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An adaptive differential evolution algorithm to solve the multi-compartment vehicle routing problem: A case of cold chain transportation problem

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Abstract:

This research paper introduces an adaptive differential evolution algorithm (ADE algorithm) designed to address the multi-compartment vehicle routing problem (MCVRP) for cold chain transportation of a case study of twenty-eight customers in northeastern Thailand. The ADE algorithm aims to minimize the total cost, which includes both the expenses for traveling and using the vehicles. In general, this algorithm consists of four steps: (1) The first step is to generate the initial solution. (2) The second step is the mutation process. (3) The third step is the recombination process, and the final step is the selection process. To improve the original DE algorithm, the proposed algorithm increases the number of mutation equations from one to four. Comparing the outcomes of the proposed ADE algorithm with those of LINGO software and the original DE based on the numerical examples In the case of small-sized problems, both the proposed ADE algorithm and other methods produce identical results that align with the global optimal solution. Conversely, for larger-sized problems, it is demonstrated that the proposed ADE algorithm effectively solves the MCVRP in this case. The proposed ADE algorithm is more efficient than Lingo software and the original DE, respectively, in terms of total cost. The proposed ADE algorithm, adapted from the original, proves advantageous for solving MCVRPs with large datasets due to its simplicity and effectiveness. This research contributes to advancing cold chain logistics with a practical solution for optimizing routing in multi-compartment vehicles.

Key words:

Adaptive differential evolution algorithm, cold chain transportation network, metaheuristics, multi-compartment vehicle routing problem.

1. Introduction

Due to the perishable nature, limited shelf life, and temperature sensitivity of agricultural goods and processed foods, consumers are becoming increasingly concerned about the quality of food products, particularly in the case of agricultural goods and processed foods. Implementing cold chain management is crucial for ensuring the safety, freshness, and overall quality of perishable products throughout the supply chain, which ultimately benefits the consumer. The cold chain is the temperature-controlled supply chain that ensures the quality and safety of products from their origin to their final consumers. Various stakeholders, including producers, wholesalers, retailers, storage

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services, and transportation services, are involved. Cold storage and cold transportation are the two primary components of the cold chain. Cold storage is the temporary storage of cold chain products prior to their transport to the market or customers, whereas cold transportation is the movement of these products from storage facilities or various stakeholders to other storage facilities or stakeholders, markets, or customers. The cold chain is essential for maintaining product quality, decreasing food spoilage, extending shelf life, and assuring food safety. It enables the storage of products while preserving their quality and facilitates transport over greater distances, ultimately resulting in greater consumer satisfaction. The impact of poor cold chain management is significant and, affecting various aspects of supply chain operations, food safety, and economic efficiency. From studies on temperature-controlled transportation, it was found that the majority of costs are incurred in the energy consumption of fuel, amounting to over 15 percent, and in temperature control or refrigeration, which accounts for 40 percent (Li et al., 2022). This is to prevent spoilage of goods, which can reach up to 30 percent, particularly in the case of agricultural products or goods that experience high levels of decay during transportation, amounting to a value of over 526 billion baht (Zhang et al., 2020; Zhu et al., 2021). Preliminary surveys indicate that in developed countries, there is a high demand for temperature-controlled products or goods, such as consumer goods (meat, milk, fresh vegetables, frozen ready-to-eat foods, and ice cream), a trend which is on the rise. However, products or goods transported from distribution centers to stores need to maintain appropriate temperatures to prevent damage, with each product type requiring different storage temperatures ranging from 0-4 degrees, 2-8 degrees, and below -18 degrees Celsius. Currently, efforts are being made to address these issues by increasing costs or expenses related to the wastage resulting from spoilage of goods in the objective equation of temperature-controlled transportation problems, including considerations of different types of trucks or vehicles used in temperature-controlled transportation (Qiu et al., 2020). The current growth of the cold chain and frozen food industry in Thailand is continuously increasing at a rate of 12.0-14.0 percent per year. This is attributed to the expansion of urban communities into fast-paced urban societies, leading to a higher demand for these products. The market for temperature controlled goods transportation, known as Cold Chain Logistics, in Thailand is trending towards a higher growth rate of 8.0 percent or an estimated value of over 26,000 million baht. Currently, there are several companies engaged in the cold chain logistics business in Thailand.

The case study company in this research is one of the companies that provides refrigerated food transportation services, covering the northeastern region of Thailand. However, based on data survey, it was found that the transportation costs of the case study company are still high due to inefficiencies caused by increasing demand for goods each year and customers ordering multiple types of products simultaneously. Additionally, the vehicles have limited capacity, with each compartment being able to accommodate only one type of product. Furthermore, there is a requirement for timely delivery to meet customer demands. Addressing these transportation challenges is complex. Therefore, one possible approach to reduce transportation costs for the case study company is to strategically plan transportation routes systematically, aiming for low costs and maximizing customer satisfaction.

Solution discovery is a challenging aspect of the Vehicle Routing Problem (VRP), a well-known optimization problem. However, it holds significant prominence in academic literature and captures the attention of numerous researchers owing to its capacity to potentially minimize transportation expenses for organizations (Chowmali & Sukto, 2021; Marinaki et al., 2023; Pitakaso et al., 2020; Tiwari & Sharma, 2023). As a result, the exploration of practical solutions in current transportation research has gained significant attention in addressing the challenges of VRP that encompass both original and remanufactured products. Extensive scholarly attention has been devoted to refining the problem's characteristics and assumptions, resulting in numerous variations of VRPs and the development of various heuristic/metaheuristic modifications to address VRP problems (Kalatzantonakis et al., 2023; Kyriakakis et al., 2022; Wichapa & Khokhajaikiat, 2018). The VRP exhibits numerous variants because different instances of the problem often entail specific conditions that transform the traditional VRP into specialized cases, posing even greater challenges for existing algorithms. The majority of VRP research is devoted to scenarios involving a particular commodity type. Nevertheless, there exist distinct circumstances in which the transportation of distinct commodities within the same compartment is not possible. Involving vehicles with multiple compartments, the Multi-Compartment Vehicle Routing Problem (MCVRP) is an expansion of the

VRP. The goal of the MCVRP is to identify the most efficient routes for a fleet of vehicles to service a group of customers, considering the capacity limitations of each vehicle's compartments. Every customer has a specific demand that needs to be fulfilled, and the vehicles are tasked with delivering goods from the depot to the customers while adhering to various constraints, including vehicle capacity, time windows, and the necessity to compartmentalize certain product categories.The MCVRP is more difficult than the traditional VRP because it requires decisions regarding compartment allocation and cargo loading (Chowmali & Sukto, 2020, 2021; Guo et al., 2022; Heßler, 2021; Ostermeier et al., 2021). Using a fleet of multi-compartment vehicles that are equipped with distinct goods that necessitate isolation from one another, the MCVRP for goods delivery entails devising the transportation routes for the delivery of multiple items from a central depot to consumers. Cars are commonly employed to transport merchandise while ensuring their segregation from other items.

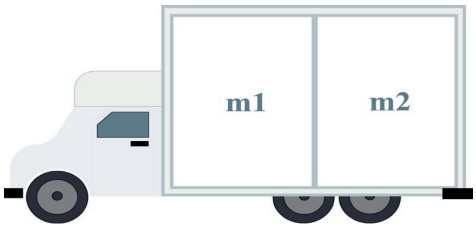


Figure 1. A vehicle with multi-compartments.

Figure1 depicts a vehicle with two compartments that is utilized for the delivery of goods; each compartment cannot contain different categories of goods. This renders the MCVRP more difficult than the standard VRP and further complicates the task of solving the problem using an exact method. Characteristics that distinguish the MCVRP (1) Each vehicle is equipped with multiple compartments, each of which possesses a distinct capacity; (2) Each compartment contains a single type of goods; (3) Each vehicle operates between a depot and a predetermined set of customers, returning to the depot; (4) A single vehicle will fulfill the demand of each customer; and (5) All other limitations persist unchanged from the initial VRP. The MCVRP in this particular scenario is exceedingly challenging to solve precisely due to its numerous characteristics.

The solution methods for MCVRPs fall into two categories (Chowmali & Sukto, 2021; Eshtehadi et al., 2020; Guo et al., 2022; Heßler, 2021): the exact method and the heuristic or metaheuristic method. Finding the optimal solution to the MCVRP is computationally intensive and challenging due to the fact that it is an NP-hard optimization problem, especially when dealing with large-scale peoblems that involve a substantial number of consumers or nodes. For the aforementioned factors, exact methods may fail to locate the optimal solution. Therefore, researchers in this field frequently prefer to solve MCVRPs using heuristic or metaheuristic approaches. Despite the fact that heuristic or metaheuristic methods cannot guarantee the global optimal solution, the obtained solutions are generally acceptable in practice. The benefit of heuristic and me-taheuristic methods is their ability to locate solutions rapidly while still producing results that are close to the optimal solution.

The DE algorithm improves the population iteratively by exploring and exploiting the search space, progressively convergent on a better solution for the VRP. DE utilizes fitness values as a means to adjust the population in an effort to determine a collection of routes that maximizes the objective function of the VRP, which may be the reduction of the total distance covered or the overall expense associated with the routes. For solving VRPs, DE is a prevalent population-based optimization algorithm. The process involves iteratively traversing the solution space in search of an optimal or nearly optimal solution by utilizing this metaheuristic algorithm. It is found that the Differential Evolution (DE) algorithm is a popular metaheuristic method widely applied to solve VRPs (Erbao et al., 2008; Moonsri et al., 2022; Punyakum et al., 2022; Sethanan & Jamrus, 2020; Souza et al., 2023; Xia et al., 2015). From the literature review, the DE algorithm is a powerful optimization algorithm that offers simplicity, robustness, and versatility. Its ability to handle various problem types, explore complex search spaces, and find high-quality solutions makes it a valuable tool for solving MCVRPs in different domains.

Consequently, the objective of this paper is to propose an adaptive differential evolution algorithm (ADE algorithm) as a solution for the cold chain transportation problem case study MCVRP. The proposed ADE algorithm provides numerous benefits. The algorithm has been modified from its original form. This algorithm is advantageous for solving MCVRPs with large datasets because it is both simpler and more effective. In addition, this research contributes to the advancement of cold chain logistics and offers a practicable solution for optimizing the routing of multiple compartment vehicles. The primary contributions of this study are the following:

1. In this paper, the original DE algorithm is modified into an ADE algorithm in order to solve the MCVRP. This will be incredibly beneficial for field research because it is simple and efficient to solve MCVRPs with massive datasets.
2. This research provides a practical solution for optimizing the cold chain logistics transport routes. This will be extremely useful for research in this discipline in nearly every country, especially agricultural nations with a large agricultural product output.

The subsequent sections of the paper are organized as follows: The pertinent literature is presented in Section 2, whereas the mathematical model and the formulation of the proposed ADE are detailed in Section 3. The paper's results and conclusion are respectively presented in Sections 4 and 5 of the paper.

2. Literature review

This section discusses heuristics/meta-heuristics and exact methodologies for solving MCVRPs for the goods delivery problem. For solving MCVRPs, Kaabachi et al. (2019) introduced a hybrid self-adaptive neighborhood algorithm and a hybrid artificial bee colony algorithm. The primary objective of the MCVRP is to reduce the overall distance covered by a minimum number of vehicles. The efficacy of the suggested algorithms is evident from the results, which are derived from a practical case study of gasoline transportation in Italy. MCVRPs: a case study of the petrol station replenishment problem were addressed by Yahyaoui et al. (2020) via an adaptive variable neighborhood search (AVNS) and a Partially Matched Crossover PMX-based Genetic Algorithm (GA). Decreased total distance traveled by used vehicles is the primary objective of the delivery procedure. According to the findings, the convergence of the optimizer towards the optimal or near-optimal solution is accelerated when vehicles with numerous compartments are utilized. A case study of glass waste recycling in which Henke et al. (2019) proposed a branch-and-cut algorithm for the MCVRP with flexible compartment sizes. The primary aim of the delivery process is to minimize the overall mileage accumulated by pre-owned vehicles. The corresponding outcomes illustrate that the algorithm effectively resolves instances comprising a maximum of 50 locations while achieving an 87% reduction in computation time when compared to instances documented in the literature. Hübner and Ostermeier (2019) offered a large neighborhood search (LNS) for MCVRPs in context of grocery distribution. A store case study, benchmark data, and random data are used to verify it. Comparing outcomes to current techniques. Adding loading and unloading expenditures affects routing and saves merchants money, according to the model's calculations. Two meta-heuristic algorithms, simulated annealing (SA) and GA, were proposed by Rabbani et al. (2017) to solve MCVRP in the context of greenhouse gas emissions. In all capacities, the researchers conclude that SA is the worst algorithm for solving this problem. In contrast to the SA algorithm, the hybrid GA-SA algorithm exhibits superior scalability compared to the GA algorithm. To solve the MCVRP: A case study of the petroleum delivery problem, Chowmali and Sukto (2021) proposed a hybrid method combining the Fisher and Jaikumar Algorithm (FJA) and Adaptive Large Neighborhood Search (ALNS). In this scenario, minimizing the total distance traveled while employing the fewest number of multi-compartment vehicles feasible is the objective. The efficacy of the proposed algorithm in resolving the MCVRP in this particular instance is demonstrated by its application to the four numerical examples. An iterated tabu search for the MCVRP in the literature was presented by Silvestrin and Ritt (2017). A number of investigations are conducted by researchers to assess the effectiveness of the iterative tabu search in comparison to previously published outcomes. We find that its solutions are consistently superior to those of existing heuristic algorithms. In their study, Efthymiadis et al. (2023) introduced a Mixed-Integer Linear Programming (MILP) approach for MCVRP, which they applied to a practical scenario involving an oil company managing a Thessalian depot and supplying five unique fuel variations to 19 filling stations. The MILP model reduces commute times by 18.6% and costs by 7.2%, resulting in cost savings for the business. Manual route planning is time-intensive and prone to error. The model and strategy will reduce the time required for transport planning, generate cost-effective routes, and account for operational constraints, thereby improving efficiency, productivity, and customer satisfaction. Guo et al. (2020) offered a hybrid method, a combination of an ant colony optimization algorithm (ACO) and variable neighborhood descent (VND), for MCVRP in the literature. The proposed algorithm is subjected to a series of numerical comparisons and statistical analyses, and the obtained results show that it is accomplished of producing outcomes that are superior to those of prior algorithms. An ALNS algorithm for MCVRP was presented by Chen et al. (2019) within the framework of an actual cold-chain distribution company. The ALNS algorithm's effectiveness and efficiency are demonstrated through experiments when compared to the manual approach, which is predominantly founded on experience. A Branch-and-Price algorithm was put forth by Mirzaei and Wøhlk (2019) for MCVRP. Computational outcomes for instances containing a maximum of 100 customers are provided, while the algorithm demonstrates optimal performance when dealing with instances consisting of up to 50 customers and four commodities.

Nevertheless, these methodologies can be broadly categorized into two distinct classifications: heuristics/meta-heuristics and exact methods. When the number of nodes is substantial, it is impossible to locate optimal excursions in a reasonable amount of time using any exact method. Hence, the literature often resorts to employing heuristic/meta-heuristic methods to tackle large-scale MCVRPs. In most of the related papers, meta-heuristics are used. The metaheuristic algorithm Differential Evolution (DE) has been widely applied in the resolution of numerous optimization challenges, including the MCVRP. MCVRP is the process of determining the optimal routes for vehicles with multiple compartments to deliver products to various customers or locations while taking into account various constraints and objectives.DE is based on evolutionary and genetic algorithmic principles. It maintains a population of candidate solutions and enhances them iteratively through mutation, crossover, and selection operations. The algorithm explores the search space by generating new candidate solutions and selecting the individuals with the highest fitness values for the next iteration. In the context of MCVRP, DE can be used to identify near-optimal solutions by optimizing the assignment of vehicles to compartments, determining the sequence of customer visits, and optimizing the routes for maximizing the profit or minimizing the total cost. During the optimization process, the algorithm dynamically modifies its parameters to improve its search capability and convergence speed. DE has demonstrated promising results in the resolution of MCVRP, delivering efficient and effective solutions. It can manage the complexity of MCVRPs and is suitable for logistics and transportation applications in the real world. The DE algorithm's effectiveness hinges on key parameters: Population Size, which balances search capability against computational load; larger populations enhance exploration (Storn & Price, 1997). Mutation Factor (F) governs variation among individuals, influencing exploration (Zhang & Sanderson, 2009). Crossover Rate (CR) affects population diversity and convergence speed, vital for exploration-exploitation balance (Das & Suganthan, 2011). Selection Mechanism determines offspring survival, impacting efficiency in solution space navigation. Optimizing these parameters for specific problems is crucial for DE's optimal performance.

The transformation of DE into Adaptive Differential Evolution (ADE) aims to rectify DE's limitations and boost its performance. ADE's dynamic parameter adaptation enhances flexibility and efficiency across various problem settings, as noted by Brest et al. (2006). It accelerates convergence and improves solution quality by adjusting search behaviors adaptively, a feature highlighted by Qin and Suganthan (2005). ADE prevents premature convergence in complex scenarios (Cui et al., 2016), and is better suited for dynamic and noisy environments (Das et al., 2009). It exhibits increased robustness in diverse optimization challenges (Neri & Tirronen, 2010), and its self-adapting nature makes it more user-friendly, reducing reliance on expert parameter tuning (Mallipeddi & Suganthan, 2010). These enhancements underscore ADE's improved adaptability, performance, and broader applicability compared to DE.

These are the important reasons for enhancing the DE algorithm into the ADE algorithm, to be used in improving the efficiency of the original DE algorithm for solving the MCVRP problem in this research. The details of the proposed methods will be presented in the following section.

3. The proposed method

The ADE algorithm is a metaheuristic approach designed for addressing the MCVRP and VRP, particularly within the framework of cold chain transportation, as evidenced by a case study. In this specific scenario of the MCVRP, the objective is to efficiently formulate route plans for a fleet of vehicles featuring multiple compartments to cater to a group of customers. Several constraints need to be considered, including vehicle capacity, compartment compatibility, and customer demands, with the aim of optimizing the overall efficiency of the routing solution. The framework for this study can be described in Figure 2.

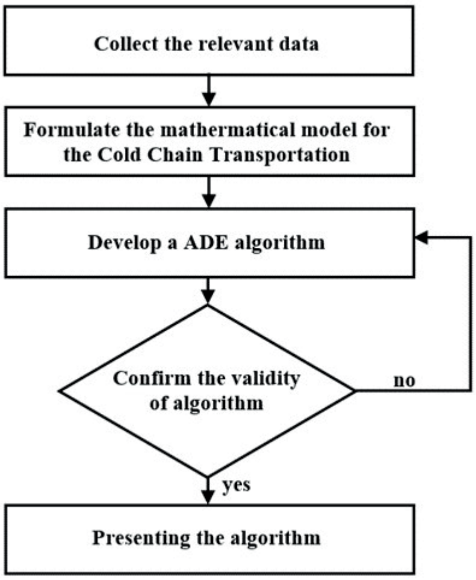


Figure 2. The framework for this study.

3.1. Data Collection

Collect data from a case study, specifically studying the transportation format and gathering information about the locations of frozen food operators or warehouses, customer locations, transportation distances between each node, customer demand for products, characteristics and capacity of vehicles used for product delivery. The study collected transportation data for 3 days in order to generate distance metrics and related information for further calculations.

3.2. The MCVRP model in context of cold chain transportation

In this section, a MILP model for coldchain transportation is presented. As an extension of MCVRP, MCVRP with a heterogeneous fleet is represented by a mathematical model that differs only slightly. Adjusting the constraints to allow for various types of vehicles enables the formulation of the MCVRP model as a MILP model. The MCVRP mathematical model for this paper is depicted in Figure 3.

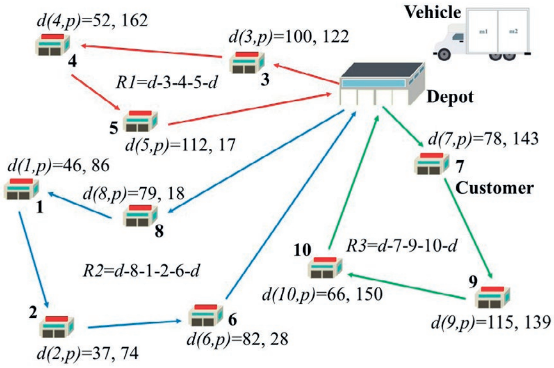


Figure 3. A distribution network for the cold chain transportation.

Indices: The model for the MCVRP in cold chain transportation can be established on a fully connected undirected network. A set of n customers and a solitary central depot (node 0) compose the network's node set N. A complete graph denoted by $G=(N, A)$, in which N is the node set and A is the arc set, is utilized. The arc between nodes i and j is denoted by the symbol (i, j). Furthermore, P signifies the assortment of distinct product categories, whereas K denotes the collection of multi-compartment vehicles that are accessible at the depot.

Parameters: The variable dt_{ij} denotes the actual distance between nodes i and j in kilometers. Customer j's demand for a particular product type p, denoted in packaging cases, is represented by d_{jp}. The capacity of vehicle k for product type p, as indicated on packaging crates, is denoted by q_{kp}. u_k represents the transportation cost per unit for vehicle k in Baht per kilometer. v_k signifies the cost of utilizing vehicle number k in Baht. L represents the maximum allowable route length.

Decision variables: The binary variable X_{ijk} is defined as follows: if node i and node j are connected by vehicle k, $X_{ijk}=1$; otherwise, $X_{ijk}=0$. Y_{jkp} is a binary variable that takes on the value 1 if a vehicle k services the product type p at node j and 0 otherwise.

$$MinZ = \sum_{i\in N}\sum_{j\in N'}\sum_{k\in K} u_k \cdot dt_{ij} \cdot X_{ijk} + \sum_{i\in N'} v_k \cdot Z_k \quad (1)$$

$$\sum_{i\in N} X_{ijk} \leq 1, \ \forall j, \forall k \quad (2)$$

$$\sum_{i\in N} X_{ijk} = \sum_{i\in N} X_{jik}, \ \forall j, \forall k \quad (3)$$

$$\sum_{i,j\in S} X_{ijk} \leq |S|-1, \forall k, \forall S, |S| \geq 2 \quad (4)$$

$$Y_{jkp} \leq \sum_{i\in N} X_{ijk}, \forall j, \forall k, \forall p \quad (5)$$

$$X_{ijk} \leq Z_k, \forall i, \forall j, \forall k \quad (6)$$

$$\sum_{k\in K} Y_{jkp} = 1, \forall j, \forall p \quad (7)$$

$$\sum_{j\in N'} d_{jp} Y_{jkp} \leq q_{kp}, \forall k, \forall p \quad (8)$$

$$\sum_{i,j\in N} dt_{ij} \cdot X_{ijk} \leq L \quad (9)$$

$$X_{ijk}, Y_{jkp} \in \{0,1\} \quad (10)$$

The objective function denoted as Equation (1) is designed to minimize the total cost, encompassing expenditures related to both transportation and vehicle utilization. According to Equation (2), each consumer j may only be visited once by each route. Equation (3) states that a multi-compartment vehicle is required to depart after entering customer *j*. As sub-tour elimination constraints, Equation (4) is derived. In the absence of a visit from vehicle *k* to customer *j*, as per Equation (5). Vehicle number *k* cannot be utilized to travel between points *i* and *j* if it has not been activated for service, as confirmed by Equation (6). Y_{jkp} is set to zero. As per Equation (7), a solitary vehicle attends to the needs of each consumer *j* who requests fuel type *p*. The quantity of each fuel cannot surpass the capacity of its compartment, as indicated by Equation (8). Equation (9) guarantees that the measured distance of the route does not surpass its utmost length. Equation (10) specifies that the variables *X* and *Y* are binary.

3.3. The proposed ADE algorithm

One of the most frequently employed techniques for resolving optimization problems is the original DE algorithm. Nevertheless, to optimize the solution's efficacy, this study implemented a greedy decoding technique to enhance the decoding process. The calculation steps of the proposed DE algorithm, called ADE algorithm, proposed are as follows. (1) Generating an initial solution: In this stage, an initial target vector code is generated, which corresponds to the population size that has been specified. The dimensions of each target vector are equivalent to the quantity of customers (*N*). Then, random numbers between [0, 1] are assigned to each coordinate of the target vector. (2) Mutation: In this step, we modified original mutation to be adaptable between diversified by random target vectors and intensified on the best of target vectors Equation (11). First, three target vectors are randomly selected and the best of vector targets $X_{best,j,g}$. Then, the random values of corresponding coordinates among the selected vectors and the best of target vectors are used to perform value mutation according to Equation (11). The factor that determines the magnitude of vector differentiation is set to a value of 2, and the last two values yield the mutated vector ($V_{i,j,g}$). In this research, the mutation process will be performed using the following method, known as " mutation.

$$V_{i,j,g} = \alpha X_{r_1,j,g} + (1-\alpha) X_{best,j,g} + F\left(X_{r_2,j,g} - X_{r_3,j,g}\right) \quad (11)$$

Table 1. Product demand data.

	Demand (Packaging box)		
Customer	Day 1	Day 2	Day 3
1	(46, 86)	(50, 88)	(26, 78)
2	(37, 74)	(34, 80)	(23, 58)
3	(100, 122)	(98, 138)	(87, 116)
4	(52, 162)	(71, 157)	(48, 164)
5	(112, 17)	(124, 18)	(109, 24)
6	(82, 28)	(85, 45)	(70, 43)
7	(78, 143)	(61, 126)	(59, 150)
8	(79, 18)	(60, 31)	(76, 20)
9	(115, 139)	(126, 154)	(101, 127)
10	(66, 150)	(85, 162)	(78, 169)
11	(179, 24)	(177, 35)	(172, 32)
12	(16, 45)	(1, 51)	(31, 61)
13	(43, 100)	(29, 118)	(26, 82)
14	(56, 138)	(57, 135)	(43, 153)
15	(172, 41)	(163, 52)	(156, 38)
16	(182, 160)	(180, 163)	(200, 161)
17	(144, 15)	(125, 20)	(152, 8)
18	(174, 186)	(178, 191)	(181, 199)
19	(188, 151)	(206, 158)	(169, 161)
20	(12, 25)	(6, 22)	(32, 35)
21	(41, 69)	(49, 51)	(32, 81)
22	(117, 76)	(124, 83)	(101, 74)
23	(26, 93)	(14, 78)	(42, 85)
24	(42, 171)	(35, 166)	(34, 156)
25	(43, 26)	(46, 24)	(24, 33)
26	(52, 51)	(72, 35)	(40, 42)
27	(197, 81)	(185, 67)	(197, 63)
28	(152, 43)	(158, 33)	(155, 29)
Total	(2603, 2434)	(2599, 2481)	(2464, 2442)

When F is the scaling factor and α is the cyclic value on generation cycle M that calcutated by g modulo M and divided by M to scale value in range [0, 1]. (3) Recombination: The recombination process involves presenting N trial vectors to generate candidate target vectors for the next generation. In this step, a subset of each $V_{i,j,g}$ and $X_{i,j,g}$ is randomly selected. These selected subsets, denoted as $X_{i,j,g}$ or $V_{i,j,g}$, are then used to create trial vectors $U_{i,j,g}$. The selection of $X_{i,j,g}$ or $V_{i,j,g}$ is performed using random values $rand_{i,j}$ as shown in Equation (12).

$$U_{i,j,g} = \begin{cases} V_{i,j,g}, \; if \; rand_{ij} \leq CR \\ X_{i,j,g}, \; otherwise \end{cases} \tag{12}$$

CR denotes the probability of a crossover.

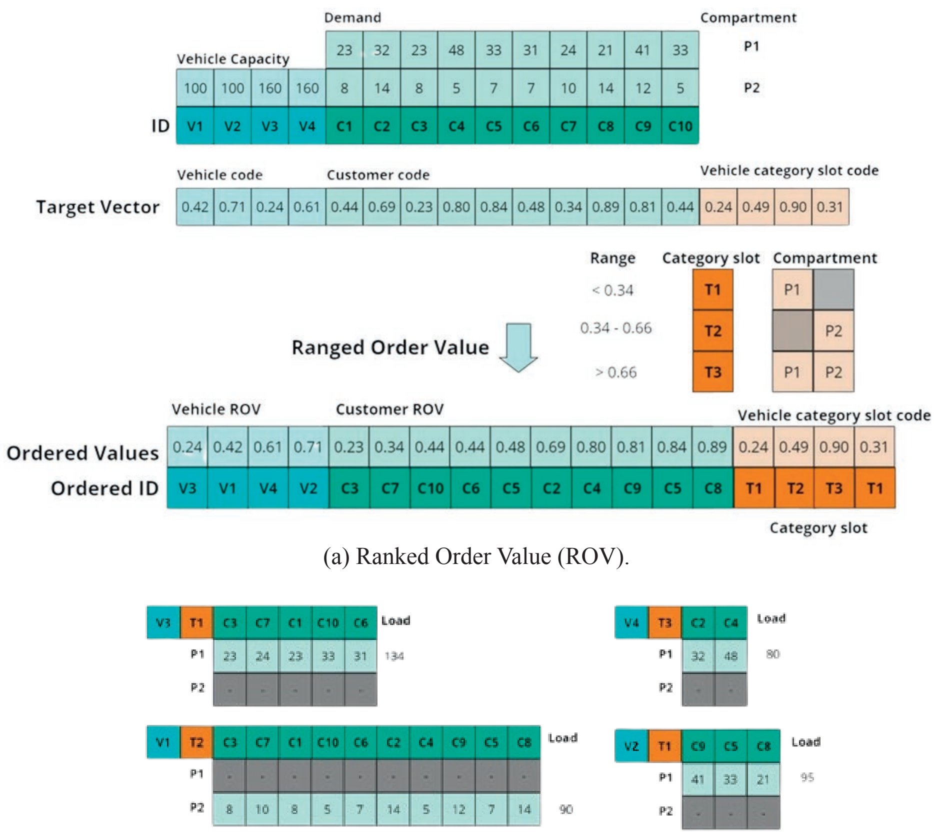
(4) Selection: The selection process involves exchanging coordinate values between the target vectors and mutated vectors for each NP, using Equation (13). This is done by comparing a randomly generated real number in the range [0, 1] with a specified change rate value, which is set to 0.8. The values are then adjusted according to the equation, resulting in a new vector called the trial vector ($U_{i,j,g}$).

$$X_{i,j,g+1} = \begin{cases} U_{i,j,\,g}, if \; f(U_{i,j,\,g}) \leq f(X_{i,j,\,g}) \\ X_{i,j,g}, otherwise \end{cases} \tag{13}$$

(5) Decoding: In this paper, the ROV decoding and Greedy decoding are use to enhancement, the DE algorithm aims for improving the effectiveness of the result for MCVRP. Figure 4 depicts the steps involved in the ROV decoding process, while Figure 5 illustrates the steps of the Greedy decoding approach.

3.4. Numerical illustrations

This research will test the proposed algorithm for solving the MCVRP problems in context of the cold chain transportation. The details of the calculations will be presented in the next section.



(a) Ranked Order Value (ROV).

(b) Generate the transportation routes.

Figure 4. The steps of ROV decoding.

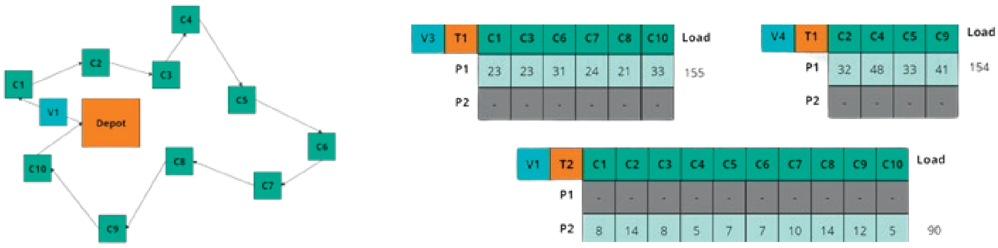


Figure 5. The steps of Greedy decoding.

4. Results

4.1. Experimental data

The study encompasses a total of 28 customers, denoted as C1, C2,..., C28, along with a centraldepot labeled as D. Further details can be found in Figure 6. The case study has 20 cargo trucks for transporting goods, consisting of two types with two compartments of the same size. Each compartment can only carry one type of goods. There are a total of 10 vehicles of type#1, each with two equally-sized cargo compartments. The overall capacity is equivalent to 100 packaging boxes. There are a total of 5 vehicles of type#2, each with two equally-sized cargo compartments. The overall capacity is equivalent to 624 packaging boxes. Additionally, there are a total of 5 trucks of type 3, with two equally-sized cargo compartments. Each vehicle can carry a total of 912 packaging boxes of goods. The company delivers goods to customers every day, and the number of customers on this case study is 28. The distances between customers are actual distances measured from Google Maps. The daily quantity of goods required by customers on day 1, day 2, and day 3 is shown in Table 1. The candidate vehicles and their capacities are shown in Table 2.

Figure 6 shows the distribution network for this case study.

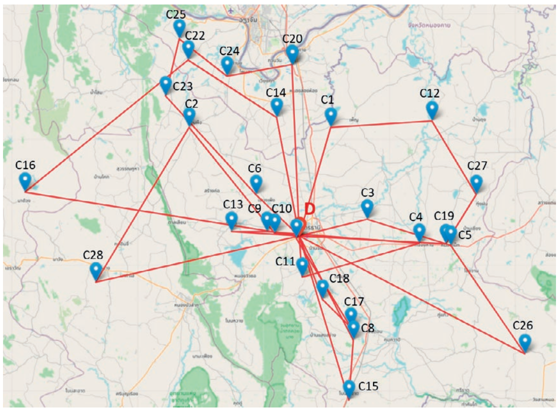


Figure 6. The distribution network.

In addition, the distance matrix for this case study is shown in Table 3.

After obtaining the relevant parameters, the proposed ADE algorithm was tested using Python. The processing system utilized is powered by an Intel(R) Core(TM) i7-9750HF CPU running at 2.60 GHz (2.59 GHz), and it is equipped with 16.0 GB of RAM. This system is proficient in handling 1,000 iterations, with a total of 100 vectors.The control parameters for the evolutionary process are CR = 0.7 and F = 2. The transportation routes and the use of cargo trucks obtained from the proposed algorithm are shown in Table 4. It can be observed that the ADE method yields the following results: The number of vehicles used is 8, consisting of eight routes, and the total distance covered is 1,466.5 kilometers.

4.2. Result comparison

After obtaining the experimental data, the researchers obtained results from a mathematical modeling approach by using LINGO software for processing to find solutions to this case. In

Table 2. The candidate vehicles and their load capacities.

Vehicle type	Compartment			Vehicle usage cost (Baht)	Unit cost (Bath/km.)
	m_1	m_2	Total		
V_1	50	50	100	800	12.78
V_2	312	312	624	1,000	17.25
V_3	456	456	912	1,400	23.32

Table 3. The distance matrix for this case study.

	D	C1	C2	C3	C4	C6	C7	C8	C9	C10	C11	C12	C13	C14
D	0	42.6	62.7	27.1	45.8	53	24	1.7	47.7	16.3	11.8	18	73.1	27.5
C1	42.6	0	61.5	49.9	54.8	61.8	53.4	40.6	79.9	49.3	48.3	56.1	33.7	60.6
C2	62.7	61.5	0	76.4	96.2	103	37.8	60	105	62.9	67.4	76.3	99.9	46.2
C3	27.1	49.9	76.4	0	28.2	35.5	40.7	37.3	53.3	36.7	35.7	38.2	53.4	47.9
C4	45.8	54.8	96.2	28.2	0	11.1	58.3	43.5	59.5	52	53.6	49	43.7	63.2
C5	53	61.8	103	35.5	11.1	0	83	68.3	84.2	76.7	78.4	73.7	61.8	87.9
C6	24	53.4	37.8	40.7	58.3	83	0	24.9	70.9	19.4	19.2	41.1	86.8	17.4
C7	1.7	40.6	60	37.3	43.5	68.3	24.9	0	49.9	15.3	10.2	20.2	76.7	26.5
C8	47.7	79.9	105	53.3	59.5	84.2	70.9	49.9	0	62.2	56.2	32.7	92.7	73.4
C9	16.3	49.3	62.9	36.7	52	76.7	19.4	15.3	62.2	0	4.9	33.5	82.7	15.4
C10	11.8	48.3	67.4	35.7	53.6	78.4	19.2	10.2	56.2	4.9	0	25.7	81.7	19.9
C11	18	56.1	76.3	38.2	49	73.7	41.1	20.2	32.7	33.5	25.7	0	90.4	43.9
C12	73.1	33.7	99.9	53.4	43.7	61.8	86.8	76.7	92.7	82.7	81.7	90.4	0	92.2
C13	27.5	60.6	46.2	47.9	63.2	87.9	17.4	26.5	73.4	15.4	19.9	43.9	92.2	0
C14	48.2	20.9	37.5	59.5	80.9	106	33.3	51.8	87.6	57.8	56.8	65.2	54.1	48.7
C15	61.5	93.7	119	67.1	73.3	98	84.7	63.7	23.8	77	69.5	62.1	115	88.3
C16	110	149	102	145	152	176	120	108	139	108	111	113	180	109
C17	45.8	78	104	51.4	57.6	82.3	67.9	48	16.5	61.3	53.8	46.4	98.8	72.6
C18	39.7	77.8	103	59.9	57	81.8	62.9	44.7	19	53.4	49.2	27.8	101	65.3
C19	53	61.7	103	35.5	11	20.1	67.8	55.2	58.4	59.2	61	54.2	50.6	70.6
C20	55.2	27.8	51.6	66.4	82.1	113	62.2	58.8	94.6	64.8	64.6	71.5	61	70.5
C21	55.4	28.1	51.9	66.7	82.4	113	62.4	59	94.8	65	64.8	71.8	61.3	76.3
C22	88.1	67.8	30.4	99.3	121	145	63.2	91.7	127	81.2	85.8	105	101	71.5
C23	75.6	72.2	17.9	86.8	108	133	50.7	79.2	115	68.7	73.3	92.5	114	59
C24	75.7	48.4	24.4	87	108	133	53.5	79.3	115	71.6	76.1	92.7	81.6	61.9
C25	95.9	71.3	38.2	107	129	153	71	102	135	89	93.6	113	104	79.4
C26	101	122	156	96.1	71.6	59.1	122	101	65.5	114	106	99	115	125
C27	73.3	62.9	107	64.5	39.8	24.6	92	79.4	92.7	83.4	85.2	78.5	39.1	94.7
C28	76.3	115	68.2	112	118	143	86.6	74.7	106	74.6	77.8	80	147	75.8

Table 3. Continued.

	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28
D	61.5	110	45.8	39.7	53	55.2	55.4	88.1	75.6	75.7	95.9	101	73.3	76.3
C1	93.7	149	78	77.8	61.7	27.8	28.1	67.8	72.2	48.4	71.3	122	62.9	115
C2	119	102	104	103	103	51.6	51.9	30.4	17.9	24.4	38.2	156	107	68.2
C3	67.1	145	51.4	59.9	35.5	66.4	66.7	99.3	86.8	87	107	96.1	64.5	112
C4	73.3	152	57.6	57	11	82.1	82.4	121	108	108	129	71.6	39.8	118
C5	98	176	82.3	81.8	20.1	113	113	145	133	133	153	59.1	24.6	143
C6	84.7	120	67.9	62.9	67.8	62.2	62.4	63.2	50.7	53.5	71	122	92	86.6
C7	63.7	108	48	44.7	55.2	58.8	59	91.7	79.2	79.3	102	101	79.4	74.7
C8	23.8	139	16.5	19	58.4	94.6	94.8	127	115	115	135	65.5	92.7	106
C9	77	108	61.3	53.4	59.2	64.8	65	81.2	68.7	71.6	89	114	83.4	74.6
C10	69.5	111	53.8	49.2	61	64.6	64.8	85.8	73.3	76.1	93.6	106	85.2	77.8
C11	62.1	113	46.4	27.8	54.2	71.5	71.8	105	92.5	92.7	113	99	78.5	80
C12	115	180	98.8	101	50.6	61	61.3	101	114	81.6	104	115	39.1	147
C13	88.3	109	72.6	65.3	70.6	70.5	76.3	71.5	59	61.9	79.4	125	94.7	75.8
C14	103	138	87.1	86.9	87	25.1	25.4	44.5	48.9	25.1	48	140	79.3	104
C15	0	169	31.7	43.5	73.6	110	110	143	130	130	151	80.8	97.9	136
C16	169	0	154	138	161	151	151	102	117	124	110	206	185	43.9
C17	31.7	154	0	21.8	65.7	91.8	92.1	125	112	112	133	72.6	90	118
C18	43.5	138	21.8	0	63.4	93.8	94.1	127	114	114	135	82.5	87.6	104
C19	73.6	161	65.7	63.4	0	97.1	97.4	130	118	118	138	63.4	30.6	127
C20	110	151	91.8	93.8	97.1	0	0.55	44.4	64.6	30.7	47.9	148	88	120
C21	110	151	92.1	94.1	97.4	0.55	0	44.3	65.8	30.1	47.8	150	89.1	118
C22	143	102	125	127	130	44.4	44.3	0	16.6	23.3	8.5	182	153	96.3
C23	130	117	112	114	118	64.6	65.8	16.6	0	35.1	24.4	169	141	83.8
C24	130	124	112	114	118	30.7	30.1	23.3	35.1	0	28.6	172	112	90.4
C25	151	110	133	135	138	47.9	47.8	8.5	24.4	28.6	0	189	129	104
C26	80.8	206	72.6	82.5	63.4	148	150	182	169	172	189	0	70	172
C27	97.9	185	90	87.6	30.6	88	89.1	153	141	112	129	70	0	154
C28	136	43.9	118	104	127	120	118	96.3	83.8	90.4	104	172	154	0

Table 4. The routes for day 1 obtained by the proposed ADE algorithm.

Vehicle		Computational using the proposed ADE algorithm					
No.	Type	Route	Distance	Total Demand	Transportion cost	Vehicle usage cost	Total cost
1	V_2	D-C15-C8-D	133.0	(251, 59)	2,294.25	1,000	3,294.25
2	V_2	D-C3-C5-C26-D	119.4	(264, 190)	3,841.58	1,000	3,059.65
3	V_2	D-C10-C2-C28-D	223.7	(255, 267)	3,858.83	1,000	4,858.83
4	V_3	D-C19-C27-C12-C1-D	199.0	(447, 363)	4,640.68	1,400	6,040.68
5	V_3	D-C11-C4-C9-C13-D	161.9	(389, 425)	3,775.51	1,400	5,175.50
6	V_3	D-C7-C17-C18-D	111.2	(396, 344)	2,593.18	1,400	3,993.18
7	V_3	D-C6-C23-C25-C24-C21-C20-D	213.6	(246, 412)	4,979.99	1,400	6,379.99
8	V_3	D-C14-C22-C16-D	304.7	(355, 374)	7,105.60	1,400	8,505.60
		28 customers	1,466.5	(2,603, 2,434)	33,089.61	10,000	43,089.61

addition, the computational results presented in Table 5 demonstrate that optimal solutions for P1 (Problem 1: 5 customers) were obtained using LINGO software, DE, and the proposed ADE. However, for other problems, the effectiveness of the ADE method in providing the best solution for each problem demonstrates that the proposed approach is highly efficient and can be applied in this case study. Furthermore, when compared to the best-known solutions achieved within 72 hours using LINGO software, the computational results for day 1 (CS-D1), day 2 (CS-D2) and day 3 (CS-D3) using the proposed ADE algorithm were superior. These results underscore the importance of implementing the suggested algorithm in this particular instance. This article provides practical implications and significant contributions to future investigations, advising scholars on how to devise innovative algorithms to tackle the NP-hard MCVRP in cold chain transportation. The ADE that has been proposed exhibits adaptability and practical utility in resolving MCVRPs, rendering it a fitting instrument for the present case study. Further, it is expected that the algorithm under consideration can be expanded to address additional VRPs that may arise in practical situations.

5. Conclusion

The distribution of goods is a significant concern that directly impacts a company's performance. Efficient distribution not only saves transportation costs but also contributes to reduced environmental impact. In various practical scenarios, the MCVRP with a diverse vehicle fleet becomes a pertinent concern. This study aims to minimize the overall cost, leading to a specific focus on the cold chain transportation problem. Addressing the requirements of 28 customers over a three-day period in northeastern Thailand, we introduce an ADE, an enhanced version of the original DE algorithm. The research

Table 5. The comparison results.

Problem	Details of customers and number of vehicles for each type (typ#1,typ#2,typ#3)	LINGO			DE	ADE
		Status	Times (hours)	Total cost	Total cost	Total cost
P1	C1-C5, (0, 2, 0)	Optimal	00:00:02	**6,936.95***	**6,936.95***	**6,936.95**
P2	C1-C10, (0, 2, 1)	Feasible	24:00:00	**10,559.60***	10,582.00	**10,559.60***
P3	C1-C15, (3, 3, 3)	Feasible	24:00:00	17,026.20	16,732.34	**16,417.78***
P4	C1-C20, (3, 3, 3)	Feasible	24:00:00	26,453.06	17,802.94	**16,981.48***
CS-D1	C1-C28, (0, 8, 2)	Feasible	72:00:00	48,940.12	45,040.81	**43,089.61***
CS-D2	C1-C28, (0, 5, 4)	Feasible	72:00:00	47,174.32	44,345.93	**41,233.92***
CS-D3	C1- C28, (0, 9, 1)	Feasible	72:00:00	47,194.96	42,708.03	**40,802.20***

initiates with the development of an MCVRP model, followed by the formulation of a MILP model tailored to a particular case study. Subsequently, the ADE algorithm is tailored to solve the MCVRP within this context. Validation of the proposed ADE algorithm is performed through numerical examples, indicating its effectiveness in solving the defined MCVRP model. Comparative analysis with Lingo software and the original DE demonstrates that the proposed ADE algorithm is more efficient in terms of total cost. This algorithm proves valuable for minimizing the total cost in the distribution network for cold chain transportation, substantiated by the effectiveness demonstrated in the case study and numerical examples.

In the context of solving the MCVRP using an ADE algorithm, there are several potential future directions to explore. Here are some ideas:

(1) Investigating alternative solution representations that better capture the MCVRP constraints, such as permutations or tour-based representations;

(2) Exploring adaptive mechanisms to dynamically control the ADE algorithm's parameters based on problem instances or the optimization process's current state;

(3) Integrating local search heuristics, like 2-opt or 3-opt, within the ADE algorithm to improve the exploration of promising solution regions;

(4) Extending the ADE algorithm to handle uncertain and dynamic scenarios by considering stochastic demand or time-varying parameters and employing robust optimization or online learning strategies;

(5) Applying the ADE algorithm to solve the MCVRP as a multi-objective optimization problem, incorporating additional objectives like minimizing travel distance, balancing load distribution, or optimizing time windows;

(6) Investigating parallel versions of the ADE algorithm to enhance efficiency and scalability for large-scale MCVRP instances, utilizing techniques such as parallel computing or distributed algorithms;

and (7) Conducting other real-world experiments and case studies to validate the ADE algorithm's performance, collaborating with industry partners and logistics providers to assess its effectiveness and compare it with existing approaches.

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