The Novel Strategy of Differential Evolution for Multi-Fleet Size and Vehicle Routing Problem in Logistics Service Providers

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Abstract. This paper focuses on determining routes for logistics service providers from distribution centers to customers with the objective of minimizing the total costs. Despite being a particular example of the vehicle routing problem (VRP), this issue is more complicated than the basic VRP, especially since each vehicle contains heterogeneous capacity. This paper presents the novel strategy of Differential Evolution (NSDE) to solve multi-fleet size and Vehicle Routing Problems in logistics service providers (MFSVRP-LSP). Our work aims to minimize distance. The validation of NSDE (i.e., DE, NSDE1, NSDE2, NSDE3, NSDE4) was conducted by the comparison of the current practice. The relative improvement (RI) between the standard DE and the NSDE1, NSDE2, NSDE3, and NSDE4 in the MFSVRP-LSP. The NSDE4 outperformed the standard DE follow by my report. Furthermore, our suggested technique can be used for similar logistics in Thailand.

Keywords: Logistics Service Providers, Vehicle Routing Problem, Differential Evolution, Sustainable logistics, time window

1 Introduction

Today, as international trade continues to grow, logistics plays a crucial role in moving goods around the world. This demand increases as businesses expand their operations. The global transport services market is expected to grow at a rate of 9.9% annually, from $6,559.71 billion in 2021 to $7,210.41 billion in 2022. With a growth rate of 9.6% per year, it's predicted to reach $10,394.13 billion by 2026 [1]. In Thailand, Logistics Service Providers (LSPs) are

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vital. They move goods, manage supply chains, and provide many logistics services to various businesses. Examples include E-commerce Logistics, Cold Chain Logistics, Freight Forwarding, Third-Party Logistics (3PL), and Express Delivery Services. Each of these cases shows the unique needs of different industries and the importance of LSPs in keeping operations running smoothly. Good management of logistics providers is essential because it influences transportation costs[2]. A common challenge for LSPs in Thailand and globally is the Vehicle Routing Problem (VRP). This is about figuring out the best routes and schedules for a fleet of vehicles to deliver goods to customers. The goal is to reduce costs, meet specific requirements, and ensure smooth operations across the supply chain [3].

In Thailand, VRP is particularly important due to its unique geography, diverse transportation infrastructure, and operational limits. Factors such as road conditions, traffic patterns, regulations, and others affect routing decisions for Thai LSPs. Current academic research on Thai LSPs offers valuable insights into how they operate, their strategies, and the challenges they face. This research helps increase our understanding, informs industry practices, and supports policies promoting sustainable growth of Thailand's logistics sector [4]. This paper focuses on reducing fuel consumption costs. Its main contribution is the development of a mutation equation for each algorithm (i.e., DE, NSDE1, NSDE2, NSDE3, NSDE4). These equations will be used in Thailand's logistics providers.

This paper is organized as follows: In Section 2, a review of the related literature is presented. Section 3 introduces the problem statement and formulation of MFSVRP-LSP and encoding step for the MFSVRP-LSP. The DE and NSDE1-4 are presented in Section 4. Finally, the computational results are discussed and our results and conclusion is detailed in Section 5.

2 Literature review

2.1 Differential Evolution Algorithm

The application of advanced algorithms in logistics management and operations scheduling has demonstrated considerable potential in addressing industry-specific challenges.

Moonsri et al. (2015) [5] utilized a Differential Evolution (DE) algorithm to address a complex scheduling problem in the hard disk drive industry. The DE algorithm yielded high improvements in the Makespan, enhancing production efficiency, and reducing delays. In 2015, Sethanan and Pitakaso [6] addressed a variant of the vehicle routing problem (VRP) in the dairy industry. They developed a modified DE algorithm to minimize total costs and truck usage, showing considerable improvements. Later, Moonsri et al. (2022) [7] proposed a Hybrid and Self-Adaptive DE algorithm (HSADE) to solve the multi-depot vehicle routing problem in Thailand's egg distribution. HSADE demonstrated an average total cost improvement of 14.13%, suggesting potential efficiency enhancements in agricultural logistics. Lastly, Moonsri et al. (2022) [8] utilized an enhanced DE algorithm, called Re-initialization Differential Evolution (RI-DE), for logistics planning in Thailand's poultry industry. The algorithm outperformed standard ones in terms of cost efficiency and computational time.

Collectively, these studies demonstrate the value of advanced algorithms in improving operational efficiency in diverse industries, with future research needed to explore their wider adaptability.

2.2 Vehicle Routing Problem

The Heterogeneous Vehicle Routing Problem (HVRP) and its numerous variants have been extensively investigated over the years. This literature review chronologically collates these studies, highlighting their main findings, the algorithms used, and areas of potential future research.

Koc et al. (2015) [9] formulated a unified hybrid evolutionary algorithm (HEA) for different variations of the HVRP. The HEA integrated several metaheuristics with innovative strategies for solution intensification and diversification. Tests proved the HEA's effectiveness across multiple HVRP types. Lai et al. (2015) [10] examined a time-constrained HVRP on a multigraph, introducing the concept of parallel arcs. The authors developed a tabu search heuristic and a polynomial-time heuristic procedure for arc selection, which effectively managed this complexity. Wu et al. (2015) [11] tackled a specific HVRP variant considering backhauls, mixed-load, and time windows. They developed a multi-attribute Label-based Ant Colony System (LACS) algorithm that demonstrated that a heterogeneous fleet is more cost-efficient under variable customer demands. Meliani et al. (2019) [12] presented a Tabu search (TS) heuristic for the HFVRP, incorporating novel procedures and an adaptive memory algorithm. Though effective for small-sized instances, the heuristic underperformed for larger ones. Queiroge et al. (2021) [13] proposed a partial optimization metaheuristic, POPMUSIC, for the capacitated vehicle routing problem (CVRP). The approach consistently enhanced initial solutions from the their' s problem, exhibiting scalability and adaptability to other routing problems.

Maxino et al. (2022) [14] presented an Adaptive Iterated Local Search (AILS) heuristic for the HFVRP. Experiments confirmed that the AILS outperformed other leading metaheuristics usually and suggested further application of this approach to larger HVRP instances. Stavropoulou (2022) [15] explored the Consistent Vehicle Routing Problem (ConVRP) with a heterogeneous fleet, introducing a hierarchical Tabu Search (HTS) framework. The study demonstrated the framework's effectiveness and provided insights on the cost implications of service consistency. Sarbijan and Behnamian (2022) [16] studied the multi-fleet feeder vehicle routing problem (Multi-Fleet FVRP). They proposed a particle swarm optimization-simulated annealing (PSO-SA) hybrid algorithm, proving to be more time-efficient while providing satisfactory solution quality. Bezerra et al. (2023) [17] addressed the Multi-Depot Vehicle Routing Problem with Time Windows, introducing a Smart General Variable Neighborhood Search with Adaptive Local Search (SGVNSALS) algorithm. The SGVNSALS outperformed other algorithms in minimizing vehicle use, though it led to an increase in total distance traveled.

These studies collectively enhance the understanding of the HVRP, presenting novel algorithmic solutions that extend its applicability, efficiency, and effectiveness in various logistics and distribution scenarios. They underline the need for continuous exploration of innovative algorithms and problem variants, with future research potentially focusing on real-world applications and dynamic factors like changing customer demands and delays. A summary of previous studies concerning the HVRP is presented in Table 1.

Table 1. Overview of Previous Research on HVRP.

Author	Year	Solution Approach
Koc et al.	2015	Hybrid Evolutionary Algorithm (HEA)
Lai et al.	2015	Tabu Search (TS) Heuristic
Wu et al.	2015	Label-based Ant Colony System (LACS)
Meliani et al.	2019	Tabu Search (TS) Heuristic
Queiroge et al.	2021	Partial Optimization Metaheuristic (POPMUSIC)
Maxino et al.	2022	Adaptive Iterated Local Search (AILS) Heuristic
Stavropoulou	2022	Hierarchical Tabu Search (HTS)
Sarbijan and Behnamian	2022	Particle Swarm Optimization-Simulated Annealing (PSO-SA) Hybrid Algorithm
Bezerra et al.	2023	Smart General Variable Neighborhood Search with Adaptive Local Search (SGVNSALS) Algorithm.

3 Problem Statement

The current practice of logistics providers relying on the proximity of customers and the expertise of freight forwarders for transportation routing can lead to inefficiencies and suboptimal routing decisions. Logistics providers traditionally prioritize serving customers based on proximity, focusing on those located closest to each other such as nearest neighbour heuristic. This approach may overlook other critical factors such as delivery time windows, traffic conditions, vehicle capacities, and overall route optimization. logistics providers may struggle to optimize routes, allocate resources effectively, and ensure timely deliveries. Transportation problems are shown in Fig. 1.

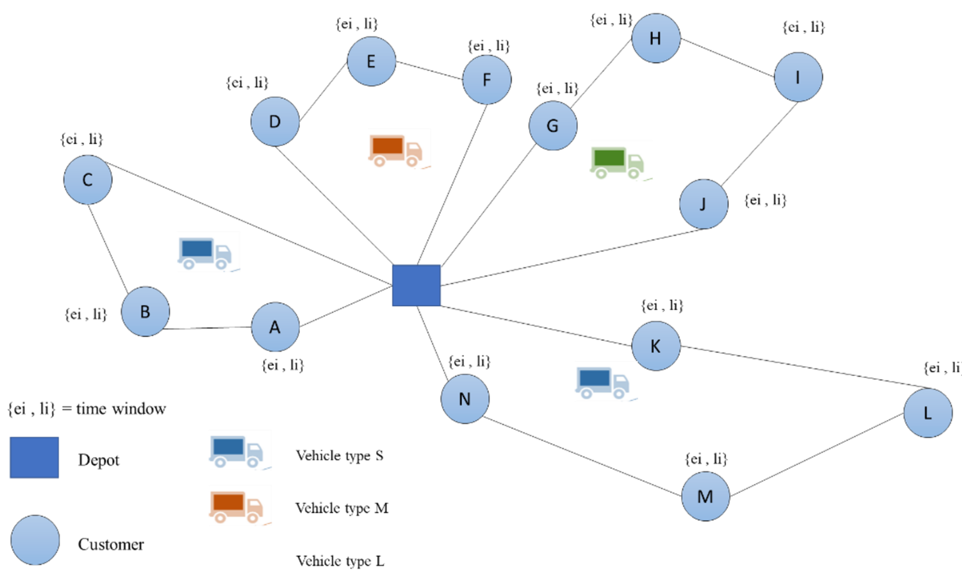

Fig. 1. This is diagram problem for the MFSVRP-LSP.

3.1 Nearest Neighbour Heuristic (NNH)

The nearest neighbour heuristic in transportation refers to a method commonly used to solve transportation problems, specifically in the context of the vehicle routing problem (VRP). In academic research, the nearest neighbour heuristic is studied and analyzed to understand its effectiveness and limitations in finding approximate solutions for transportation optimization. The nearest neighbour heuristic in transportation involves examining its algorithmic approach, performance, and impact on solution quality. Researchers investigate the heuristic's ability to construct initial routes or tour sequences by iteratively selecting the nearest unvisited location or customer from the current location. The traditional approach of logistics providers prioritizing customers based on proximity, where they focus on serving customers located closest to each other, can be considered a form of the nearest neighbour heuristic. The nearest neighbour heuristic is a simple algorithmic approach commonly used in solving transportation problems, including the Vehicle Routing Problem (VRP). In the context of logistics routing, the nearest neighbour heuristic involves selecting the nearest unvisited customer location from the current position and serving that customer next. By repeatedly applying this nearest neighbour selection process, logistics providers create a sequence of customer visits that is based on proximity.

3.2 Encoding Step

The encoding scheme in DE is straightforward. Each candidate solution, also known as an individual, is represented as a D-dimensional vector or the number of customers, where NP is the number of populations or the number of solutions. the encoding involves representing each candidate solution as a vector of real numbers between 0 to 1. Each component of the vector corresponds to a variable in the problem. (see Table 2)

Table 2 Encoding of all algorithms.

NP	Customer1	Customer2	Customer3	Customer4	Customer5
1	0.916	0.261	0.847	0.480	0.752
2	0.885	0.390	0.378	0.409	0.124
3	0.678	0.234	0.066	0.515	0.029
4	0.976	0.487	0.236	0.879	0.940
5	0.340	0.545	0.188	0.489	0.505

4 Research Methodology

4.1 Differential Evolution Algorithm

This research develops a Differential Evolution algorithm to solve a transportation problem [18]. (see Fig. 2.)

4.1.1 The Traditional DE

Initialization: Generate an initial population of candidate solutions. Each solution represents a possible assignment of customers to vehicles or routes. Randomly assign customers to vehicles while respecting the capacity constraints

Design an objective function that measures the quality of a solution based on the problem's objectives. In the case of a transportation problem, the objective function can be to minimize the total distance travelled.

Mutation: Implement the mutation process specific to the transportation problem. In this step, modify the candidate solutions by combining or perturbing their elements to create new candidate solutions. For example, you can swap customers between routes or perform random alterations in the assignment of customers to vehicles.

Crossover: Implement the crossover process, which combines information from multiple candidate solutions to generate new solutions. Determine how to exchange or combine elements from different solutions to create offspring solutions. The crossover process in a transportation problem may involve reassigning customers between different routes.

Selection: Select the best solutions from the parent population and the offspring population based on their fitness values (evaluated using the objective function). The selection process determines which solutions survive to the next generation.

Termination criteria: set termination criteria to determine when to stop the algorithm. This can be a maximum number of iterations or a predefined level of convergence. The pseudo code algorithm of differential evolution is shown in Table. 3.

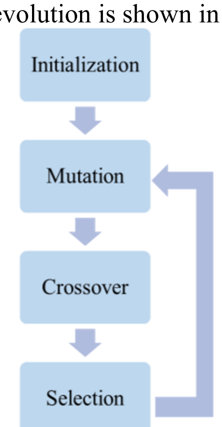

Fig. 2. Differential Evolution Process

The parameter of the research includes the number of the population define as 50 populations, the iteration of calculation is set to 200 iterations. Each iteration represents one cycle of the DE algorithm, where the population is evolved and updated based on the defined operators, the crossover rate is set to 0.8. A crossover operation combines genetic information from two parent solutions to create new offspring solutions. [18], the distance of each path is set to between 20 km to 70 km, and the number of customers is set to between 20 to 170.

4.1.2 The Novel Strategy of Differential Evolution 1-4 (NSDE1-4)

The novel strategy of Differential Evolution (DE) refers to a new approach or modification introduced to the standard DE algorithm in order to enhance its performance, overcome limitations, or address specific problem characteristics. The strategy can involve changes in the mutation, crossover, or selection processes, or a combination of these components.

Table 3 The pseudo code algorithm of Differential Evolution (DE)

Algorithm1: Traditional differential Evolution Algorithm

setting parameter
CR= 0.8
Generate the initial population of vectors in the D-dimensional search space
for k to iteration
    for i to number of populations
      random 3 vector: $X_1 \neq X_2 \neq X_3$

```
        generate mutant vector according to (1)
        V_i = X_1 + F(X_2 - X_3)                (1)
        for j to customer
              generate a trial vector U_i
              random vector = rand()
              if  random vector  < CR
                    U_ij = V_ij
              else
                    U_ij = X_ij
        end
        evaluate U_i
        if X_i > U_i
         X_i = U_i
        else
         X_i = X_i
      end
end
```

The mutant vector is generated using the equation below

DE/Best/1 [19]

$$V_i = X_{best} + F(X_{r1} - X_{r2}) \quad (2)$$

DE/Best/2 [19]

$$V_i = X_{best} + F(X_{r1} - X_{r2}) + F(X_{r3} - X_{r4}) \quad (3)$$

DE/rand to be best and current/2 [20]

$$V_i = X_{r1} + F(X_{best} - X_{r2} + X_{r3} - X_i) \quad (4)$$

DE/Best/3 [20]

$$V_i = X_{best} + F\,(X_{r2} - X_{r3} + X_{r4} - X_{r5} + X_{r6} - X_{r7}) \quad (5)$$

In this research develop the mutation equation. From Table 4. we can see that using the detail of each NSDE.

Table 4 Details of the Novel Strategy differential evolution (NSDE)

Define	Details mutation equation*				
	Eq. (1)	Eq. (2)	Eq. (3)	Eq. (4)	Eq. (5)
NSDE1	✓	✓			
NSDE2		✓	✓		
NSDE3			✓	✓	
NSDE4				✓	✓

***Note:** Random between equations in each iteration

4.2 Decoding Step

The process of decoding the problem through the Rank Order Value (ROV) method involves arranging the dimensions within the vector in ascending order. This sequenced arrangement subsequently determines the progression in which the vehicle serves the customers, a progression dictated by the respective ROV. Fig 3 presents an illustration of a customer sequence, generated using the ROV method.

1	2	3	4	5	6	7	8
0.59	0.24	0.25	0.2	0.19	0.75	0.38	0.41

5	4	2	3	7	8	1	6
0.19	0.2	0.24	0.25	0.38	0.41	0.59	0.75

Fig. 3. Rank Order Value (ROV) method

Vehicle capacity is selected through a randomization process. If a vehicle cannot accommodate more cargo than its available capacity, it must randomize the new vehicle and the new vehicle's capacity again. This method continues to randomize vehicle capacities until all customer demands are met. Figs. 4(A) and 4(B) illustrate this process of vehicle capacity randomization for each vector. Fig. 4. provides an example of vehicle capacity randomization. In this scenario, each customer requires 10 units of cargo, and the capacities of large, medium, and small vehicles are 40, 30, and 20 units, respectively.

Vehicle capacity randomization for vector i= 1

L				M			L
5	4	2	3	7	8	1	6
0.19	0.2	0.24	0.25	0.38	0.41	0.59	0.75

(a)

Vehicle capacity randomization for vector i= 2

S		S		L			
5	4	2	3	7	8	1	6
0.19	0.2	0.24	0.25	0.38	0.41	0.59	0.75

(b)

Fig. 4. Selection of vehicle capacity randomization

Let

$$RI = \frac{Sol_{nnh} - Sol_{heu}}{Sol_{nnh}} \times 100 \tag{6}$$

Where

RI = the relative improvement (percent) between Sol_{nnh} and Sol_{heu}

Sol_{nnh} = the solution obtained from the nearest neighbour heuristic

Sol_{heu} = the solution obtained from all proposed heuristic algorithms (i.e., DE, NSDE1-4)

5. Result and Conclusion

The experiment was run on a PC with an 11th Gen Intel(R) Core (TM) i7-1165G7 @ 2.80GHz RAM (8 GB RAM) and the proposed solution technique was programmed using MATLAB software, version R2022a. The proposed method was test 16 test instances. From 16 instances, the NSDE 4 is 62.5% efficient in finding the near optimal solution, while the original DE, the NSDE1, the NSDE 2, and the NSDE 3 were 6.25%, 6.25%, 6.25% and 25.00% efficient, respectively (see Table 5 and 6). From Table 7, the NSDE 4 can improve the solution quality of the nearest neighbour heuristic (NNH) by 37.55%, while the original DE, the NSDE1, the NSDE 2, and the NSDE 3 were 19.57 %, 24.66 %, 27.98% and 33.47% efficient, respectively. The NSDE may lead to better-quality solutions compared to the standard DE algorithm. By introducing innovative mechanisms in mutation, crossover, or selection, the algorithm can explore the search space more effectively, leading to improved convergence and finding better solutions. In additional, the novel strategy may lead to improved algorithm efficiency, including faster convergence or reduced computational time. By incorporating adaptive mechanisms or innovative operators, the algorithm can converge more quickly towards optimal or near-optimal solutions, reducing the number of required iterations or evaluations. We suggest that an extension of NSDE be applied to similar problems in other industries.

Table 5 Computational results of the small size test instances.

Instances	#Customer	NNH	Our proposed solution (Km)				
			DE	NSDE1	NSDE2	NSDE3	NSDE4
1	20	760	700	760	600	500	680
2	30	1020	980	900	900	720	620
3	40	920	700	680	560	560	520
4	50	990	840	740	860	960	620
5	60	920	740	680	820	560	520
6	70	1080	1040	920	980	840	810
7	80	1080	700	920	940	840	660
8	90	1260	1160	660	720	660	700
9	100	1200	820	1000	960	660	760
10	110	1200	1000	760	440	740	900
11	120	1280	1080	760	900	740	620
12	130	1320	920	780	760	800	740
13	140	1220	900	940	800	900	640
14	150	1160	760	680	680	600	600
15	160	1200	800	1140	840	920	880
16	170	1340	1240	1020	1000	860	820

Note: the highlight shows the best algorithm in each instance

Table 6 The percentage of proposed method is finding the near optimal solution.

Algorithm	DE	NSDE1	NSDE2	NSDE3	NSDE4
Number of wins	1	1	1	4	10
(%)	6.25	6.25	6.25	25	62.5

Table 7 The relative improvement of all the proposed algorithm compares with current practice (NNH).

Instances	Relative Improvement (%)				
	DE	NSDE1	NSDE2	NSDE3	NSDE4
1	7.89	0.00	21.05	34.21	10.53
2	3.92	11.76	11.76	29.41	39.22
3	23.91	26.09	39.13	39.13	43.48
4	15.15	25.25	13.13	3.03	37.37
5	19.57	26.09	10.87	39.13	43.48
6	3.70	14.81	9.26	22.22	25.00
7	35.19	14.81	12.96	22.22	38.89
8	7.94	47.62	42.86	47.62	44.44
9	31.67	16.67	20.00	45.00	36.67
10	16.67	36.67	63.33	38.33	25.00
11	15.63	40.63	29.69	42.19	51.56
12	30.30	40.91	42.42	39.39	43.94
13	26.23	22.95	34.43	26.23	47.54
14	34.48	41.38	41.38	48.28	48.28
15	33.33	5.00	30.00	23.33	26.67
16	7.46	23.88	25.37	35.82	38.81
Average	19.57	24.66	27.98	33.47	37.55

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