International Journal of Innovative Computing, Information and Control
Volume **21**, Number **1**, February **2025**

ICIC International ©2025 ISSN 1349-4198
pp. **261–272**

GREEN LOGISTICS IN ONLINE RETAILING: LOW-CARBON TWO-ECHELON VEHICLE ROUTING PROBLEM (LC2EVRP) IN LARGE-SCALE ONLINE SUPERMARKETS

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Received May 2024; revised September 2024

Abstract. *Measuring the carbon emissions of logistics in online retailing is crucial for global decarbonization efforts. Large-scale online supermarkets now constitute a significant share of the entire online retail industry. To decrease the cost and carbon emission and examine their involvement in carbon trading in China, the paper presents a solution procedure for the low-carbon two-echelon vehicle routing problem (LC2EVRP) of online supermarkets. First, a mixed integer programming model is built for the LC2EVRP. Then, the paper analyzes the rules and inherent relations of the two stages of LC2EVRP. The pre-assignment genetic algorithm hybridized variable neighborhood search algorithm (PAGA-VNS) is built to address the LC2EVRP. Its pre-assignment customers are based on the principle of proximity and employ a neighborhood search strategy to perturbed assignment. Finally, with a real large-scale online supermarket as the background, numerical cases are constructed to demonstrate the efficiency of the solution algorithm.*
Keywords: Low-carbon, Two-echelon vehicle routing problem, Neighbourhood search algorithm, Genetic algorithm, Online supermarket

1. **Introduction.** Online retailing is immensely popular globally. In 2023, China's online retail sales hit 12.3 trillion yuan, driving a 32.1% growth in consumer goods retail [1]. As global efforts to reduce carbon emissions intensify, various industries, including China's logistics sector – responsible for about 9% of the nation's total emissions [2] – are increasingly engaging in carbon trading. In online retail, logistics are a major contributor to carbon emissions. Measuring these emissions is crucial for global decarbonization. Large-scale online supermarkets, quickly embraced by consumers, now make up a significant part of online retail. This study examines their logistics activities and involvement in carbon trading in China.

Large-scale online supermarkets, specializing in the sale of daily fast-moving consumer goods, differ from conventional online retailing. Given the large number of customers and the need for prompt deliveries, there is often a significant increase in delivery trips and travel distances resulting in a significant amount of carbon emissions. Integrating carbon trading mechanisms into online supermarket logistics to reduce carbon emissions presents a significant academic challenge. This study examines a two-echelon logistics network of large-scale online supermarkets, including depots, satellites, and customers, framed as

DOI: 10.24507/ijicic.21.01.261

a two-echelon vehicle routing problem (2EVRP). The vast order volumes and complex logistics in large online supermarkets make solving the 2EVRP challenging, especially when factoring in carbon emissions and customer satisfaction, requiring rapid solutions for large customer bases.

In addressing the large-scale online supermarket delivery problem under low-carbon constraints, this literature review comprehensively summarizes previous research from two key perspectives: 2EVRP and the two-echelon green vehicle routing problem (2EGVRP).

Research in the field of large-scale online supermarket logistics has predominantly focused on the development of optimization models for specific delivery process [3]. To address the limitations of single-echelon optimization, the 2EVRP emerges as a variation of the classical vehicle routing problem (VRP) [4]. Important resources in this field include a review covering over 60 articles on the 2EVRP [5]. Many studies have developed 2EVRP variants that enhance real-world applicability, especially in warehousing [6] and satellite [7] operations, providing valuable modeling references for this paper. In terms of solution algorithms, both exact and heuristic algorithms are used to solve the 2EVRP. The labeling algorithm and the branch-and-price algorithm are two widely used exact algorithms [8]. Due to the long computational times of exact algorithms for large-scale NP-hard problems, many studies now prefer using heuristic algorithms for faster resolution [9]. The experimental instances involve customer quantities ranging from 20 to 100.

The 2EGVRP [10] extends the 2EVRP by integrating additional environmental considerations [11] such as vehicle load, speed, road gradients, and traffic congestion. Previous research on the 2EGVRP has primarily focused on the objective function (mono- or multi-objective) [12] and vehicle fleet composition (homogeneous or heterogeneous) [13]. In this study focusing on large-scale online supermarkets, we pay particular attention to customer scale, which typically ranges from 50 to 200 in existing literature [14,15].

Research on 2EVRP offers insights into two-tiered mathematical modeling, while 2EGVRP analyzes the trade-off between low-carbon and economic goals. However, for large-scale online supermarkets, timely problem-solving is challenging due to brief decision times and high customer volume. Existing solutions are inadequate to accommodate its customer scale. For resolving green delivery challenges in large-scale online supermarkets and addressing issues with a massive customer base, this paper's specific research contributions are as follows.

1) Establishing a multi-objective low-carbon two-echelon vehicle routing problem (LC-2EVRP) model: We have integrated carbon trading into the model by considering the actual distribution network structure of online supermarkets and utilizing load-based fuel consumption formulas. In contrast to prior VRP studies in the online supermarket distribution domain, our research accounts for multi-tier distribution, load-dependent route selection, carbon emission trading mechanisms, and stricter time constraints to align with real-world scenarios. This has also enriched the theoretical research about carbon emissions in 2EGVRP.
2) Efficient large-scale solving method: To optimize this NP-hard model, we introduce a novel solution approach that efficiently addresses online supermarket logistics issues through alternating customer pre-assignment and route generation. We demonstrate the efficiency of our algorithm in solving large-scale online supermarket delivery problems under the context of carbon trading, as compared to prior algorithms. The proposed algorithm solves large-scale instances with 100-1000 customer locations within reasonable timeframes. In experiments with classic instances, the approach achieved an average reduction of 70% in computation time compared to other algorithms. While

PAGA-VNS reaches optimal values that are 5% to 20% higher, this is an acceptable trade-off given our goal of rapidly solving large-scale online supermarket logistics issues. Our focus is on generating feasible, near-optimal solutions quickly rather than strictly achieving the absolute optimal values.

Section 2 provides a comprehensive description of the LC2EVRP. Section 3 provides a comprehensive and detailed description of the algorithm. In Section 4, we compared the results obtained using our solution method with those from classical approaches found in the literature. We also conducted sensitivity analysis by altering parameters closely related to carbon emissions in the model. The last section wraps up the study and explores potential directions for future research.

2. Modeling Framework.

2.1. Problem description. In this paper, the 2EVRP for online supermarkets can be defined as follows. In the same area, a depot delivers products to multiple customers within a specified time frame using satellites. Each customer's demand must be met in full, and the orders cannot be subdivided for delivery from the satellite to the customer. The optimization objective is to fulfill order requirements while minimizing delivery time and the overall delivery cost. The schematic diagram of the problem is illustrated in Figure 1.

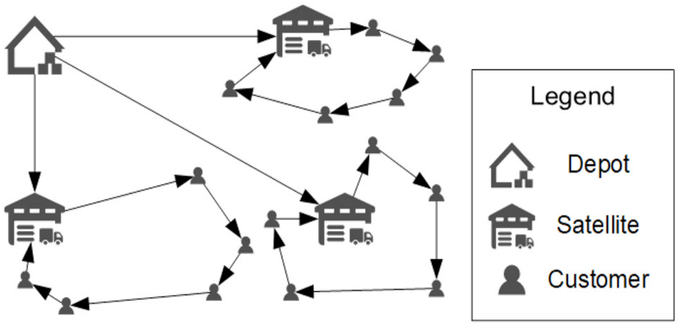

FIGURE 1. Two-echelon schematic diagram of online supermarket delivery problem

Model assumptions: 1) Customer site demands are predetermined and do not exceed vehicle capacities; 2) Each customer site is serviced by only one vehicle; 3) Both depot and satellite have unlimited vehicle availability without usage restrictions; 4) Satellites operate efficiently without waiting queues for arriving vehicles; 5) Distribution must utilize satellites, as direct routes from the depot to customer sites are prohibited; 6) Each vehicle departs from a single starting point, completes its tasks, and returns there to await further allocation; 7) Similar vehicles are used within each network tier.

2.2. Notations. The sets include depots (D), candidate satellites (S), and candidate customers (C), with respective vehicles classified into first echelon (V_1) and second echelon (V_2). Each depot or satellite has a capacity N_i, $i \in D \cup S$, and the vehicles have defined capacities C_1 and C_2 for the first and second echelons. The vehicles' operational speeds are denoted by k_1 and k_2. Operational costs are represented by fixed costs f_v and f_w for the first and second echelon vehicles. Distance between arc (i, j) d_{ij}, $i, j \in D \cup S \cup C$ and demand of customers D_j, $j \in S$ are also detailed. Decision variables x_{ijv} and y_{ijw} are binary, indicating the traversal of arcs by vehicles $v \in V_1$ and $w \in V_2$. The quantities of freight transported along these arcs are Q_{ijv} and Q_{ijw}. The logistics model also incorporates environmental considerations such as carbon quotas Q, emissions per unit of fuel

E_f, price per unit of fuel P_f, and carbon trading price per unit of carbon emissions P_c. Additional parameters include internal engine resistance k; engine operational speed N_e; engine displacement V; vehicle curb weight μ; fuel-to-air mass ratio ξ; heating value of diesel fuel κ; drive train efficiency ε; diesel engine efficiency ω; aerodynamic drag coefficient C_d; rolling resistance coefficient C_r; frontal surface area A; air density ρ; conversion factor for emissions ψ; gravitational constant g; road angle φ.

2.3. **Objective function formulation.** The objective function established in this paper primarily consists of three components: vehicle fixed costs C_{fix}, carbon emission costs C_e, and delivery time-related costs C_n. As represented in Equation (1), C_{fix} encompasses expenses such as daily maintenance and repair costs of trucks, driver wages, and other overhead costs that are independent of the actual traveling distances.

$$C_{fix} = \sum_{i\in D}\sum_{j\in S}\sum_{v\in V_1} x_{ijv} f_v + \sum_{i\in S}\sum_{j\in C}\sum_{w\in V_2} y_{ijw} f_w \tag{1}$$

The comprehensive modal emission model [16] is employed to compute the fuel consumption, denoted as F. To elucidate the critical factors of route decision and speed involved, specific variables in the fuel consumption formula are consolidated. The fuel consumption formula is represented as Equation (2). Among them, $\mu_1 = \lambda k N_e V$, $\mu_2 = \lambda\gamma\beta$, $\mu_3 = \lambda\gamma\alpha$, $\lambda = \frac{\xi}{\kappa\psi}$, $\gamma = \frac{1}{1000\varepsilon\omega}$, $\beta = 0.5 C_d A \rho$, $\alpha = g\sin\varphi + gC_r\cos\varphi$. Following this, the fuel consumption is employed to evaluate both the fuel cost in Equation (3) and the carbon emission cost in Equation (4).

$$\begin{aligned} F = {} & \mu_1 \sum_{i\in D\cup S}\sum_{j\in D\cup S}\sum_{v\in V_1} x_{ijv}\frac{d_{ij}}{k_1} + \mu_1' \sum_{i\in S\cup C}\sum_{j\in S\cup C}\sum_{w\in V_2} y_{ijw}\frac{d_{ij}}{k_2} \\ & + \mu_2 \sum_{i\in D\cup S}\sum_{j\in D\cup S}\sum_{v\in V_1} x_{ijv} d_{ij} (k_1)^2 + \mu_2' \sum_{i\in S\cup C}\sum_{j\in S\cup C}\sum_{w\in V_2} y_{ijw} d_{ij} (k_1)^2 \\ & + \mu_3 \sum_{i\in D\cup S}\sum_{j\in D\cup S}\sum_{v\in V_1} x_{ijv} d_{ij} (\mu + Q_{ijv}) + \mu_3' \sum_{i\in S\cup C}\sum_{j\in S\cup C}\sum_{w\in V_2} y_{ijw} d_{ij} (\mu + Q_{ijw}) \end{aligned} \tag{2}$$

$$C_{fuel} = P_f F \tag{3}$$

$$C_e = P_c(E_f F - Q) + C_{fuel} \tag{4}$$

Equation (5) defines the total waiting time cost as the sum of each customer's waiting time multiplied by the time cost coefficient η. This coefficient converts time into cost, ensuring dimensional consistency within the objective function. In the formula, $time_i$ represents the total travel duration from the depot to customer location i, determined by the customer delivery sequence and vehicle speed. The variable n denotes the total number of customers.

$$C_n = \eta \sum_{i=1}^{n} time_i \tag{5}$$

2.4. **Modeling LC2EVRP routes.** The mathematical model of this problem can be expressed as follows.

$$\min C_{fix} + C_e + C_n \tag{6}$$

$$\sum_{j\in D\cup S} x_{ijv} Q_{ijv} \le C_1, \quad \forall i \in D, \forall v \in V_1 \tag{7}$$

$$\sum_{j\in S\cup C} y_{ijw} Q_{ijw} \le C_2, \quad \forall i \in S, \forall w \in V_2 \tag{8}$$

$$\sum_{v\in V_1}\sum_{j\in D\cup S} x_{ijv}Q_{ijv} \le N_i, \quad \forall i \in D \cup S \tag{9}$$

$$\sum_{w\in V_2}\sum_{j\in S\cup C} y_{ijw}Q_{ijw} \le N_i, \quad \forall i \in S \tag{10}$$

$$\sum_{i\in D}\sum_{j\in D\cup S}\sum_{v\in V_1} x_{ijv}Q_{ijv} = \sum_{i\in S}\sum_{j\in S\cup C}\sum_{w\in V_2} y_{ijw}Q_{ijw} = \sum_{j\in C} D_j \tag{11}$$

$$\sum_{i\in S}\sum_{j\in S\cup C} y_{ijw}Q_{ijw} = \sum_{i\in S\cup C}\sum_{j\in S\cup C} y_{ijw}D_j, \quad \forall w \in V_2 \tag{12}$$

$$\sum_{i\in S\cup C}\sum_{w\in V_2} y_{ijw} = 1, \quad \forall j \in C \tag{13}$$

$$\sum_{i\in D, j\in D\cup S} x_{ijv} \le 1, \quad \forall v \in V_1 \tag{14}$$

$$\sum_{i\in S, j\in S\cup C} y_{ijw} \le 1, \quad \forall w \in V_2 \tag{15}$$

$$\sum_{i\in S'}\sum_{j\in S'} x_{ijv} \le |S'| - 1, \quad \forall v \in V_1,\, S' \subseteq S,\, |S'| \ge 2 \tag{16}$$

$$\sum_{i\in C'}\sum_{j\in C'} y_{ijw} \le |C'| - 1, \quad \forall w \in V_2,\, C' \subseteq C,\, |C'| \ge 2 \tag{17}$$

$$\sum_{w\in V_2} y_{ijw} = 0, \quad i, j \in S \tag{18}$$

$$\sum_{i\in D\cup S}\sum_{v\in V_1} x_{ijv}Q_{ijv} - \sum_{i\in D\cup S}\sum_{v\in V_1} x_{jiv}Q_{jiv} = \sum_{i\in S\cup C}\sum_{w\in V_2} y_{ijw}Q_{jiw}, \quad \forall j \in S \tag{19}$$

$$\sum_{i\in S\cup C}\sum_{w\in V_2} y_{ijw}Q_{ijw} - \sum_{i\in S\cup C}\sum_{w\in V_2} y_{ijw}Q_{jiw} = D_j, \quad \forall j \in C \tag{20}$$

Constraints (6) minimize fixed, carbon emission, and time costs. Constraints (7) and (8) ensure vehicles do not exceed weight capacities. Constraints (9) and (10) protect depot and satellite storage limits. Constraint (11) guarantees all secondary network customer orders are fulfilled. Constraint (12) aligns unloading volumes with customer demands in the secondary echelon. Constraint (13) stipulates each customer is visited once. Constraints (14) and (15) ensure that each vehicle departs from a single starting point. Constraints (16) and (17) eliminate sub-tours and ensure vehicles return to origin after deliveries. Constraint (18) forbids satellite transshipment. Constraints (19) and (20) balance goods flow in primary and secondary networks.

3. **Pre-Assignment Genetic Algorithm Hybridized Variable Neighborhood Search Algorithm (PAGA-VNS) for LC2EVRP.** To efficiently and effectively address the LC2EVRP, this study proposes an alternating approach that combines a customer pre-assignment method with a genetic algorithm hybridized variable neighborhood search algorithm. This method can greatly reduce the number of feasible solutions and thus the scale of solution space of the LC2EVRP while ensuring results are not trapped in local optima.

Specifically, customer pre-assignment involves allocating customers to appropriate satellites based on specific rules. Once the allocation is completed, the entire LC2EVRP is decomposed into several one-echelon VRPs, including the routing problem from each satellite to its corresponding customers and a routing problem from the depot to the satellites. Moreover, to avoid the potential issue of getting trapped in a local optimum by performing customer assignment only once, a perturbation step of customer assignment is introduced into the entire solution process. The implementation of perturbation in customer assignment enables variable neighborhood search and reduces the risk of converging to suboptimal solutions. The algorithm flow is shown in Figure 2.

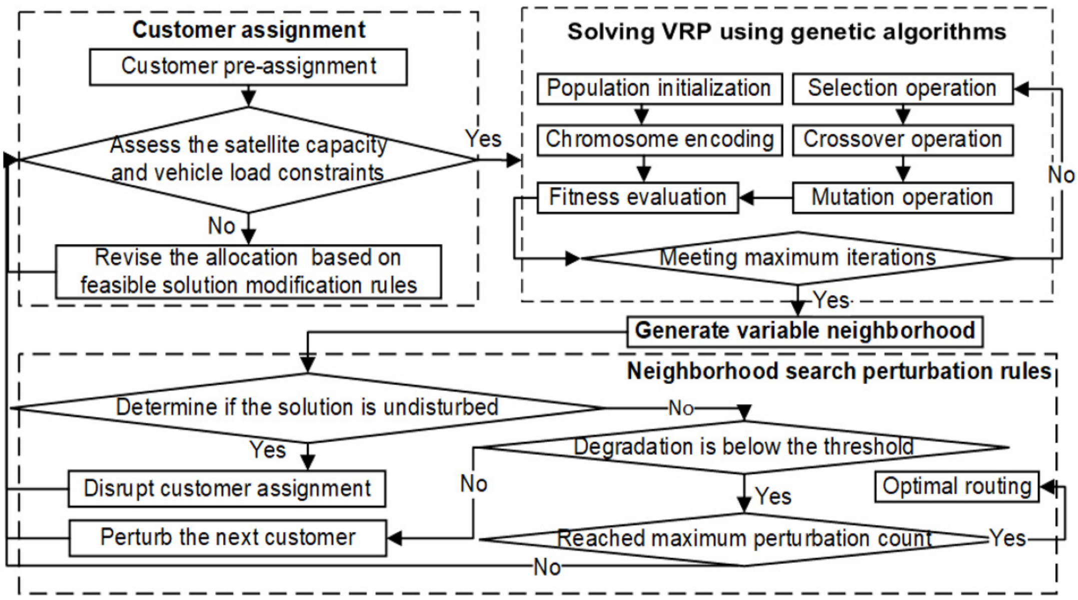

FIGURE 2. Schematic representation of the algorithm for the LC2EVRP

3.1. **Initial customer assignment.** The customer pre-assignment module is designed to allocate customers to the nearest satellites while ensuring that customer demand does not exceed satellite capacity. Employing a strategy that prioritizes the allocation of high-demand customers serves to reduce instances of violating satellite capacity constraints, thereby enhancing the efficiency of the allocation process. The process involves sorting customers by demand, assigning each to the nearest satellite, and checking for capacity and load restrictions. If violations occur, reassignment to the next nearest one occurs until a suitable match is found.

3.2. **Neighborhood search perturbation rules.** The customer assignment method, combined with genetic algorithms (GA), facilitates globally feasible routing but may limit reaching the optimal solution due to initial assignments. To avoid local optima, we introduce a perturbation algorithm that uses variable neighborhood search strategy, altering one customer at a time to explore new allocations. After perturbing an assignment, we check for compliance with satellite capacity, workload balance, and vehicle load constraints. If not met, the process halts, and a new assignment is explored. Otherwise, we assess the objective function value. The search stops if the solution worsens beyond a set threshold δ compared to the best solution. If deterioration is within δ, we perturb another customer and continue the search for an improved solution.

The specific rules for generating the local neighborhood during the perturbation process are as follows. Firstly, the distances between each customer and the assigned satellites are computed. Subsequently, the distances between each customer and the nearest unassigned satellite are calculated. The difference between these two distances is then computed, and the differences for all customers are sorted in ascending order to obtain a neighborhood ranking table. Within the perturbation algorithm, neighbors are searched sequentially according to the order in the neighborhood ranking table. The generation of perturbed solutions is based on the neighborhood ranking table, involving the reassignment of the nearest customer, not yet allocated to a satellite, to that satellite.

4. **Computational Experiments.** The PAGA-VNS described in this paper was coded in MATLAB and ran on a machine equipped with a 1.60 GHz Intel Core TM i5-8250U processor under the Windows 10 operating system.

4.1. **Validation of the algorithm for solving LC2EVRP.** For the experiments, we utilized the widely recognized datasets [4]. However, the existing instances only encompass 50 customers. To address large-scale scenarios, we randomly generated 1000 customer instances. Table 1 presents the parameters for vehicle fleets in the first and second tiers of the network, derived from both classic literature [17] and empirical research on actual vehicles used by typical logistics companies in Beijing, China. The remaining parameters relevant to the LC2EVRP model objectives are set as follows: $N_i = 50$ t, $P_f = 7$ CNY/L, $E_f = 2.25$ kg/L, $P_c = 30$ CNY/L, $Q = 0$ kg, $\eta = 30$, $k_1 = 100$ km/h, $k_2 = 60$ km/h. We set the carbon price at 30 CNY/L, which is aligned with the relatively stable carbon trading price in China during 2018, as referenced by the official China carbon trading website. Additionally, since not considering the impact of carbon quotas on routing, the carbon quota is initially set to zero, meaning that all carbon emissions incur costs for the company. The solution results and computation times are presented in Table 2.

TABLE 1. Vehicle parameters

First-echelon vehicle parameters				Second-echelon vehicle parameters			
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
k	0.2 kJ/rev/L	ω	0.9	k	0.2 kJ/rev/L	ω	0.9
N_e	33 km/h	C_d	0.7	N_e	45 km/h	C_d	0.8
V	5 L	C_r	0.01	V	9 L	C_r	0.02
μ	8000	A	3.912 m^2	μ	2500	A	12.84 m^2
ξ	1	ρ	1.2041	ξ	1	ρ	1.2041
κ	44 kJ/kg	g	9.81 m/s^2	κ	102 kJ/kg	g	9.81 m/s^2
ψ	737 g/L	φ	0	ψ	737 g/L	φ	0
ε	0.4	f_v	500 CNY	ε	0.6	f_w	600 CNY

TABLE 2. Large-scale customer algorithmic results

Scale	100	200	300	400	500
Comp. time (s)	27.35	51.6	75.47	116.75	118.04
Final solution	17903.09	54060.57	111943.94	180851.98	280178.44
Scale	600	700	800	900	1000
Comp. time (s)	135.59	148.9	172.74	188.15	270.9
Final solution	366663.98	543093.42	650469.89	867846.24	1061695.85

Table 2 demonstrates the proposed method scales efficiently as the number of customers increases. Computational time grows from 27 seconds for 100 customers to 270 seconds for 1000, reflecting the greater complexity of solving larger scales model. In terms of solution quality, the cost of the optimal route rises significantly, from 17903 for 100 customers to 1061695 for 1000, underscoring the challenges of larger logistics networks.

Despite this growth in both computational time and solution cost, the method consistently provides results within reasonable timeframes, even for the largest instances. This highlights the algorithm's efficiency and suitability for real-world urban logistics, where rapidly generating near-optimal solutions for up to 1000 customer locations is crucial for operational success. The experimental outcomes affirm the method's capability to handle complex, large-scale logistics scenarios effectively.

4.2. **Validating the efficiency of the PAGA-VNS in 2EVRP.** To assess the effectiveness of our algorithm for similar problems, we compared it against established algorithms like the math-based heuristic (MBH) [18], adaptive genetic algorithm (AGA), and PAGA-VNS using 2EVRP benchmark instances [4,19]. As shown in Figure 3, our algorithm cuts solution time by an average of 70%, especially in large-scale scenarios, outperforming traditional approaches. While PAGA-VNS reaches optimal values 5% to 20% higher, previous algorithms were limited to smaller customer bases (20-50), unsuitable for our large-scale study. Results are detailed in Table 3, with "CT" for computing time and "RC" for route cost.

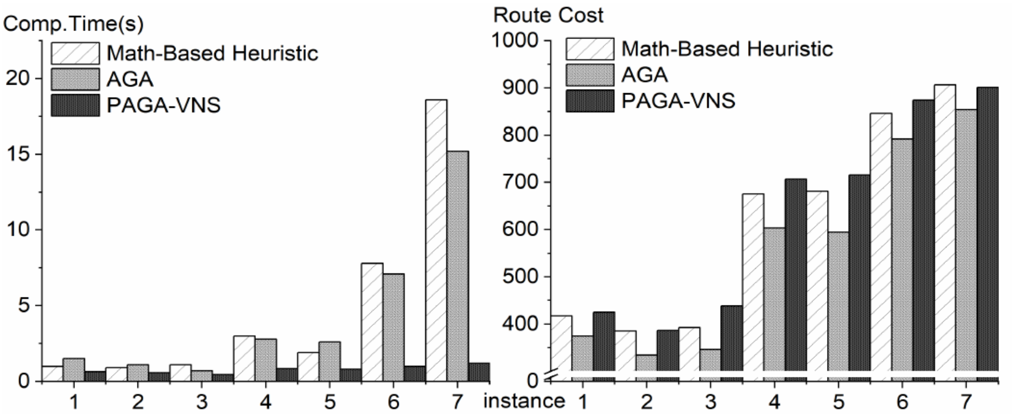

FIGURE 3. Solution times and route cost of different algorithms

TABLE 3. Algorithm comparison for classic case results

Instances	d	s	c	MBH		AGA		PAGA-VNS	
				CT	RC	CT	RC	CT	RC
E-n22-k4-s06-17	1	2	21	1	417.07	1.5	374.81	**0.64**	424.91
E-n22-k4-s08-14	1	2	21	0.9	384.96	1.1	333.85	**0.57**	386.42
E-n22-k4-s12-16	1	2	21	1.1	392.78	0.7	346.31	**0.46**	438.52
E-n33-k4-s16-22	1	2	32	3	675.36	2.8	603.57	**0.84**	706.93
E-n33-k4-s22-26	1	2	32	1.9	680.9	2.6	594.48	**0.8**	715.18
E-n51-k5-s39-41	1	2	50	7.8	845.94	7.1	791.56	**0.99**	873.78
E-n51-k5-s40-43	1	2	50	18.6	906.68	15.2	854.14	**1.2**	901.3
random	1	2	200	–	–	–	–	31.63	7057.28
random	1	2	400	–	–	–	–	58.37	14177.1
random	1	2	600	–	–	–	–	88.04	22622.75
random	1	2	800	–	–	–	–	113.35	29495.32
random	1	2	1000	–	–	–	–	137.7	38925.29

4.3. **Investigation of carbon emission factors in the LC2EVRP model.**

4.3.1. *Carbon quota and carbon price.* This experiment section examines how variations in carbon quota and trading price impact distribution decisions, key factors in carbon emissions costs. With carbon emissions at roughly 40 kg under a 0-carbon quota scenario, the quota is set between 0 to 50 kg. Table 4 displays changes in carbon emissions and costs across different trading mechanisms. Location data for examples comes from E-n51-k5-s40-43, providing a consistent analysis foundation. Vehicle speeds for the first and second echelons are set at 60 km/h and 30 km/h, based on road type. The results indicate that variations in carbon quotas and prices minimally affect route decisions, as distances and demand among customer locations in classic instances are relatively uniform. This occurs because, in classic cases, distances and demand across customer locations are evenly distributed. Consequently, critical factors such as travel distances and vehicle load, which significantly influence carbon emissions, do not undergo substantial optimization due to route decisions. The paper next examines how different vehicle speeds in two-echelon systems can reduce carbon emissions. Additionally, as carbon prices and quotas rise, emission costs decrease, allowing companies to profit by selling unused quotas at market prices, resulting in negative carbon costs.

Table 4. Carbon emissions (CE) and costs (C) at different carbon prices and quotas

Q (kg) / P_c (CNY/L)	0		10		20		30		40		50	
	CE	C	CE	C	CE	C	CE	C	CE	C	CE	C
$P_c = 30$	43	1315	41	939	43	703	42	370	42	87	43	−205
$P_c = 50$	44	2218	42	1647	44	1211	43	699	44	214	42	−354
$P_c = 70$	43	3056	43	2320	43	1678	42	872	43	254	43	−436

4.3.2. *Two-echelon variable speed strategies and their impact on carbon emission costs.* Experimenting with different vehicle speeds in the two echelons addresses two main issues. Firstly, warehouses often lie on city outskirts requiring larger, faster vehicles for highway travel, while deliveries within urban centers use smaller, slower vehicles. Secondly, vehicle speed directly affects carbon emissions, with higher speeds increasing fuel consumption and emissions, and lower speeds decreasing them. These experiments help balance delivery efficiency and environmental impact. Vehicle speeds are set at 30 to 80 km/h for urban areas and 60 to 10 km/h on highways. The remaining parameters are set as follows: $P_c = 30$ CNY/L, $Q = 0$ kg.

The comprehensive mode emissions model suggests optimal fuel consumption at 30 km/h [20], but real constraints necessitate higher speeds. Table 5 confirms at higher speeds increase carbon emissions, pointing to slower speeds as an emission-reduction strategy,

Table 5. Carbon emissions under two-echelon variable speeds

k_1 \ k_2	30	40	50	60	70	80
60	40.1572	67.2289	102.0279	141.6499	191.8163	269.8602
70	42.2794	70.0061	105.9208	144.2146	198.6197	271.4605
80	43.3585	71.2107	109.022	145.5015	198.7487	275.1772
90	46.6167	72.4425	109.0248	148.1533	205.3256	280.2605
100	49.3066	74.9927	112.8075	153.2057	210.6133	284.419

TABLE 6. Customer satisfaction and vehicle speed

k_1, k_2 \ η	5	10	20	30	40	50	60	70
$60, 30$	6026*	6580	7696	8762	10349	10974	12043	12974
$70, 40$	6064	6550*	7459*	8257	9256	10099	10674	11886
$80, 50$	6530	6777	7477	8135*	8855*	9981	10535	11489
$90, 60$	6921	7666	7797	8356	8991	9643*	9984*	10638
$100, 70$	7631	7666	8060	8621	9048	9798	10381	10242*
$110, 80$	8005	8156	8714	9142	9566	9976	10450	10919

*: Under identical time-related cost factors η, the scenario with the lowest cost.

albeit at the cost of delivery time. The investigation into the impact of speed variations on total costs, considering different time-related cost factors η, is detailed in Table 6. As η increases, the speed necessary to achieve the optimal objective function also rises, resulting in higher carbon emissions at these speeds. This presents a dilemma for large online supermarkets in balancing emission reductions with customer satisfaction, necessitating managerial adjustments based on corporate priorities and customer expectations.

5. **Conclusions.** This paper investigates the LC2EVRP in the logistics network of a large-scale online supermarket, comprising depot, satellites, and customers. In this context, we have explored a variant of the 2EVRP, known as LC2EVRP, which introduces constraints related to carbon trading costs and customer waiting times.

The proposed PAGA-VNS, as demonstrated through computational experiments, exhibits significant advantages in computation time when confronted with large-scale problems. Additionally, an investigation into carbon pricing, quota settings in carbon trading policies, and the influence of different vehicle speeds on the model's optimal solution is conducted. Numerical experiments reveal a delicate balance between customer satisfaction, economic costs, and environmental conservation. Sensitivity analysis provides valuable insights, indicating that, in the absence of considering customer satisfaction, the optimal solution in the LC2EVRP model is not highly sensitive to the current moderately carbon trading environment. These research findings hold the potential to offer practical management insights for large online supermarket companies, governmental institutions, and customers.

A meaningful direction for future research is to investigate the variable-speed vehicle routing problem, aiming to make decisions regarding vehicle speeds that strike a balance between higher customer satisfaction and lower carbon emissions. Another relevant research avenue involves further establishing rational carbon control mechanisms that incentivize companies to reduce carbon emissions.

Acknowledgment. This work was supported by the program of the National Natural Science Foundation of China (72071078, 72101230, 72394374) and China Postdoctoral Science Foundation (2023M730166).

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