A Multi-Objective Sustainable Vehicle Routing Approach with Flexible Time Window

ISBN: 978-1-943295-24-1

Arpan Paul
Siba Sankar Mahapatra
National Institute of Technology
(arpanpaul12@gmail.com)
(mahapatrass2003@gmail.com)

This study proposes a sustainable vehicle routing problem that considers economic, environmental, and social objectives within a realistic, variable-speed scenario. The model aimed to minimize fuel consumption and transport costs while maximizing customer satisfaction. Fuel consumption has two parts, depending on the speed variation and the fixed part. Time windows are designed using generalized bell membership functions, offering flexibility to handle uncertainty better than classical time windows. The solution approach leverages ant colony optimization, while sensitivity analysis examines how input variables impact objectives, providing a robust tool for sustainable and realistic decision-making in transportation planning.

Keywords: Sustainable Vehicle Routing, Multi-Objective Optimization, Variable-Speed Transportation, Flexible Time Windows, Ant Colony Optimization

1. Introduction

Logistics plays a crucial role in the development of any nation as it contributes significantly to the nation's gross domestic product (GDP) due to its ability to facilitate the movement of goods, people, and resources. An efficient transportation system facilitates industries in handling raw materials and distributing finished products in an effective way to expand their business. However, excessive carbon emissions have become an obstacle to the long-term sustainability of transportation as it is the primary cause of global warming (Li et al., 2024). Thus, the logistic networks should primarily be designed to minimize carbon emissions by reducing fuel consumption. Secondarily, profits are the ultimate goal of any organization, so the minimization of transportation costs should be considered when structuring a vehicle routing problem (VRP). Social issues must be considered alongside environmental and economic factors to make a transportation model fully sustainable. Therefore, customer satisfaction is considered the third objective, which needs to be maximized. The fuel consumption consists of two parts: constant fuel consumption and variable fuel consumption due to variations in speeds. The time windows of the customers are modeled as a generalized bell membership function for more flexibility in customer preferences. Thus, the problem is formulated as a mixed integer linear programming model considering all three sustainability issues.

The capacitated vehicle routing problem (CVRP) is one of the simplest forms of VRP, where a number of customers are served by a set of vehicles with limited capacity from a distribution center. CVRP deals with the total traveled distance, traveling time, and other parameters on a demand basis (Praveen et al., 2022). This study is an extension of the CVRP that considers sustainability along with heterogeneous vehicles, flexible time windows, and time periods. The consideration of heterogeneous vehicles is crucial because they have various fuel consumption rates, speed ranges, specifications, and maintenance costs, making Vehicle Routing Problems (VRP) a complex combinatorial optimization challenge (Behnamian et al., 2023). Due to its NP-hard nature, a metaheuristic algorithm is an excellent approach as it can explore an ample solution space to provide a sufficiently good solution (Consoli, 2006). Ant colony optimization (ACO), a population-based approach, is chosen to solve the current problem and explore a broad solution space. ACO also effectively handles heterogeneous vehicles by allowing ants to consider various vehicle types and their capacities (Alba et al., 2012).

The rest of the paper is organized as follows. Section 2 performs a relevant study of the past literature. In Section 3, the mathematical model is constructed, and the problem is formulated. The solution approach is presented in Section 4. Section 5 performs the experimental analysis. Finally, the conclusions are made, and future research directions are provided in Section 6.

2. Literature Review

More than sixty years have passed since Dantzig and Ramser (1959) introduced the vehicle routing problem. After that, many studies have been performed that considered various extensions of the classical VRP. This section has studied brief literature that mainly considered green or sustainable VRP. Niu et al. (2018a) performed a real-world open vehicle routing problem considering the minimization of fuel consumption and driver wages with the help of third-party logistics. They studied the effect of various vehicle types and found that the mean total cost is the lowest for light-duty vehicles (Niu et al., 2018b). Messaoud et al. (2018) formulated a green dynamic VRP to minimize total carbon dioxide emissions by incrementing the loading rate and reducing the empty runs for sustainable transportation. They addressed their problem using benchmark datasets from the Green Vehicle Routing Problem (GVRP), incorporating some modifications. Rabbani et al. (2018) presented a time-dependent GVRP with time windows under stochastic uncertainty. Their study considered objective functions of different sizes and varying situations to minimize total transportation cost and pollution, as well as maximize customer satisfaction and vehicle reliability. Hooshmand et al. (2019) presented a novel extension of the VRP with the consideration of alternative fuel-powered vehicles (AFV) in a time-dependent scenario to minimize carbon dioxide emissions, considering refueling decisions. Ashtineh and Pishvaee (2019) have also performed a life cycle analysis of alternative fuel-powered VRP to evaluate economic and environmental performance considering variable engine speed. They have shown that there will be a significant reduction in GHG emissions for AFVs compared to conventional diesel-based vehicles. A pollution location-inventory-routing problem was introduced by Karakostas et al. (2020), integrating both economic and environmental decisions, taking heterogeneous vehicles into account. Shi et al. (2020) have developed a robust optimization model of VRP with synchronized visits and uncertain scenarios like uncertain service time and travel time, taking GHG emissions as their objective.

Abdullahi et al. (2021) studied the sustainability dimensions for the GVRP, considering transportation cost, fuel consumption, and cost of accidental risk as their objectives. They performed a sensitivity analysis to observe the impact of each sustainability dimension and revealed that there would be a slight reduction in total costs when considering all three sustainability dimensions together. Zarouk et al. (2022) proposed a GVRP with stochastic demands, variable travel times, and soft customer time windows to minimize energy consumption and maximize customer satisfaction. Behnamian et al. (2023) presented a GVRP with a refueling constraint, considering clean fuel to be a crucial factor for reducing environmental pollution. They have taken Speed-dependent fuel consumption as their objective function, which is minimized using various technologies for refueling. A mathematical model of VRP with split pickup and delivery was established by Ren et al. (2023), considering traffic conditions to minimize fixed cost, carbon emission cost, and penalty cost when serving multi-category goods. Lou et al. (2024) proposed a low-carbon VRP that considers time-dependent speeds, road conditions, and time windows to minimize total carbon emissions. They validated their proposed model through a case study with traffic data. Their research shows that the consideration of time-dependent speeds and speed fluctuation reduces a noticeable reduction in carbon emissions. Gülmez et al. (2024) presented a green delivery routing problem by considering flexible time windows to minimize overall costs, use of fossil fuel, and customer satisfaction. Their research revealed that incorporating multiple time windows eases deliveries and provides greater flexibility. Table 1 represents the objective function and operational considerations of the previous literature and the considerations for the current study.

Table 1 *Comparative Analysis of Objectives and Operational Considerations*

Reference	Objective Function Consideration				Operational Consideration		
	Fuel Consumption /Carbon Emission	Transportation/Routing Costs	Multi-Objective	Sustainability	Time Period	Heterogeneous Fleet	Flexible/ Soft Time Windows
Niu et al. (2018)							
Messaoud et al. (2018)							
Rabbani et al. (2018)							
Hooshmand et al. (2019)							
Ashtineh and Pishvaee (2019)							
Karakostas et al. (2020)							
Shi et al. (2020)							
Abdullahi et al. (2021)							
Zarouk et al. (2022)							
Behnamian et al. (2023)							
Ren et al. (2023)							
Lou et al. (2024)							
Gülmez et al. (2024)							
This study							

The literature review explored various aspects, including minimizing fuel consumption, carbon emissions, and transportation costs, while considering factors like vehicle types, time-dependent scenarios, and time windows consideration. Most of the literature emphasizes the advancement in addressing both economic and environmental objectives in VRP. However, the social dimensions are less studied in the VRP context, which makes the model a sustainable one. The contribution of the paper is outlined below, depending on the shortcomings of the studied literature.

1. This study considered all three sustainability issues, i.e., economic, environmental, and social considerations.
2. A generalized bell membership function is considered for customers' time windows.
3. A mixed fleet of vehicles is considered with various speeds, weights, and engine modules.

4. The model is tested on several benchmark instances and applied to a logistics distribution center from the literature for its verification and applicability.

3. Problem Formulation and Mathematical Modelling

3.1 Problem Description

The problem is structured as a closed-loop logistics distribution network, where a distribution center (denoted as 0) serves a group of N customers with known demands and time windows $[a_i, b_i]$. The service is carried out using a mixed fleet of vehicles $(M = \{1, 2,..., |M|\})$ over various time periods $(T = \{1, 2,..., t\})$. The number of available vehicles of type $m \in M$ is n^m. The weight capacity of vehicle type m is Q^m. Distance traveled between nodes (i, j) by vehicle m is d_{ij}. The binary variable x_{ij}^{mt} is equal to 1, if vehicle m travels in time period t within nodes (i, j). The product weight carried between nodes (i, j) by vehicle m in time period t is a_{ij}^{mt} with speed v_t^m. q_i^{mt} represents the product weight delivered to customer i by vehicle m in time period t. Moreover, the following assumptions are made.

There is a single distribution center.

- Each customer is served once by one vehicle during the specified time period.
- Each route starts and ends at the distribution center.
- The demand of each customer is known previously.
- The total customer demands do not exceed the total vehicle capacity.
- All picked-up goods must be delivered to the customers.

3.2 Amount of Fuel Consumption (FC)

According to the International Energy Agency (IEA), logistics accounts for around 24% of greenhouse gas (GHG) emissions, and ground transport contributes around 72% of the total logistics carbon emissions (Gülmez et al., 2024). Therefore, it is essential to consider the carbon emissions generated by road transportation as an objective function. The amount of fuel consumed consists of two parts. The first part, which consists of constant fuel consumption, is taken from the Comprehensive Modal Emissions Model (CMEM) equation introduced by Barth et al. (2004). The second part, with variable fuel consumption, is adopted from Behnamian et al. (2023) and is calculated from the inverse mileage of the vehicles. The vehicle's engine module and weight module are responsible for the fixed fuel consumption part. The speed module is responsible for the variable fuel consumption part, which consists of instantaneous speed (v_t^m), ideal speed (v_{ideal}^m) for the lowest fuel consumption and the maximum speed (v_{max}^m). The speed values of the vehicles are obtained from real-time Google Maps. The amount of fuel consumption (in liters) is shown in equation (1). The amount of fuel consumption due to variations in speeds for various types of vehicles is shown in figure 1. It shows that at a speed range of 35-40 km/hr, all types of vehicles perform well in terms of fuel consumption, and the consumption amount increases gradually with the increase in vehicle speed.

$$\text{FC} = \lambda d_{ij}\left[\frac{K^m E^m V^m}{v_t^m} + \left(W^m + A_{ij}^{mt}\right)\gamma^m \alpha + \left(v_t^m\right)^2 \beta^m \gamma^m + \left(\frac{v_t^m - v_{ideal}^m}{v_{max}^m}\right)^2 R^m\right] \tag{1}$$

Where, $\lambda = \varepsilon / (\psi\kappa)$, $\gamma^m = 1 / (1000\eta_{if}\eta)$, $\alpha = (\tau + g\sin\theta + gC_r\cos\theta)$, $\beta^m = 0.5\text{Cd}\rho A^m$, η = fuel efficiency. Other parameters are described in Table 2 with their specific values.

Table 2 *Vehicle Common Parameters with their Values (Obtained from Cheng et al., 2017)*

Notation	Description	Typical Value
τ	Acceleration (m/s²)	0
g	Gravitational constant (m/s²)	9.81
θ	Slope of the road (degree)	0
C_r	Rolling resistance coefficient	0.01
η	Efficiency of diesel engines	0.45
ρ	Density of air (kg/m³)	1.2041
ε	Fuel-air mass ratio	1
ψ	Conversion factor (L/g)	737
κ	Heating value of diesel (kJ/g)	44
C_f	Unit cost of diesel fuel (£/L)	0.7382
C_e	Unit carbon emission cost (£/kg)	0.248
σ	Carbon emission for unit fuel consumption (kg/L)	2.669
Cd	Driver cost (£/min)	0.0022

Table 3 *Vehicle-Specific Parameters and their Values (Obtained from Cheng et al. 2017)*

Notation	Description	Type of Commercial Vehicle		
		Light	Medium	Heavy
K^m	Engine friction factor (kJ/rev/L)	0.25	0.2	0.15
E^m	Speed of engine (rev/s)	39	33	30.2
V^m	Displacement of engine (L)	2.77	5	6.66
W	Curb weight (kg)	4672	6328	13154
η^m_{if}	Drive train efficiency	0.4	0.45	0.5
C^m_d	Aerodynamics drag coefficient	0.6	0.6	0.67
Q^m	Capacity (kg)	2585	5080	17236
A^m	Vehicle frontal area (m^2)	9	9	9.8
n^m	Number of vehicles of type m	6	3	2
Mc^m	Maintenance costs of vehicle m (£)	1.08	1.35	2.43
R^m	Speed-dependent fuel consumption per km	0.11	0.14	0.2

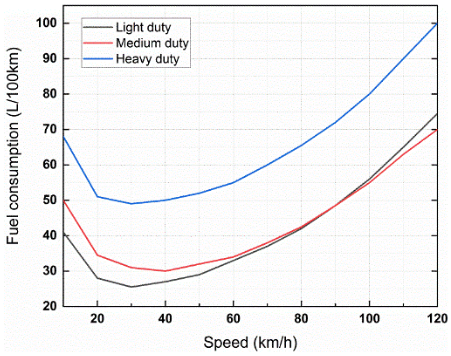

Figure 1 *Representation of Variation in Fuel Consumption Due to Changes in Speed for Different Vehicles (Source: Cheng et al., 2017)*

3.3 Transportation Cost (TC)

Transportation costs consist of three main parts: driver costs, maintenance costs, and carbon emissions costs, as shown in equation (2). The driver cost is comprised of the costs due to time spent traveling, servicing, and waiting. The maintenance costs are responsible for fixed costs due to inspection, oil change, parts repair, and replacement. The third part includes the carbon tax due to emissions of the vehicles computed from the amount of fuel consumption.

$$\mathrm{TC} = \left(St_i + \frac{d_{ij}}{v^m_t}\right)Cd + Mc^m + \lambda d_{ij}(C_f + C_e\sigma)\left[\frac{K^m E^m V^m}{v^m_t} + (W^m + A^{mt}_{ij})\gamma^m\alpha + \left(v^m_t\right)^2\beta^m\gamma^m + \left(\frac{v^m_t - v^m_{ideal}}{v^m_{max}}\right)2R^m\right] \quad (2)$$

Where, St_i is the service time for node i.

3.4 Customer Satisfaction (CS)

Customer satisfaction in the Vehicle Routing Problem (VRP) is an essential metric that reflects how well the vehicle routing solution meets customer needs regarding service quality. Time windows significantly influence customer satisfaction in delivery services, as they are essential in ensuring the convenience and dependability of the delivery process (Gülmez et al., 2024). This paper considered the customers' time windows as a generalized bell membership function (GBMF) instead of a classical time window function (CTWF). The GBMF provides a more flexible, realistic, and adaptable approach to modeling customer satisfaction compared to the CTWF. The customer satisfaction comprised of the GBMF is presented in equation (3).

$$\mathrm{CS} = \mathrm{Id}_i \times \mu_i \quad (3)$$

Where Id_i= importance degree of customer i, and the GBMF, $\mu_i(T_{a_i}, a_i, b_i, c_i) = \frac{1}{1 + \left|\frac{(T_{a_i} - c_i)}{a_i}\right|2b_i}$ with T_{a_i} as the arrival time of a vehicle at node i, a_i as width, c_i as center and b_i is responsible for the slope of node i (Yilmaz, 2015). Therefore, customer satisfaction can be rewritten in equation (4).

$$\mathrm{CS} = \left(\frac{q^{mt}_i}{\sum q^{mt}_i}\right)\frac{1}{1 + \left|\frac{(T_{a_i} - c_i)}{a_i}\right|2b_i} \quad (4)$$

The GBMF and the CTWF are shown in figure 2, along with various critical points such as the earliest arrival time (EAT), the start of the classical time window (CTWS), the end of the classical time window (CTWE), and the latest arrival time (LAT).

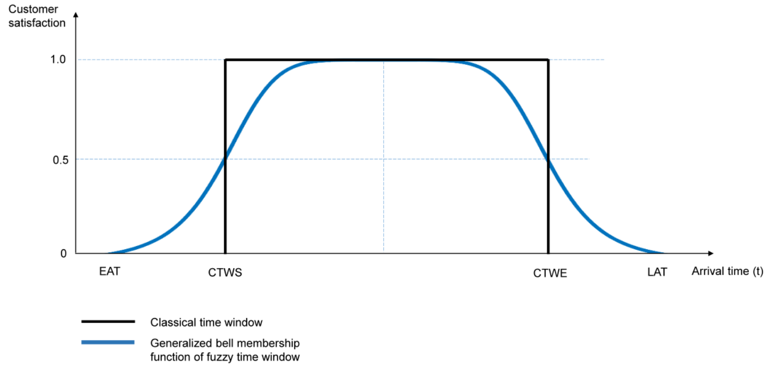

Figure 2 *The Variation of Customer Satisfaction with Arrival Time*

The constraints corresponding to the three objective functions are expressed below in equations (5)-(14).

$$\sum_{i\in N}\sum_{m\in M}x_{ij}^{mt}\le 1,\ \forall\ j\in N\backslash\{0\},t\in T \quad (5)$$

$$\sum_{j\in N}x_{ij}^{mt}=\sum_{j\in N}x_{ji}^{mt},\ \forall\ m\in M,i\in N,\ t\in T \quad (6)$$

$$\sum_{i\in N}A_{ij}^{mt}-\sum_{i\in N}A_{ji}^{mt}=q_j^{mt},\ j\in N\backslash\{0\},\ m\in M,\ t\in T,\ i\ne j \quad (7)$$

$$q_j^{mt}x_{ij}^{mt}\le A_{ij}^{mt},\ \forall\ i,j\in N,\ m\in M,\ t\in T \quad (8)$$

$$A_{ij}^{mt}\le (Q^m)x_{ij}^{mt},\ \forall\ i,j\in N,\ m\in M,\ t\in T \quad (9)$$

$$\sum_{i\in N}x_{0i}^{mt}\le n^m,\ \forall\ i\in N,\ m\in M,\ t\in T \quad (10)$$

$$T_{a_i}-T_{a_j}+St_i+Wt_i+d_{ij}(x_{ij}^{mt}/v_t^m)\le L_{ij}\left(1-x_{ij}^{mt}\right),\ \forall\ i\in N,\ j\in N\backslash\{0\},\ m\in M,\ t\in T,\ i\ne j \quad (11)$$

$$a_i\le T_{a_i}\le b_i,\ \forall\ i\in N\backslash\{0\} \quad (12)$$

$$T_{a_i}-s_j+St_i+Wt_i+d_{j0}(x_{j0}^{mt}/v_t^m)\le L_{ij}\left(1-x_{j0}^{mt}\right),\ \forall\ i\in N,\ j\in N\backslash\{0\},\ m\in M,\ t\in T,\ i\ne j \quad (13)$$

$$x_{ij}^{mt}\in\{0,\ 1\},\ \forall\ i,j\in N,\ m\in M,\ t\in T \quad (14)$$

Constraints (5) indicate that each customer is visited once during the period. Constraints (6) are specifying the vehicle balance equations. Capacity constraints of vehicles are described by constraints (7). Constraints (8) and (9) are responsible for the load-carrying capacities of the vehicles. Constraints (10) specify the maximum number of vehicles of each type. The time window constraints of the customers are designated in constraints (11)-(13), with $L_{ij}=\max\left(0,b_i+St_i-a_i+\ d_{ij}/v_t^m\right)$ and s_j denoting the total time traveled on a route with $s_j=y_j+t_j+d_{j0}/v_t^m$. The binary variable is defined in constraints (14).

Constraints (8) and (9) are non-linear, containing multiplication of decision variables. The Big-M method, as used by Alinaghian and Zamani (2019), is applied to the linearization of the constraints and is shown in equations (15)-(17).

$$q_j^{mt}\le A_{ij}^{mt}+M(1-x_{ij}^{mt}) \quad (15)$$

$$A_{ij}^{mt}-M\left(1-x_{ij}^{mt}\right)\le Q^m \quad (16)$$

$$A_{ij}^{mt}\ge\ -Mx_{ij}^{mt} \quad (17)$$

4. Solution Approach

Ant colony optimization (ACO) is applied to solve the multi-objective optimization problem. A partial rank correlation coefficient (PRCC) sensitivity analysis is also conducted to gain insights into the input-output relationships among the parameters. Figure 3 illustrates the research methodology proposed in this study.

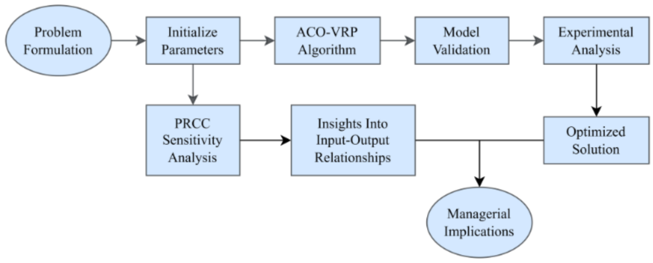

Figure 3 *Proposed Framework for the Research*

4.1 ACO Algorithm

The ACO algorithm is a metaheuristic algorithm proposed by Dorigo and Di Caro (1999). It was introduced as a tool to solve the traveling salesman problem, and later on, it is being used to solve VRP effectively, as it can solve NP-hard problems (Li et al., 2020). The algorithm is based on the searching behaviour of ants, where the ants release pheromones on their way, and the subsequent ants follow the shortest path with higher pheromone concentration. Colorni et al. (1991) proposed the formula for the probabilistic decision rule of the ACO, as shown in equation (18).

$$PB_{ij}^{m} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{m \in NH_i^k} [\tau_{ik}]^{\alpha}[\eta_{ij}]^{\beta}} \quad \forall\, j \in NH_i^k \tag{18}$$

Where, PB_{ij}^{m} denotes the probability of ant m $(m = 1,2,...M)$ to proceed from node i to node j. The pheromone value and the heuristic information are indicated by τ_{ij} and η_{ij} on arc (i,j). α and β represent the pheromone importance factor and heuristic importance factor, respectively. The possible neighbourhood of ant m is represented as NH_i^k.

The pheromone update rules of ACO introduced by Colorni et al. (1991) are presented in equations (19) and (20). Here, ρ is the pheromone evaporation degree, Q denotes the total amount of pheromone released and $\Delta\,\tau_{ij}^{k}$ is the amount of pheromone deposited on edge (i,j) by m^{th} ant between time t and $(t+1)$.

$$\tau_{ij}\left(t+1\right) = \left(1-\rho\right)\tau_{ij}\left(t\right) + \sum_{m=1}^{M} \Delta\,\tau_{ij}^{m}\left(t\right) \tag{19}$$

$$\Delta\,\tau_{ij}^{m} = \begin{cases} Q/d_{ij}, & \text{if ant } m \text{ travels in edge } (i,j) \\ 0\quad, & \text{otherwise} \end{cases} \tag{20}$$

Algorithm 1 presents the pseudo-code of the ACO-based VRP algorithm.

Algorithm 1: ACO-Based Vehicle Routing Problem
1. Initialization:
Define problem parameters (number of vehicles, customer demands, distance matrix, etc.).
Set ACO parameters: number of ants, number of iterations, pheromone importance factor (α), heuristic importance factor (β), pheromone evaporation rate (ρ), and initial pheromone level (τ_0).
Initialize pheromone trails (τ_{ij}) on all edges (i, j) to a small positive constant.
Define heuristic information (η_{ij}).
2. Main Loop (for each iteration):
For each iteration:
For each ant k:
Start from the depot
While not all customers are visited:
Select the next customer j using the probability rule (balance between pheromone τ_{ij} and heuristic η_{ij})
Move to customer j and add customer j to the ant's tour
Update the vehicle's current load
If vehicle is full or all customers are visited:
Return to depot and start a new route
End If
End While
End For
Evaporate pheromone on all edges: $\tau_{ij} \leftarrow (1 - \rho) \times \tau_{ij}$
For each ant k:
For each edge (i, j) in the ant's tour:

Deposit pheromone on the edges: $\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau_{ij}$, where $\Delta\tau_{ij} = Q / L_k$ (Q is a constant, L_k is the length of the k^{th} ant's tour)
End For
End For
3. Best Solution Update:
Compare current ant solutions with the best solution so far
If an ant's solution is better:
Update the global best solution
End If
End For
4. Termination:
If maximum number of iterations is reached:
Exit loop **End If**
5. Output:
Return the best solution found (routes and total distance).

5. Experimental Analysis

5.1 Computational System Specifications and Parameter Settings

The main parameters that affect the performance of the ACO algorithm are the number of ants (m), maximum number of iterations $(maxIter)$, pheromone importance factor (α), heuristic importance factor (β), pheromone evaporation rate (ρ) and total pheromone release (Q). These parameters are selected through a number of experiments by Li et al. (2020). The optimal values of these parameters are m=20, $maxIter$= 100, α=2, β=5, ρ=0.4 and Q=100, which are chosen for this study.

The computational system is equipped with an Intel(R) Core(TM) i7-2600 CPU running at 3.40 GHz, 12 GB of RAM, and operated on the Windows 10 platform. The computations were performed using MATLAB R2021b.

5.2 Model Validation

The ACO-based VRP model is tested on a number of well-known VRP benchmark instances from Solomon (1987) with 25, 50, and 100 nodes. The instances are selected randomly from the available benchmark instances. The results for the instances are shown in Table 4. Also, the optimal routes and iteration performances for the three instances are presented in figures 4 and 5, respectively.

Table 4 *Results of Benchmark Instances*

Instance	Number of Nodes	Number of Vehicles	Optimal Distance (km)
R106	25	6	518.39
RC101	50	6	833.05
C201	100	9	1168.39

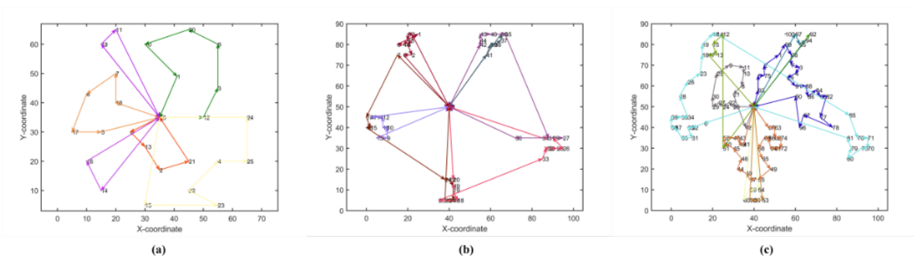

Figure 4 *Optimized Paths for the Instances (a) 25 Nodes, (b) 50 Nodes, and (c) 100 Nodes*

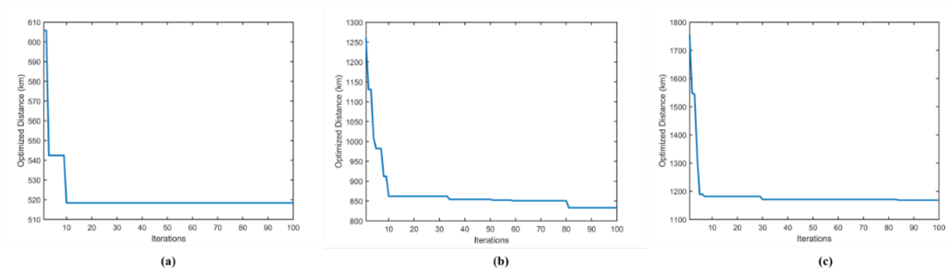

Figure 5 *Iteration Performances of the Instances (a) 25 Nodes, (b) 50 Nodes, and (c) 100 Nodes*

5.3 Sensitivity Analysis

A sensitivity analysis is performed to visualize the relationships between the input parameters and the objective functions. PRCC sensitivity analysis is utilized to study the output sensitivity to each input parameter, as shown in figure 6. The results are shown in Table 5, which revealed that vehicle speed has the most significant influence in the case of FC, followed by distance and load on the vehicle. Vehicle speed is also the most crucial factor for TC, followed by distance, fuel price, and driver wage. The analysis also revealed that load has a very insignificant influence on transportation costs. Concerning CS, the importance degree of the customers has the highest impact, while the arrival time of the vehicles to the customer points is of low importance. The negative sign of the PRCC values indicates the inverse relationship between the inputs and objective functions. Furthermore, lower p-values (= 0 or ≈ 0) suggest statistically significant relationships, whereas the higher p-values confirm the relationships are not statistically significant.

Table 5 *Results of PRCC Sensitivity Analysis with P-Values*

Objective	Input Variable	PRCC Value	p-value
FC	Distance	0.527	0.005
	Load	0.053	0.794
	Speed	-0.843	0
TC	Distance	-0.577	0.002
	Load	0	1.0
	Speed	-0.681	0
	Fuel Price	0.367	0.06
	Driver Wage	0.105	.603
CS	Importance Degree	0.949	0
	Arrival Time	0.316	0.108

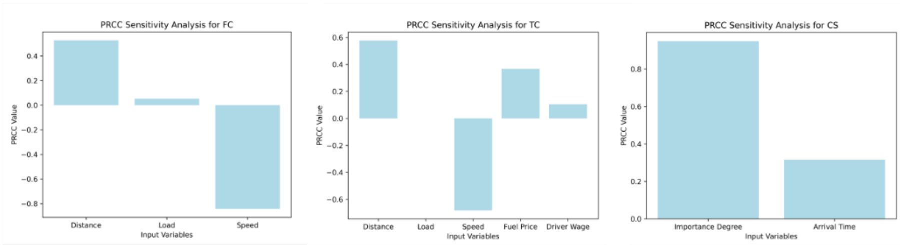

Figure 6 *PRCC Sensitivity Analysis Results for Each Output*

5.4 Experimental Analysis

For the applicability of the proposed model, it is applied to a logistics distribution center. The details of the customers used in this study are obtained from Li et al. (2020). The number of vehicles of each type is selected to serve all the customers at a time. The customer-related information, such as coordinates, demands, time windows, and service times, are shown in Table 6.

Table 6 *Customer-Related Information (Li et al., 2020)*

Customer No.	X-Coordinate (km)	Y-Coordinate (km)	Demand (kg)	Earliest Time	Latest Time	Service Time (min)
0	651.49	3262.69	--	6:00	18:30	--
1	690.95	3292.71	250	6:00	14:30	15
2	654.96	3238.10	350	7:30	18:30	21
3	660.84	3279.95	700	8:00	15:30	42
4	655.45	3279.86	800	7:00	16:30	48
5	644.44	3264.24	350	7:00	14:30	21
6	628.88	3251.58	750	6:30	13:30	45
7	653.88	3290.42	600	6:30	17:00	36
8	659.26	3264.12	750	8:00	14:00	45
9	685.13	3274.12	650	9:00	12:00	39
10	601.68	3302.16	400	6:00	12:00	24
11	660.06	3266.58	400	8:00	13:30	24
12	602.72	3253.59	800	6:00	16:30	48
13	628.30	3260.53	400	8:30	16:00	24
14	670.12	3271.63	700	6:00	14:00	42
15	633.20	3271.69	700	9:00	13:00	42
16	598.54	3252.48	900	7:00	15:00	54
17	695.97	3277.53	700	6:30	10:30	42
18	656.49	3269.95	400	6:30	12:00	24
19	658.53	3272.59	250	6:30	12:00	15
20	664.91	3252.67	600	7:30	14:00	36
21	601.54	3280.18	1200	7:30	14:00	72
22	618.34	3275.17	400	6:00	14:00	24
23	638.94	3273.85	450	7:00	11:30	27
24	647.76	3271.02	700	7:30	11:00	42
25	682.16	3239.80	1000	8:00	16:30	60
26	641.11	3277.38	300	8:00	16:00	18

27	644.88	3277.62	150	7:00	12:00	9
28	643.89	3255.11	1200	6:30	16:00	72
29	621.29	3239.48	800	7:00	17:00	48
30	688.03	3290.66	550	8:00	11:00	33
31	611.33	3255.55	500	8:00	16:30	30
32	638.20	3301.79	500	8:30	13:30	30
33	690.82	3299.04	450	7:30	16:30	27
34	654.87	3255.63	750	8:30	13:30	45
35	699.47	3284.12	400	7:00	17:00	24
36	626.80	3289.62	750	7:30	16:30	45
37	679.63	3274.57	600	7:30	16:30	36
38	692.99	3245.47	550	6:30	16:00	33
39	640.68	3264.94	900	6:30	12:00	54
40	637.24	3287.77	0800	6:30	13:30	48
41	659.19	3290.56	1200	8:00	13:30	72
42	647.72	3274.21	800	6:00	15:00	48
43	682.03	3261.41	900	7:00	14:00	54
44	693.66	3267.76	550	8:30	14:30	33
45	626.83	3248.00	550	7:30	14:00	33

5.5 Result and Discussion

The selected ACO parameters were implemented in the experimental study over the obtained distribution company. The final optimized route network is shown in figure 7. It covers a total distance of 1030.07 km with the help of 11 heterogeneous vehicles to serve 45 customers. The sub-routes of the vehicles are presented in Table 7.

Table 7 *Presentation of the Sub-Routes of the Vehicles*

Vehicle Number	Distance Traveled (km)	Sub-Route
1	32.12	0 → 5 → 39 → 28 → 0
2	40.37	0 → 34 → 8 → 11 → 18 → 19 → 0
3	41.47	0 → 24 → 42 → 27 → 26 → 23 → 0
4	56.14	0 → 4 → 3 → 14 → 0
5	127.51	0 → 30 → 1 → 33 → 35 → 17 → 0
6	78.87	0 → 15 → 36 → 40 → 0
7	85.41	0 → 45 → 29 → 6 → 13 → 0
8	152.75	0 → 22 → 21 → 10 → 32 → 0
9	96.76	0 → 43 → 9 → 44 → 0
10	121.15	0 → 2 → 20 → 25 → 38 → 0
11	89.64	0 → 7 → 41 → 37 → 0

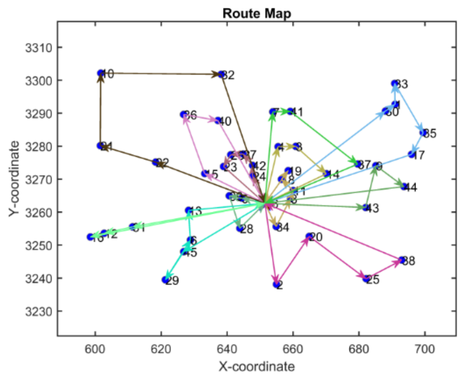

Figure 7 *Final Optimized Route Network*

From the experimental analysis, the results obtained are as follows:

- Total distance of optimal route: 1030.07 km
- Total traveling time by all the vehicles: 1653.92 min
- Average customer satisfaction: 49.55%
- Total fuel consumption: 85.11 L
- Total transportation cost: 205.72 £.

The convergence curve obtained with the selected parameter settings is shown in figure 8. The downward trend of the curve with iteration progress indicates that the ACO algorithm effectively improves the solution over time. However, tuning the ACO parameters may improve the efficiency or convergence time depending on the specific goals.

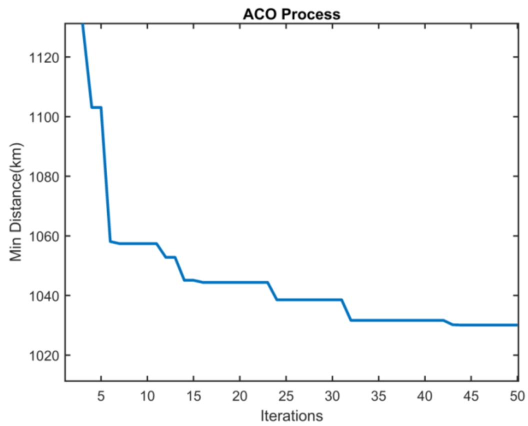

Figure 8 *Iteration Performance of the Final Route*

5.6 Managerial Implications

This study presents a decision-support model for complex transportation networks, offering a near-accurate approximation of objective function values. The model integrates economic, environmental, and social dimensions, aligning with the three pillars of sustainability. Therefore, this study will help logistics companies model their transportation network by selecting suitable objective functions depending on their customized requirements. The key findings and managerial implications are illustrated below.

- *Distance and Speed:* Significant correlations with FC and TC suggest these are critical factors. Managers can optimize routes, apply clustering strategies, and leverage technology to find efficient paths. Emphasizing consistent, higher average speeds (within safe limits) and implementing speed-monitoring systems can enhance fuel and cost efficiency.
- *Fuel price:* Despite marginal significance, fuel price remains a significant expense, influenced by market fluctuations. Managers should track price trends, consider alternative fuels, and explore bulk purchasing agreements to control fuel costs.
- *Driver wage:* While wage impacts on TC are minimal, aligning driver schedules and compensation with performance incentives can ***improve*** productivity and satisfaction without substantial cost increases.
- *Customer satisfaction:* The strong correlation between the importance degree and CS underscores the value of meeting core customer needs. Managers should prioritize timely deliveries, product condition, and other high-impact factors, regularly updating services based on customer feedback. Arrival time, though not highly significant alone, still contributes to CS and should be balanced with reliability and communication.

This model provides logistics companies with insights to refine routing, manage costs, and improve customer satisfaction, helping achieve more sustainable and efficient operations.

6. Conclusion and Future Research

The current study proposes a multi-objective sustainable vehicle routing problem with time windows consideration in a time-dependent scenario. It considered all three sustainability issues to reduce carbon emission and transportation costs and maximized customer satisfaction with the help of the ACO algorithm. Customer satisfaction is modelled as a generalized bell membership function that considers flexible time windows. Furthermore, in fuel consumption calculation, a variable part is considered due to changes in vehicle speeds in between.

The study contributed to both the theory of VRP study through the enrichment of the vehicle routing optimization model. It also contributed to the practicality of the VRP study by applying the proposed model to a case company. So, the study will help logistics companies to plan their own distribution routes to attain sustainable development. Still, there are some limitations to this study. However, some key areas for further research include integrating renewable energy sources for vehicle recharging, hybrid vehicle routing models, the impact of policy regulations on sustainable VRP solutions, etc.

7. References

1. Abdullahi, H., Reyes-Rubiano, L., Ouelhadj, D., Faulin, J. and Juan, A.A., (2021), ‘Modelling and multi-criteria analysis of the sustainability dimensions for the green vehicle routing problem’, European Journal of Operational Research, Vol.292 (1), 143-154.
2. Alba, E., Luque, G. and Nesmachnow, S., (2013), ‘Parallel metaheuristics: recent advances and new trends’, International Transactions in Operational Research, Vol.20 (1), 1-48.
3. Alinaghian, M. and Zamani, M., (2019), ‘A bi-objective fleet size and mix green inventory routing problem, model and solution method’, Soft Computing, Vol.23, 1375-1391.
4. Ashtineh, H. and Pishvaee, M.S., (2019), ‘Alternative fuel vehicle-routing problem: A life cycle analysis of transportation fuels’, Journal of Cleaner Production, Vol.219, 166-182.
5. Barth, M., Scora, G. and Younglove, T., (2004), ‘Modal emissions model for heavy-duty diesel vehicles’, Transportation Research Record, Vol.1880 (1), 10-20.
6. Behnamian, J., Ghadimi, M. and Farajiamiri, M., (2023), ‘Data mining-based firefly algorithm for green vehicle routing problem with heterogeneous fleet and refueling constraint’, Artificial Intelligence Review, Vol.56 (7), 6557-6589.
7. Cheng, C., Yang, P., Qi, M. and Rousseau, L.M., (2017), ‘Modeling a green inventory routing problem with a heterogeneous fleet’, Transportation Research Part E: Logistics and Transportation Review, Vol.97, 97-112.
8. Colorni, A., Dorigo, M. and Maniezzo, V., (1991), ‘Distributed optimization by ant colonies’, In Proceedings of the first European Conference on Artificial Life, Paris, France, Vol.142, 134-142.
9. Consoli, S. and Darby-Dowman, K., (2006), ‘Combinatorial optimization and metaheuristics’, Brunel University.
10. Dantzig, G.B. and Ramser, J.H., (1959), ‘The truck dispatching problem’, Management science, Vol.6 (1), 80-91.
11. Dorigo, M. and Di Caro, G., (1999), ‘Ant Colony Optimization: a New Meta-Heuristic’, In Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406), Vol.6 (1470-1477). IEEE.
12. Gülmez, B., Emmerich, M. and Fan, Y., (2024), ‘Multi-objective Optimization for Green Delivery Routing Problems with Flexible Time Windows’, Applied Artificial Intelligence, Vol.38 (1), 2325302.
13. Hooshmand, F. and MirHassani, S.A., (2019), ‘Time dependent green VRP with alternative fuel powered vehicles’, Energy Systems, Vol.10, 721-756.
14. Karakostas, P., Sifaleras, A. and Georgiadis, M.C., (2020) ‘Adaptive variable neighbourhood search solution methods for the fleet size and mix pollution location-inventory-routing problem’, Expert Systems with Applications, Vol.153, 113444.
15. Yongbo Li, Hamed Soleimani, Mostafa Zohal, (2019), ‘An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives’, Journal of Cleaner Production, Vol.227, 1161-1172,
16. Li, Y., Lim, M.K., Tan, Y., Lee, Y. and Tseng, M.L., (2020), ‘Sharing economy to improve routing for urban logistics distribution using electric vehicles’, Resources, Conservation and Recycling, Vol.153, 104585.
17. Li, Y., Lim, M.K., Xiong, W., Huang, X., Shi, Y. and Wang, S., (2024), ‘An electric vehicle routing model with charging stations consideration for sustainable logistics’, Industrial Management & Data Systems, Vol.124 (3), 1076-1106.
18. Lou, P., Zhou, Z., Zeng, Y. and Fan, C., (2024), ‘Vehicle routing problem with time windows and carbon emissions: a case study in logistics distribution’, Environmental Science and Pollution Research, Vol.31, 41600–41620.
19. Messaoud, E., El Idrissi, A.E.B. and Alaoui, A.E., (2018), ‘The green dynamic vehicle routing problem in sustainable transport’, In 2018 4th International Conference on Logistics Operations Management (GOL), 1-6. IEEE.
20. Niu, Y., Yang, Z., Chen, P. and Xiao, J., (2018a), ‘Optimizing the green open vehicle routing problem with time windows by minimizing comprehensive routing cost’, Journal of Cleaner Production, Vol.171, 962-971.
21. Niu, Y., Yang, Z., Chen, P. and Xiao, J., (2018b), ‘A Hybrid Tabu Search Algorithm for a Real-World Open Vehicle Routing Problem Involving Fuel Consumption Constraints’, Complexity, Vol.2018 (1), 5754908.
22. Praveen, V., Keerthika, P., Sivapriya, G., Sarankumar, A. and Bhasker, B., (2022), ‘Vehicle routing optimization problem: a study on capacitated vehicle routing problem’, Materials Today: Proceedings, Vol.64, 670-674.

23. Rabbani, M., Bosjin, S., Yazdanparast, R. and Saravi, N., (2018), 'A stochastic time-dependent green capacitated vehicle routing and scheduling problem with time window, resiliency and reliability: a case study', Decision Science Letters, Vol.7 (4), 381-394.
24. Ren, T., Luo, T., Jia, B., Yang, B., Wang, L. and Xing, L., (2023), 'Improved ant colony optimization for the vehicle routing problem with split pickup and split delivery', Swarm and Evolutionary Computation, Vol.77, 101228.
25. Shi, Y., Zhou, Y., Ye, W. and Zhao, Q.Q., (2020), 'A relative robust optimization for a vehicle routing problem with time-window and synchronized visits considering greenhouse gas emissions', Journal of Cleaner Production, Vol.275, 124112.
26. Solomon, M.M, (1987), 'Algorithms for the Vehicle Routing and Scheduling Problems With Time Window Constraints', Operational Research, Vol.35 (2), 254–265.
27. Yilmaz, M., (2015), 'Evaluation of total antioxidant capacity (TAS) by using fuzzy logic', British Journal of Mathematics & Computer Science, Vol.8 (6), 433-446.
28. Zarouk, Y., Mahdavi, I., Rezaeian, J. and Santos-Arteaga, F.J., (2022), 'A novel multi-objective green vehicle routing and scheduling model with stochastic demand, supply, and variable travel times', Computers & Operations Research, Vol.141, 105698.