters.

Based on this notion, the proposed algorithm is presented below to form clusters of clients from a distribution of clients.

Algorithm

Step 01: Identify the location of the n demand points and their demands.

Step 02: Use the gravity model formula to determine the optimal location of the central warehouse (V_0)

Step 03: Set $S_0 = \{V_1, V_2, V_3, \dots, V_n\}$, $A = \emptyset$, an empty set and $k = 0$

Step 04: Set $t = 0$, $k = k+1$, $S_0 = S_0 \cup A$, and define a new empty set S_k

Step 05: If $t \leq 1$,

let the distance from V_t to the nodes of S_0 be $d_{V_tV_i}$, $V_i \in S_0$. Let V_r of S_0 is at the minimum distance from V_t and set $V_{t+1} = V_r$. Set $d_{V_tV_{t+1}} = \min \{d_{V_tV_i}, V_i \in S_0\}$ and $t = t+1$.

Else

let the distance from V_l to nodes of S_0 be $d_{V_lV_i}$, $V_i \in S_0$. Let V_r of S_0 is at the minimum distance from V_l and set $V_{t+1} = V_r$. Set $d_{V_lV_{t+1}} = \min \{d_{V_lV_i}, V_i \in S_0\}$ and $t = t+1$.

Step 06: If $t \leq 1$, insert V_r to S_k , assign $V_l = V_t$ and remove V_r from S_0 and go to Step 05.

Step 07: If $t > 1$ and $l = 1$, then

If $d_{V_tV_0} \geq d_{V_tV_l}$, then insert V_t to S_k , assign $V_l = V_t$ and remove V_r from S_0 .

Otherwise, let the distance from V_l to nodes of S_0 be $d_{V_lV_i}$, $V_i \in S_0$. Let V_r of S_0 is at the minimum distance from V_l and set $V_{t+1} = V_r$. Set $d_{V_lV_{t+1}} = \min \{d_{V_lV_i}, V_i \in S_0\}$ and $t = t+1$.

If $d_{V_tV_0} \geq d_{V_tV_1}$ and $d_{V_tV_2} \geq d_{V_tV_1}$ then insert V_t to S_k , assign $V_l = V_t$, and remove V_r from S_0 .

Else insert V_r into the set A , and remove V_r from S_0 .

Step 08: If $t < n$, go to Step 05.

Step 09: If A is non-empty, go to Step 4.

Step 10: Stop

Genetic algorithm approach to solve the single depot capacitated vehicle routing problem

Inputs:

Number of demand points(n)

Geographical coordinates(x, y)

Depot $(0, 0)$
 Demands (D)
 Number of vehicles (K)
 Vehicle capacity (Q)
 Iteration time limit (t)

Output: Optimal set of routes

Step 1: Consider a random population.

Step 2: Calculate total demand (D) and length (L) of each route.

Step 3: If $D >$ capacity of the vehicle, discard that solution. Otherwise, go to step 4.

Step 4: Select the two shortest routes.

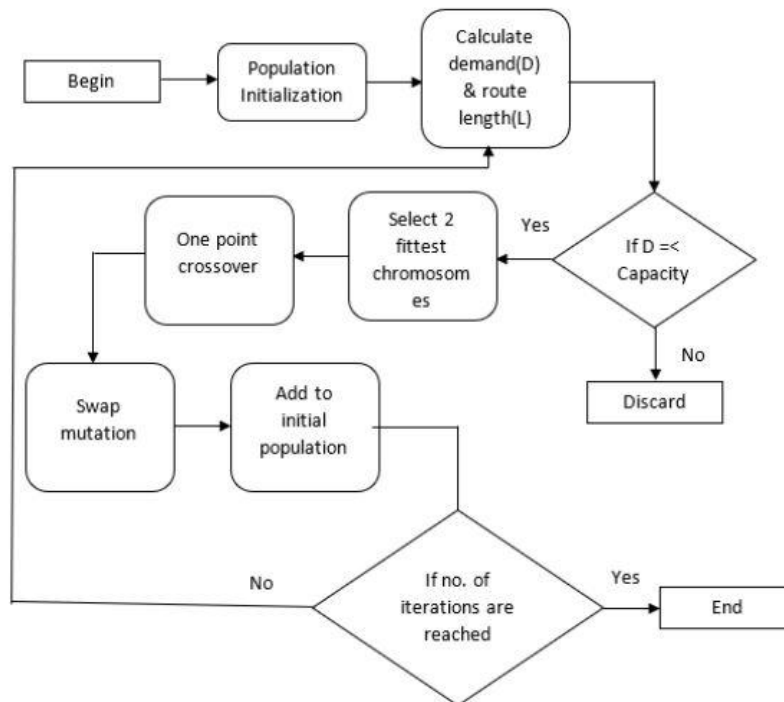
Step 5: Generate 2 off-springs by performing one-point crossover.

Step 6: Select two random genes of each chromosome and flip them.

Step 7: If the stopping criteria are true, stop the procedure. Otherwise, add the offspring to the population and proceed.

Here, the algorithm needs a time limit as an input to obtain the optimal solution. So, the stopping criteria is reaching a certain number of iterations. For this problem, the optimal solution was reached in 30 seconds, with 200 steps. This algorithm is used to determine the order of the optimal client points (route list). However, the total distance for a journey is calculated manually using Google’s distance algorithm (since the algorithm does not provide the route length as an output). The program was designed to give the route map as an output. A flowchart diagram of the Genetic algorithm is shown in Figure 5 below, and can also be described in pseudo-code format as shown below.

Figure 5: Flowchart representation of the Genetic Algorithm



We have developed a Python computational program for the Genetic algorithm, which is provided in Appendix A.

Genetic Algorithm

Require: No. of demand points (n) ; depot; geographical coordinates (x,y) ; demands (D) ; no. of vehicles (K) ; vehicle capacity (Q) ; iteration time limit (t)

Ensure an optimal set of routes

Initialize population

Repeat

Evaluate D and route length L

If $D \leq Q$ **then**

```

Proceed
Else
End procedure
end if
while  $D \leq Q$  do
select the fittest two individuals
perform one-point crossover
perform swap mutation
add to the new generation
end while
until t is reached

```

6. Comparative study

6.1. Calculation of the optimal distances

Calculation of the optimal distances of each of the pairs of towns following the algorithm of Jayarathna et. al. (2022).

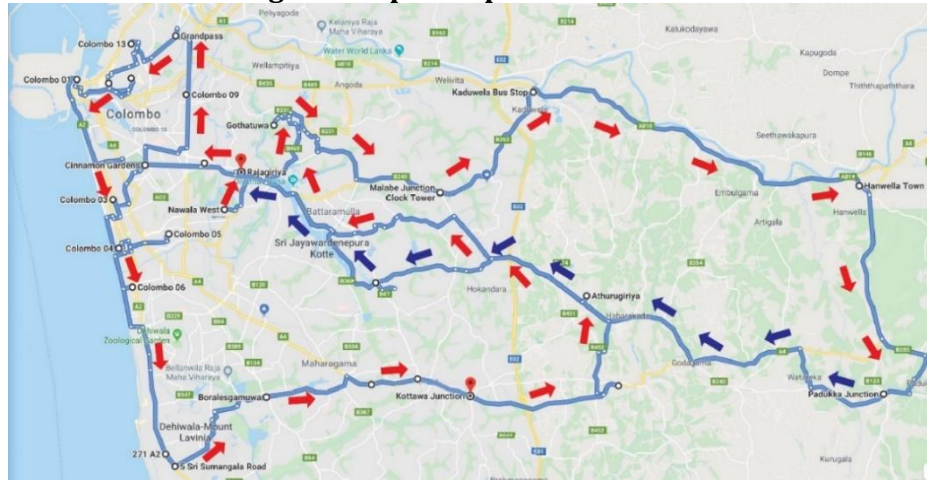
Table 4 shows the starting and the ending towns of each of the sub-tours of cluster 1, along with optimal distances travelled (Google distances) and the total distance traveled inside cluster 1.

Table 4: Arrangement of cluster 1

Starting Town	Ending Town	Distance Traveled (Km)	Transshipment Node
Central Warehouse	Rajagiriya	2.3	No
Rajagiriya	Colombo 08	1.8	Yes
Colombo 08	Colombo 07	2.2	Yes
Colombo 07	Colombo 10	1.6	Yes
Colombo 10	Colombo 01	1.2	Yes
Colombo 01	Colombo 12	1.8	Yes
Colombo 12	Colombo 11	1.3	Yes
Colombo 11	Colombo 13	2.9	Yes
Colombo 13	Colombo 14	2.4	Yes
Colombo 14	Colombo 09	2.6	Yes
Colombo 09	Colombo 03	5.1	Yes
Colombo 03	Colombo 04	2.5	Yes
Colombo 04	Colombo 05	2.4	Yes
Colombo 05	Colombo 06	3.6	Yes
Colombo 06	Dehiwala	3.1	Yes
Dehiwala	Mt. Lavinia	1	Yes
Mt. Lavinia	Rathmalana	1.5	Yes
Rathmalana	Boralasgamuwa	4.6	Yes
Boralasgamuwa	Maharagama	3.1	Yes
Maharagama	Pannipitiya	2	Yes
Pannipitiya	Kottawa	2	Yes
Kottawa	Homagama	4.8	Yes
Homagama	Athurugiriya	4	Yes
Athurugiriya	Thalawathugoda	8	Yes
Thalawathugoda	Battaramulla	5.7	Yes
Battaramulla	Gothatuwa	5.6	Yes
Gothatuwa	Malabe	8.9	Yes
Malabe	Kaduwela	6.3	Yes
Kaduwela	Hanwella	15.4	Yes
Hanwella	Padukka	8.6	Yes
Padukka	Central Warehouse	31.6	Yes
Total distance traveled inside cluster 1		149.9 Km	

The optimal path of cluster 1 is shown in Figure 6. In this figure, the red arrows represent the central warehouse locations leading to the final destination (final client) through the route plan, and the blue arrows represent the final clients leading to the central warehouse location accordingly.

Figure 6: Optimal path of cluster 1



Source: Jayarathna et. al. (2022) method

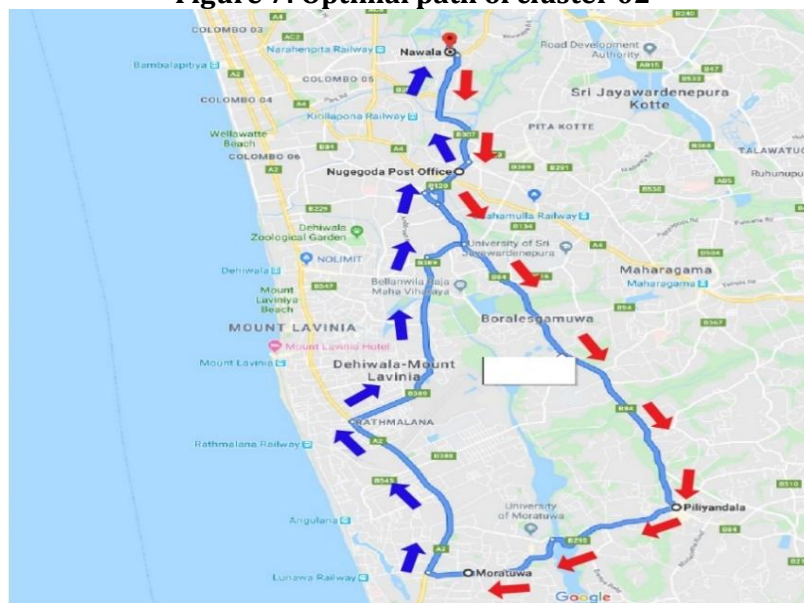
Table 5 shows the starting and ending towns of each subtour in cluster 2, along with the optimal distances travelled (Google distances) and the total distance travelled within cluster 2.

Table 5: Arrangement of the Cluster 2

Starting Town	Ending Town	Distance Traveled (Km)	Transshipment Node
Central Warehouse	Nugegoda	5.2	No
Nugegoda	Piliyandala	8.4	Yes
Piliyandala	Moratuwa	5	Yes
Moratuwa	Central Warehouse	16.1	No
Total distance traveled inside the cluster 2			34.7 Km

The optimal path of cluster 2 is shown in Figure 7.

Figure 7: Optimal path of cluster 02



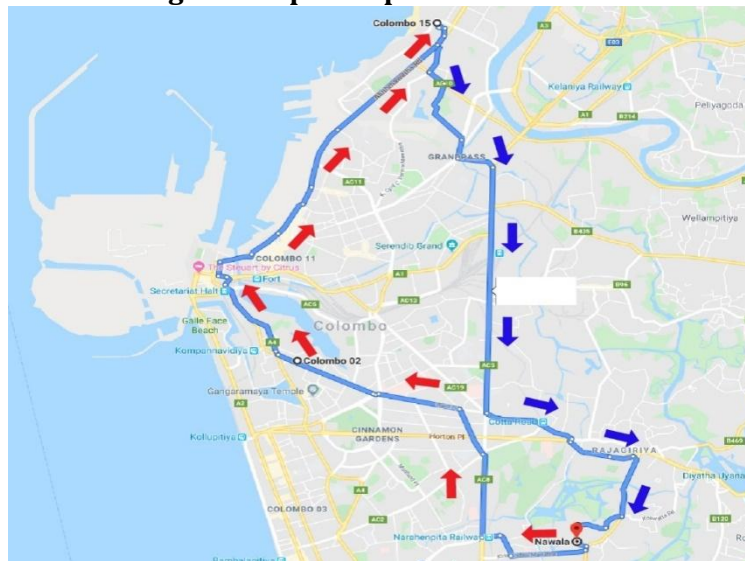
Source: Jayarathna et. al. (2022) method

Table 6 shows the starting and ending towns of each of the subtours of cluster 3 along with optimal distances travelled (Google distance) and the total distance traveled inside cluster 3.

Table 6: Arrangement of the Cluster 3			
Starting Town	Ending Town	Distance Traveled (Km)	Transshipment Node
Central Warehouse	Colombo 02	7.3	No
Colombo 02	Colombo 15	7.3	Yes
Colombo 15	Central Warehouse	11.2	No
Total distance traveled inside the cluster 3		25.8 Km	

The optimal path of cluster 3 is shown in Figure 8.

Figure 8: Optimal path of cluster 03



Source: Jayarathna et. al. (2022) method

Table 7 shows the optimal distance traveled in each of the three clusters and the total distance under the first method.

Table 7: Total Distance traveled in each of the three clusters	
Discription	Distance Travelled
Cluster 01	149.9
Cluster 02	34.7
Cluster 03	25.8
Total Distance	210.4

6.2. The optimal distances of each of the pairs of towns following the proposed heuristic algorithm

Table 8 shows the starting and ending towns of each subtour of cluster 1, along with the optimal distances travelled (Google distances) and the total distance travelled within cluster 1 under the proposed heuristic method.

Table 8: Arrangement of the cluster 1

Starting Town	Ending Town	Distance Traveled (Km)	Transshipment Node
Central Warehouse	Rajagiriya	2.3	No
Rajagiriya	Colombo 08	1.8	Yes
Colombo 08	Colombo 07	2.2	Yes
Colombo 07	Colombo 10	1.6	Yes
Colombo 10	Colombo 01	1.2	Yes
Colombo 01	Colombo 12	1.8	Yes
Colombo 12	Colombo 11	1.3	Yes
Colombo 11	Colombo 13	2.9	Yes
Colombo 13	Colombo 14	2.4	Yes
Colombo 14	Colombo 09	2.6	Yes
Colombo 09	Colombo 03	5.1	Yes
Colombo 03	Colombo 04	2.5	Yes
Colombo 04	Colombo 05	2.4	Yes
Colombo 05	Colombo 06	3.6	Yes
Colombo 06	Dehiwala	3.1	Yes
Dehiwala	Mt. Lavinia	1	Yes
Mt. Lavinia	Rathmalana	1.5	Yes
Rathmalana	Boralasgamuwa	4.6	Yes
Boralasgamuwa	Maharagama	3.1	Yes
Maharagama	Pannipitiya	2	Yes
Pannipitiya	Kottawa	2	Yes
Kottawa	Homagama	4.8	Yes
Homagama	Athurugiriya	4	Yes
Athurugiriya	Thalawathugoda	8	Yes
Thalawathugoda	Battaramulla	5.7	Yes
Battaramulla	Gothatuwa	5.6	Yes
Gothatuwa	Malabe	8.9	Yes
Malabe	Kaduwela	6.3	Yes
Kaduwela	Hanwella	15.4	Yes
Hanwella	Padukka	8.6	Yes
Padukka	Central Warehouse	31.6	No
Total distance traveled inside cluster 1		149.9 Km	

The optimal path of cluster 1 is shown in Figure 9.

Figure 9: Optimal path of cluster 01 – proposed method

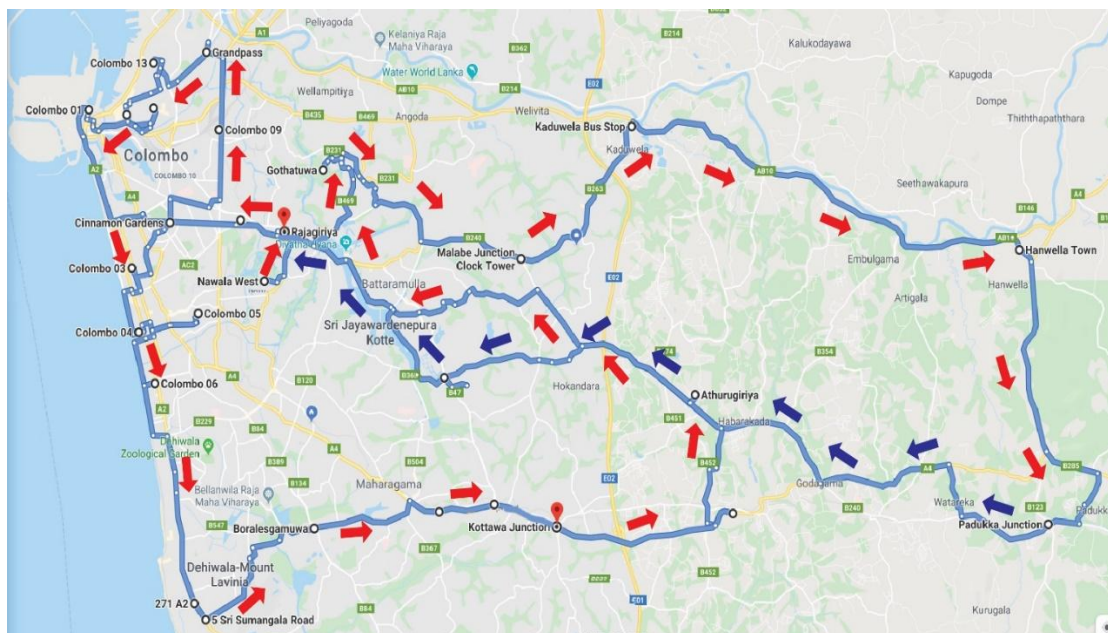


Table 9 shows the starting and ending towns of each of the subtours of cluster 2, along with optimal distances travelled (Google distances) and the total distance traveled inside cluster 2.

Starting Town	Ending Town	Distance Traveled (Km)	Transshipment Node
Central Warehouse	Nugegoda	5.2	No
Nugegoda	Piliyandala	8.4	Yes
Piliyandala	Moratuwa	5	Yes
Moratuwa	Colombo 02	18.2	No
Colombo 02	Colombo 15	7.3	
Colombo 02	Central Warehouse	11.2	
Total Distance Travel inside the cluster 2		55.3 Km	

The optimal path of cluster 2 is shown in Figure 10.

Figure 10: Optimal path of cluster 02 - proposed method

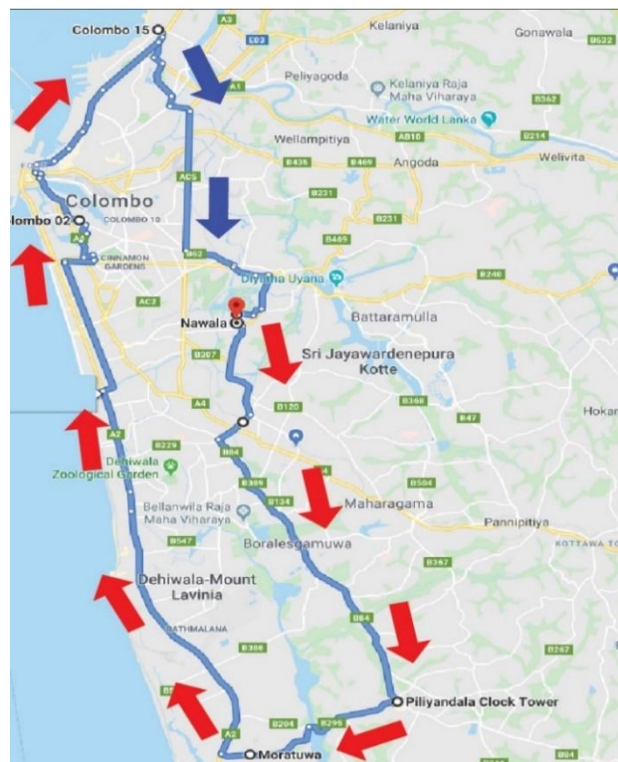


Table 10 shows the optimal distance traveled in each of the two clusters and the total distance traveled under the proposed heuristic method.

Discription	Distance Traveled
Cluster 01	149.9
Cluster 02	55.3
Total distance traveled	205.2

6.3. Analysis based on Genetic algorithm

Added all the data of (X, Y) coordinates and demands to the Python code and ran the program. Table 11 below shows the cluster arrangement of all the demand points.

Table 11: Cluster arrangement - genetic algorithm

Route No.	Route	Route Length
1	0-25-30-35	13.5
2	0-21-11	7.04
3	0-31-32-33-29	26.73
4	0-24-34-22-23	25.74
5	0-16-19-26-27-28-18	57
6	0-17-15	12.54
7	0-20-2-13-12	17.45
8	0-6-7-5	21.41
9	0-4-1-8-9	17.1
10	0-14-3-10	15.94
Total Length		214.45

Figure 11: Cluster arrangement - genetic algorithm

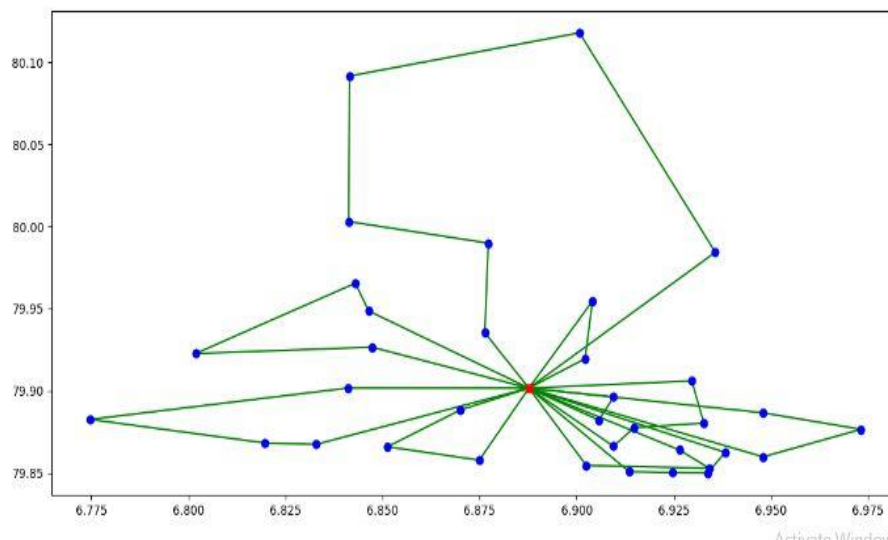


Figure 11 shows the arrangement of clusters of the problem under the Genetic algorithm method. Table 12 below presents a comparative study of total distance traveled and the relevant costs across four methods. The percentage of cost savings by the developed heuristic method is also highlighted in the table.

Table 12: A comparative study of the total distance traveled and the costs under four different methods

Method	Total Distance Travel (Km)	Cost Per Km (Rs.)	Daily Cost	Monthly Cost
Company Existing Method	256	41.71	10677.76	320333
Ganepola et al. (2018)	220	41.71	9176.2	275286
Genetic Algorithm	214.5	41.71	8946.8	268404
Jayarathna et al. (2022)	210.4	41.71	8775.8	263274
Proposed heuristic	205.2	41.71	8558.9	256767
Total cost saving of the proposed heuristic compared to the Company's Existing Model				63566 (19.84%)
Total Cost saving of the proposed heuristic compared to the Ganepola et al. (2018)				18519 (6.73%)
Total Cost saving of the proposed heuristic compared to the Genetic algorithm				11637 (4.34 %)
Total Cost saving of the proposed heuristic compared to the Jayarathna et al. (2022)				6507 (2.47%)

Table 12 highlights the cost savings that the proposed heuristic algorithm can induce in a real-life instance. Using the proposed heuristic, the cost savings can be accrued as large as 19.84% compared to

the company's existing decentralized method, 4.34% compared to the Genetic algorithm, and 6.73% and 2.47% compared to the two recent methods.

6.4. Cost-benefit analysis for another ten real-world problems

Also, we have solved ten real-world problems by applying our proposed heuristic and Genetic algorithm. The demand data are collected from milk suppliers, soft drink suppliers, vegetable suppliers, and wholesale product suppliers, which are shown in Table 13. For these problems, the results from our heuristic method are compared with those from all other methods, as shown in Table 13. The significant cost savings demonstrate the superiority of our proposed heuristic over all other methods in this table. When the number of demand points is within 10, one can usually manually plan the optimal transportation arrangement. However, when the number of demand points exceeds 10, this cannot be solved manually. Instead, it needs a computer program based on the algorithm.

Table 13: Cost-Benefit Analysis of another ten real-world applications

Index	Area of application	Total Demand Points	Total Cost Saving of the proposed heuristic compared to the Company's Existing Method (%)	Total Cost saving of the proposed heuristic compared to Ganepola et al. (2018)'s method (%)	Total Cost savings of the proposed heuristic compared to Jayarathna et al. (2022)'s method (%)	Total Cost saving of the proposed heuristic compared to the Genetic Algorithm (%)
1	Fresh Milk Supplier	5	10	2	0.5	0.5
2	Fresh Milk Supplier	10	10	3	0.5	0.5
3	Soft drink supplier	15	7	3	1	1
4	Wholesale product distributor	20	8	3.5	1	1
5	Vegetable supplier	25	15	4	1	1
6	Wholesale product distributor	30	15	5	2	1.5
7	Soft drink supplier	35	20	6	2	2
8	Vegetable supplier	40	15	6	2	2
9	Wholesale product distributor	45	22	7	3	2
10	Soft drink supplier	50	25	9	4	3

The above results clearly indicate the significant benefits of the proposed heuristic method.

7. Conclusion and recommendation

Based on secondary data collected from SAP and the agent's operational data at Lion Brewery Ceylon PLC, we have developed a central warehouse strategy. The Colombo region has been divided into 35 demand regions, and the demand value of each point has been identified. After determining the locations of each demand point (latitude and longitude), the gravity model (Andersson, 1979) is used to identify the location of the new central warehouse. It is situated at a latitude of 6.90255 and a longitude of 79.88668. The primary purpose of this research is to build a new model to minimize the total distance travelled in distributing products in a region. According to the existing method by Ganepola et al. (2018) for the given location, all demand points in the Colombo district are divided into five main clusters, and a Hamiltonian cycle has been used to obtain the optimal path within each subcluster. Trucks are used to redistribute goods, which are allocated following each of the optimal paths generated by the Hamiltonian cycle. Following the Gravity model (Andersson, 1979), the location of the central warehouse is determined, and then, using our developed algorithm, all demand points in the Colombo region are clustered. An optimal path connecting each subcluster has been determined. Finally, the total distance was determined by optimizing truck allocation using the newly developed heuristic algorithm. The superior performance of our proposed heuristic algorithm is demonstrated relative to existing

algorithms through solutions to a beer distribution problem instance and 10 additional real-world problem instances. The computational investigations highlight the significant cost savings that can be achieved with the newly proposed heuristic compared to all other studied methods. Thus, this research contributes to the beer supply chain, a crucial component of the soft drink supply chain, in delivering this drink at reduced cost and, consequently, with lower prices. This price reduction of soft drinks and beer will certainly alleviate the sufferings of people in Sri Lanka to a certain extent during this time of economic crisis, following the post-COVID period and the Russia-Ukraine war.

This study found that centralized distribution strategies provide a greater cost-benefit than decentralized distribution strategies. Although the proposed heuristic is applied to the Colombo region, it can be extended to a larger region for improved results. The multi-depot vehicle routing problem, based on linear/nonlinear programming modeling techniques, may be applied to achieve better results for the problem studied in this paper. Therefore, further research can be conducted to develop a cost-effective model that reduces the overall costs of transportation, warehouse operations, and administration in the warehouse-vendor dilemma.

In this study, we have sought to determine whether any centralized method would be more advantageous than the currently used decentralized methods. We have observed that the centralized warehouse system is better when a smaller number of customers need to be served, whereas the decentralized warehouse system is better when a larger number of customers need to be served. A combination of both warehouse types, i.e., the hybrid one, is also possible; in this case, customers are supplied not only from a central warehouse but also from other warehouses that function as branches, regional, or transshipment warehouses. However, more research is needed on hybrid warehouses, which can be considered a further research scope for the topic. Also, we pay attention to the distance covered by all the methods. However, if we take into account the cost of renting a warehouse, office overhead, and operating expenses, the analysis will be more extensive than this one. Therefore, further research can be conducted to develop a model that is cost-effective and reduces overall transportation, warehouse, and administrative costs.

Abbreviations

CVRP Capacitated Vehicle Routing Problem

CVRPPAD Capacitated Vehicle Routing Problem with Pickups and Alternative Delivery

MDVRP Multi-Depot Vehicle Routing Problem

PLC Private Limited Company

SAP ERP System Application & Product Enterprise Resource Planning

VRP Vehicle Routing Problem

VRPPD Vehicle Routing Problem with Pickups and Delivery

VRSPD Vehicle Routing Problem with Simultaneous Pickup and Delivery

VRPTWS Vehicle Routing Problem with Time Windows

Acknowledgement

This research work is dedicated to the memory of Z. A. M. S. Juman, of the Department of Mathematics, Faculty of Science, University of Peradeniya, Peradeniya, who initiated this research but passed away in a road accident.

Declarations

- **Funding** – No funding was received for conducting this study.
- **Conflicts of interest/Competing interests** – The authors have no **conflicts of interest/** competing interests to declare that are relevant to the content of this article.
- **Ethics approval and consent to participate** - Not applicable
- **Consent for publication** – All authors agreed to publication
- **Availability of data and material** – Not applicable
- **Materials and/or Code availability** - Not applicable

Authors' contributions

D. G. N. D. Jayarathna: Conceptualization, Visualization, Methodology, Computation, Investigation, Formal analysis, Writing– original draft;

M. A. Hoque: Writing– review & editing, Supervision, Investigation, Formal analysis, Validation;

G. H. J. Lanel: Writing– review & editing, Supervision, Investigation, Validation.

Citation information

Jayarathna, D.G.N.D., Hoque, M. A., & Lanel, G. H. J. (2025). Optimal solution techniques to the vehicle routing problem arising in Lion Beer distribution in Sri Lanka. *Journal of Sustainable Development of Transport and Logistics*, 10(2), 29-52. doi:10.14254/jsdtl.2025.10-2.2.

References

- Andersson, J. E. (1979). A Theoretical Foundation for the Gravity Equation. *American Economic Review*, 69(1), 106–16.
- Arnold, F., Gendreau, M., & Sorensen, K. (2019). Efficiently solving very large scale routing problems. *Computers & Operations Research*, 107, 32–42. <https://doi.org/10.1016/j.cor.2019.03.006>
- Cordeau, J. F., Gendreau, M., Hertz, A., Laporte, G., & Sormany, J. S. (2005). New Heuristics for the Vehicle Routing Problem, In: A. Langevi and D. Riopel, Eds., *Logistics Systems: Design and Optimization*, Springer, New York, pp. 279-297. https://doi.org/10.1007/0-387-24977-X_9
- Das, S., & Borthakur, M. A. (2006). Mixed Constrained (Identical) Vehicle Routing Problem for Time Minimisation. *OPSEARCH* 43, 31–48. <https://doi.org/10.1007/BF03398758>
- Desaulniers, G., Desrosiers, J., & Spoorendonk, S. (2011). Cutting planes for branch-and-price algorithms. *Networks*, 58(4), 301-310. <https://doi.org/10.1002/net.20471>
- De Silva, A. (2001). Combining constraint programming and linear programming on an example of bus driver scheduling. *Annals of Operations Research*, 108, 277. <https://doi.org/10.1023/A:1016075431943>.
- Goeke, D., & Schneider, M. (2015). Routing a mixed fleet of electric and conventional vehicles. *European Journal of Operational Research*, 245(1), 81-99. <https://doi.org/10.1016/j.ejor.2015.01.049>
- Gábor, N., & Saïd, S. (2005). Heuristic algorithms for single and multiple depot vehicle routing problems with pickups and deliveries. *European Journal of Operational Research*, 162(1), 126-141. <https://doi.org/10.1016/j.ejor.2002.11.003>
- Ganepola, D., Jayarathna, N. D., & Madhushani, G. (2018). An intelligent cost optimized central warehouse and redistribution root plan with truck allocation system in Colombo region for Lion Brewery Ceylon PLC. *Journal of Sustainable Development of Transport and Logistics*, 3(2), 66-73. <https://doi.org/10.14254/jsdtl.2018.3-2.4>
- Gendreau, M., Laporte, G., & Potvin, J. Y. (2002). Metaheuristics for the VRP In: P. Toth and D. Vigo, Eds., *The Vehicle Routing Problem. SIAM Monographs on Discrete Mathematics and Applications*, Philadelphia, 129-154. <https://doi.org/10.1137/1.9780898718515.ch6>
- Goetschalckx, M. (2011). Springer Science Business Media LLC, *Supply Chain Engineering* New York. <https://doi.org/10.1007/978-1-4419-6512-7>
- Hosny, M., & Fatima, S., (2011). A survey of genetic algorithms for the university timetabling problem. *International proceedings of computer science and information technology*, 13.
- Jayarathna, D. G. N. D., Lanel, G. H. J., & Juman, Z. A. M. S. (2019). A contemporary Recapitulation of Major Findings on Vehicle Routing Problems: Models and Methodologies. *International Journal of Recent Technology and Engineering*, 8(2S4), 581-585. <https://doi.org/10.35940/ijrte.B1115.0782S419>
- Jayarathna, D. G. N. D., Lanel, G. H. J., & Juman, Z. A. M. S. (2021). An intelligent cost-optimized warehouse and redistribution root plan with truck allocation system: Evidence from Sri Lanka. *Journal of Business and Social Science Review*, 2(10).

- Jayarathna, D.G.N.D., Lanel, G. H. J., Juman, Z.A. M. S. (2022). *Industrial vehicle routing problem: a case study*. *Journal of Shipping and Trade*, 7(1), 1-27. <https://doi.org/10.1186/s41072-022-00108-7>
- Jayarathna, N. D., & Jayawardene, C.J. (2019). Application of clusters in a transportation network. *Journal of Mathematics and Informatics (JOMI)*, 7(1), 17, 21-29, <https://doi.org/10.22457/jmi.130aav17a3>.
- Jayarathna, N. (2024). Optimizing petroleum redistribution in Sri Lanka: A cost-benefit transportation model. *Journal of Sustainable Development of Transport and Logistics*, 9(1), 121-136. <https://doi.org/10.14254/jsdtl.2024.9-1.9>
- Jayarathna, D. G. N. D., Lanel, G. H. J., & Juman, Z. A. M. S. (2021). Modeling a cost benefit transportation model to optimize the redistribution process: Evidence study from Sri Lanka. *Journal of Sustainable Development of Transport and Logistics*, 6(2), 43-59. <https://doi.org/10.14254/jsdtl.2021.6-2.3>
- Jayarathna, N., & Jayasooriya, J. (2018). Identify & Analysis socio-economic impacts upon the people in the vicinity of the Hambanthota Port Project. R4TLI-2018, *3rd International Conference on Research for Transport & Logistics Industry*.
- Jayarathna, N., Lanel, J., & Juman, Z. A. M. S. (2020). Five years of multi-depot vehicle routing problems. *Journal of Sustainable Development of Transport and Logistics*, 5(2), 109-123. <https://doi.org/10.14254/jsdtl.2020.5-2.10>
- Jayarathna, N., Lanel, J., & Juman, Z. A. M. S. (2021). Survey on ten years of multi-depot vehicle routing problems: mathematical models, solution methods and real-life applications. *Sustainable Development Research*, 3(1), 36-52. <https://doi.org/10.30560/sdr.v3n1p36>
- Jayarathna, N., Lanel, J., Juman, S. (2019). A contemporary recapitulation of major findings on vehicle routing problems: models and methodologies. *International Journal of Recent Technology and Engineering*, 8(2S4), 581-585. <https://doi.org/10.35940/ijrte.B1115.0782S419>
- Koç, Ç., Laporte, G., & Tükenmez, İ. (2020). A review on vehicle routing with simultaneous pickup and delivery. *Computers & Operations Research*, 122, 104987. <https://doi.org/10.1016/j.cor.2020.104987>
- Laporte, G. (2009). Fifty years of vehicle routing. *Transportation Science*, 43(4), 408-416. <https://doi.org/10.1287/trsc.1090.0301>
- Montané, F. A. T., & Galvão, R.D. (2002). Vehicle routing problems with simultaneous pick-up and delivery service. *OPSEARCH*, 39, 19–33. <https://doi.org/10.1007/BF03398667>
- Privé, J., Renaud, J., Boctor, F., & Laporte, G. (2006). *Solving a vehicle-routing problem arising in soft-drink distribution*. *Journal of the Operational Research Society*, 57(9), 1045–1052. <https://doi.org/10.1057/palgrave.jors.2602087>
- Rousseau, L. M., Gendreau, M., Pesant, G., & Focacci, F. (2004). Solving VRPTWs with constraint programming based column generation. *Annals of Operations Research*, 130, 199. <https://doi.org/10.1023/B:ANOR.0000032576.73681.29>.
- Sitek, P., & Wikarek, J. (2019). Capacitated vehicle routing problem with pick-up and alternative delivery (CVRPPAD): model and implementation using hybrid approach. *Annals of Operations Research*, 273(1-2), 257-277. <https://doi.org/10.1007/s10479-017-2722-x>
- Vidal, T., Laporte, G., & Matl, P. (2020). A concise guide to existing and emerging vehicle routing problem variants. *European Journal of Operational Research*, 286(2), 401-416. <https://doi.org/10.1016/j.ejor.2019.10.010>
- Urquhart, M.E., & Viera, O. A. (2002). Vehicle routing system supporting milk collection. *OPSEARCH*, 39, 46–54. <https://doi.org/10.1007/BF03398669>

Appendix A

Ganepola et. al (2018)'s approach.

The first step of this approach is to find a route plan with an optimal path by using Lingo software. Lingo is a software developed for finding optimal solutions to linear and nonlinear optimization problems. The Hamiltonian cycle sample model is adjusted for the solution of the problem studied in this paper by using Lingo software. Hamiltonian cycle provides the optimal path to each of the main clusters. The adjusted Hamiltonian cycle sample problem is given below. Using this model, one can find the optimal delivering path within a cluster.

MODEL:

! Traveling Salesman Problem for the cities of

New Facility, Colombo 01, Colombo 09, Colombo 11, Colombo 12, Colombo 13, Colombo 14, Colombo 15;

SETS: CITY / 1.. 8/: U; !U(I) = sequence no. of city;

LINK(CITY, CITY):

DIST, ! The distance matrix;

X; !X(I, J) = 1 if we use link I, J;

ENDSETS

Python code for Genetic Algorithm

```
\begin{lstlisting}[language=Python]
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image, ImageDraw, ImageFont
rnd = np.random
rnd.seed(0)
n = a # nombre of clients
xc = np.array([x1,x2,...xa])
yc = np.array([y1,y2,...ya])
plt.plot(xc[0], yc[0], c='r', marker='s')
plt.scatter(xc[1:], yc[1:], c='b')

N = [i for i in range(1, n+1)]
V = [0] + N
A = [(i, j) for i in V for j in V if i != j]
c = {(i, j): np.hypot(xc[i]-xc[j], yc[i]-yc[j]) for i, j in A}
Q = b
q = np.array([d1,d2,...,d3])
from gurobipy import Model, GRB, quicksum
mdl = Model('CVRP')
x = mdl.addVars(A, vtype=GRB.CONTINUOUS)
u = mdl.addVars(N, vtype=GRB.CONTINUOUS)
mdl.modelSense = GRB.MINIMIZE
mdl.setObjective(quicksum(x[i, j]*c[i, j] for i, j in A))
mdl.addConstrs(quicksum(x[i, j] for j in V if j != i) == 1 for i in N)
mdl.addConstrs(quicksum(x[i, j] for i in V if i != j) == 1 for j in N)
mdl.addConstrs((x[i, j] == 1) >> (u[i]+q[j] == u[j])
for i, j in A if i != 0 and j != 0)
mdl.addConstrs(u[i] >= q[i] for i in N)
mdl.addConstrs(u[i] <= Q for i in N)
mdl.Params.MIPGap = 0.1
mdl.Params.TimeLimit = 30 # seconds
mdl.optimize()
active_arcs = [a for a in A if x[a].x > 0.99]
for i, j in active_arcs:
```

```
plt.plot([xc[i], xc[j]], [yc[i], yc[j]], c='g', zorder=0)
plt.plot(xc[0], yc[0], c='r', marker='s')
plt.scatter(xc[1:], yc[1:], c='b')
plt.show()
\end{lstlisting}
```

- Immediate, universal access to your article on publication
- High visibility and discoverability via the JSDTL website
- Rapid publication
- Guaranteed legacy preservation of your article
- Discounts and waivers for authors in developing regions

