Efficient Route Optimization for Ice Distribution: Enhanced VRPTW with Customer Retention Strategies

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ABSTRACT

This study addresses the Vehicle Routing Problem with Time Windows (VRPTW) in the context of ice distribution by introducing a novel mathematical model that incorporates practical constraints essential for real-world applications. These constraints include customer retention strategies and quality preservation methods, which are important for maintaining customer satisfaction and product integrity. The objective is to minimize the total costs, including fuel expenses, standard and bonus driver wages, missed delivery penalties, and costs related to a quality preservation strategy. Given the NP-hard nature of this problem, this study proposes a hierarchical cluster-first-route-second approach and a Differential Evolution (DE) algorithm to solve large-scale problems. The effectiveness of these methods was examined and compared through test cases involving various problem sizes using real-world data from an ice distribution company in Thailand. The results show that the hierarchical cluster-first-route-second approach is more effective for the practical problem. Using capacitated K-means clustering, this hierarchical approach groups customers, enabling the solution of manageable subproblems through Mixed-Integer Linear Programming (MILP). The proposed method not only provides cost-effective and scalable solutions, but also outperforms traditional methods in terms of computation time and feasibility for large-scale applications. This study offers significant theoretical contributions by extending VRPTW models and providing practical implications for optimizing distribution strategies in competitive market environments, leading to substantial cost reductions and enhanced operational efficiency.

Keywords-ice distribution optimization; vehicle routing problem with time windows; capacitated k-means clustering; hierarchical clustering; mixed integer linear programming; differential evolution

I. INTRODUCTION

Ice is a vital commodity with a significant role in various global markets. Beyond its uses in food preservation and beverage cooling, ice is crucial in sectors, such as construction, healthcare, food processing, and tourism. The global ice market is projected to experience substantial growth from 2023 to 2031 due to its versatility [1]. Additionally, the increasing threat of global warming, with predictions of a 1.5°C temperature rise between 2030 and 2052 due to human-induced greenhouse gas emissions, is expected to boost the demand for ice [2]. This anticipated demand surge will likely drive further growth in the ice-making industry. Over the past century, the ice manufacturing industry has seen consistent growth, resulting in increased competition [3]. However, the industry faces challenges, such as maintaining consistent temperatures during production, storage, and transportation. Supply Chain Management (SCM) and the unpredictability of Industry 4.0 networks, including feedback loops and system dynamics, pose significant concerns in production and logistics systems [4, 5]. Ice production and storage require significant energy consumption for continuous temperature control [6]. Transportation also adds complexity, as refrigeration-equipped vehicles are needed to preserve product quality during transit, leading to higher fuel consumption and costs [7]. Additionally, ice manufacturers deal with declining sales as a result of increased competition. Therefore, maintaining high product quality, timely delivery, and accurate shipment estimates are necessary to retain customers. These issues highlight the need for operational efficiency and cost-effectiveness.

This study addresses the practical challenges encountered by an ice manufacturing company in Thailand, where consumption is high. The company faces competition in route delivery, and delays can lead to customers refusing to purchase products as they may already have secured supplies from other sources. To maintain customer retention, the company implements a strategy to pass customer locations within a limited extended time frame, even if arriving outside the specified time window, to prevent permanent customer loss. Customer satisfaction depends on both timely delivery and product quality. Despite vehicle refrigeration, heat transfer during transportation can cause the ice to melt. To maintain product quality, the company fully packs vehicles to prevent melting. Moreover, several cost-related issues in ice distribution planning are a major concern. Late deliveries outside the customer's time window lead to lost sales, and loading extra products into vehicles to maintain delivery quality incurs additional costs. In addition, bonus costs to incentivize employee performance are considered.

In temperature-controlled distributions, such as cold chain logistics, transporting products requires careful attention to maintain temperature and humidity levels [8]. Ensuring timely delivery and maintaining product quality is crucial to customer satisfaction, adding more cost factors to consider. Consequently, the Vehicle Routing Problem with Time Windows (VRPTW) is a popular approach in this field. The studies carried out in [9-12] focused on VRPTW in temperature-controlled distributions. These studies decomposed various cost components and integrated additional transportation-related factors into their objective functions, such as refrigeration operational costs, penalties, and product damage costs. Maintaining temperature control is especially critical in the distribution of ice products. However, few studies have been conducted in this area. Authors in [13] focused on minimizing fuel costs in the ice distribution, considering a scenario with only two vehicles. A mathematical model was developed to recommend a strategy that involves driving to the furthest destination first and then delivering backward to the distribution center. In [7], the capacitated VRP was addressed in ice distribution by incorporating time windows and multiple products to minimize total costs, including travel, driver, and penalty costs. Mixed-Integer Linear Programming (MILP) was used to solve small-size problems, and a Differential Evolution (DE) algorithm with local search was developed to address large-size problems. In [4], VRPTW was addressed by considering the fleet size and road conditions for ice distribution to minimize travel costs. This approach combined hybrid Particle Swarm Optimization (PSO) and Adaptive Large Neighborhood Search (ALNS) algorithms, tailored to the specific needs of ice product distribution. However, VRPTW, being NP-hard, becomes more complex with added conditions and factors. For large-scale problems, exact methods are often impractical due to computational challenges. Therefore, many studies use heuristics and metaheuristics to find feasible solutions.

To provide feasible delivery planning solutions and enhance customer satisfaction, customers are often grouped into clusters based on their location or delivery conditions [14]. A hierarchical cluster-first-route-second approach is one of the constructive heuristic methods deployed to handle large-scale problems [15]. A hierarchical approach allows the problem to be divided into different levels, with distinct methods applied at each level [16]. In [17, 18], a two-phase method was followed, which included clustering and distribution routing to solve VRPTW. K-clustering, especially the k-median and k-means, is the most popular model to solve the general clustering problem [19]. To prove the effectiveness and efficiency of this method, K-means, K-medoids, and DBSCAN were compared for customer grouping, solving VRPHTW implementing an MILP model. The K-means provided optimal routes at lower costs [20]. Many studies, such as [21, 22], utilized K-means clustering in the initial phase to reduce the problem's scale, optimizing the route distribution. These studies highlight the importance of cluster determination in minimizing total costs for VRPTW.

Metaheuristic algorithms are the most researched, developed, and widely applied to solve various problems [23]. Commonly used metaheuristic algorithms in route planning include Ant Colony Algorithms (ACA) [24, 25], Tabu Search (TS) [26, 27], Genetic Algorithms (GA) [28], PSO algorithms [29], DE [30], and Simulated Annealing Algorithms (SAA) [31]. DE is one of the most effective evolutionary algorithms for numerical optimization problems due to its positive feedback performance and use of simple operations - mutation, crossover, and selection - on initial vectors to generate competitive solutions [32, 33]. Its straightforward nature and rapid convergence make it very effective for numerical optimization, including VRPTW applications. Numerous studies have employed DE to solve VRPTW, aiming to provide efficient and high-quality solutions. In [34], DE was utilized for VRPTW, incorporating service times and driver-specific time windows. In [35], a sort-based DE algorithm was introduced, which incorporated Pareto dominance for dual-objective optimization. In [36], postman delivery routing was optimized using both PSO and DE, finding that both methods reduced travel distances and outperformed current practices, with DE being more effective than PSO. In [37], the Multi-Objective VRPTW (MOVRPTW) was examined, improving a differential mutation strategy to improve the likelihood of generating feasible solutions and improving population convergence. In the context of ice distribution, DE has been used to provide an efficient solution and reduce transportation costs [7].

Very few studies addressed vehicle routing problems specific to the ice industry. Furthermore, as far as is known, no study on VRPTW for ice distribution has considered the combination of conditions and restrictions. This study addresses this gap by incorporating time window violations to improve customer retention. It also considers bonus costs to incentivize employee performance, as well as costs associated with maintaining product quality. This approach aims to enhance the efficiency of ice distribution operations by incorporating real-world constraints to cope with the market's increasing competitiveness. Therefore, this study aims to develop a novel mathematical programming model to optimize the ice transportation process. This model, formulated as MILP, effectively addresses VRPTW specific to the ice industry. Key considerations include delivery time windows, varying fuel consumption rates according to vehicle age, vehicle capacity constraints, different product types, and customer retention requirements. The objective is to find optimal ice distribution routes with minimum total costs, including fuel expenses, standard and bonus driver remuneration, missed service costs, and product quality preservation expenditures. Owing to the complexity of VRPTW, exact methods are often impractical for large-scale problems. As a result, this study proposes alternative approaches to find optimal solutions to a large-scale real-world problem. These include a hierarchical approach known as cluster-first-route-second, as well as a DE metaheuristic algorithm. The solutions obtained from these three different methods are compared for their efficiency to be evaluated in terms of objective results and computation times to identify the most suitable approach. The goal is to find an appropriate solution that efficiently adapts to real-world data and operates within practical computation time constraints. This study is the first to investigate various objective functions and problem characteristics related to ice distribution operations. By optimizing routes and adapting to changing conditions, the proposed method enables the ice industry to overcome the unique challenges associated with transporting this specific category of merchandise.

II. DEFINITION OF THE PROBLEM

The ice manufacturing company based in Thailand specializes in producing various types of ice products, including tube ice, small tube ice, cube ice, and flake ice. Its distribution network consists of a single depot serving 83 customers, each requiring different daily amounts of these products. The company operates a fleet of homogeneous vehicles, categorized into three groups based on age: three new vehicles, two medium-aged vehicles, and two old vehicles, each with different fuel consumption rates. Vehicles travel at an average speed of 50 km/h and have a maximum capacity of 150 ice bags, each weighing 20 kg. Drivers are paid a standard wage of 300 baht per day and must deliver a minimum of 70 units of ice products, with bonuses awarded for exceeding this threshold. The operation time is from 6:00 a.m. to 3:30 p.m., adhering to this timeframe for all deliveries. Each customer specifies their preferred earliest and latest arrival times, creating time windows for deliveries.

In this context, the VRPTW presents specific considerations. If a vehicle arrives at a customer location earlier than the designated time window, there are no associated costs, but the vehicle must wait until the earliest service time. Arriving later than the latest allowable service time results in missed sales opportunities and incurs costs due to unsold goods. This ice transportation is unique in that even if a customer does not receive service within the time window, the vehicle must still pass within a 90-minute extension to avoid permanent customer loss. This process ensures that customers perceive the ice delivery service as still operating on their route, thus maintaining customer retention. Furthermore, to prevent ice products from melting and sustain their form during transportation, the company implements a quality preservation strategy by fully loading the vehicle with ice products. If the total shipping demand falls below the vehicle's capacity, the company adds supplementary ice tube products to increase density and reduce the air-exposed surface area. These unsold and supplementary products are returned for processing into flake ice, incurring additional costs. Currently, deliveries are managed by designated vehicles and drivers, with routes determined by driver experience. However, this often leads to significant transportation costs due to vehicle misallocation and inefficient route sequencing. Given these considerations, this study aims to minimize costs related to fuel, driver wages including bonuses, missed deliveries, and the quality preservation strategy. The combination of these elements is crucial to optimizing ice distribution operations. Figure 1 shows an overview of the problem.

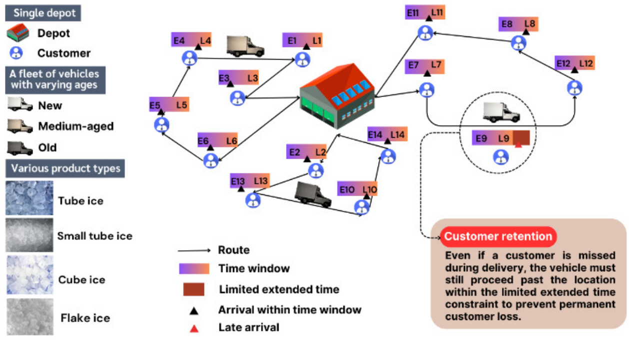

Fig. 1. Schematic of the problem.

III. METHODOLOGY

To address this problem, this study proposes a mathematical model that considers the various constraints of ice distribution. However, solving this VRPTW by using an exact method was not feasible within a reasonable timeframe. Therefore, this study employs a hierarchical cluster-first-route-second approach and a DE algorithm to effectively address large-scale problems. The results obtained from these three methods are compared for their differences to be assessed and the most suitable solution to be identified.

A. Mathematical Model

The VRPTW can be described in the form $G = (V, A)$, where $V = \{0, 1, \dots, N\}$ denotes the set of customers or nodes, with vertex 0 representing the depot. The set $A = \{(i, j): i, j \in V, i \neq j\}$ is a set of arcs connecting each customer location i to j. The distance between customer i to j is symmetrically represented by E_{ij}. A mixed linear programming mathematical model was developed to obtain the optimal solution.

1) Indices and Sets

Customer $i, j, h = 1,2 \dots, N$.

Vehicles $k = 1,2 \dots, K$.

Ice products $p = 1,2 \dots P$.

2) Input Parameters

N is the number of customers.

K is the number of vehicles.

P is the number of product types

E_{ij} is the traveling distance from customer i to j (km).

F_k is the fuel consumption cost of vehicle k (bath/km).

DC is the standard driver wage (bath).

MO is the minimum number of product standards (units).

Q_k is the capacity of vehicle k (units).

d_{ip} is the amount of product p to be delivered to customer i (units).

TD_i is the total demand of customer i (units).

a_i is the earliest arrival time allowed by customer i.

b_i is the latest arrival time allowed by customer i.

S_i is the service time at customer i (mins).

BC is a driver's bonus for exceeding the standard daily quantity of delivered goods (baht/unit).

AC is the cost of additional products for maintaining the quality of delivering goods (baht/unit).

OP_p is the cost of lost sales of product p from missed customers (baht/unit)

$TMAX$ is the maximum time for delivery (mins).

TPK is the time per kilometer of vehicle (min/km).

MP is the extended time for driving during which customers are not serviced (mins).

M is a large positive number.

3) Decision Variables

V_k becomes 1 when vehicle k is used and 0 otherwise.

X_{ijk} becomes 1 when vehicle k travels from customer i to customer j and 0 otherwise.

Y_{ik} becomes 1 when vehicle k services customer i and 0 otherwise.

LT_{ik} becomes 1 when vehicle k misses service at customer i and 0 otherwise.

TA_{ik} is the arrival time of vehicle k at customer i.

TO_{ik} is the departure time of vehicle k at customer i.

BO_k is a driver's bonus of vehicle k (units).

Add_k is the number of additional products for maintaining the quality of delivering goods for vehicle k (units).

DIS_k is the total distance of vehicle k (km).

4) Objective function

$$MinZ = \sum_{k=1}^{K}(F_k * DIS_k) + \sum_{k=1}^{K}\big((DC * V_k) + (BC * BO_k)\big) + \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{p=1}^{P}(OP_p * d_{ip} * LT_{ik}) + \sum_{k=1}^{K}(AC * Add_k) \quad (1)$$

5) Constraints

$$\sum_{j=1}^{N} X_{0jk} \leq 1 \qquad \forall_k \in \{1, \ldots K\} \quad (2)$$

$$\sum_{i=1}^{N} X_{i0k} \leq 1 \qquad \forall_k \in \{1, \ldots K\} \quad (3)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} X_{ijk} \leq N * V_k \qquad \forall_k \in \{1, \ldots K\} \quad (4)$$

$$\sum_{i=0}^{N} X_{ihk} - \sum_{j=0}^{N} X_{hjk} = 0 \qquad \forall_h \in \{1, \ldots N\}, \forall_k \in \{1, \ldots K\} \quad (5)$$

$$\sum_{i=1}^{N}\sum_{k=1}^{K} X_{ijk} = 1 \qquad \forall_j \in \{1, \ldots N\} \quad (6)$$

$$\sum_{k=1}^{K} Y_{ik} = 1 \qquad \forall_i \in \{1, \ldots N\} \quad (7)$$

$$\sum_{j=1}^{N} X_{jik} = Y_{ik}, \forall_i \in \{1, \ldots N\}, \forall_k \in \{1, \ldots K\} \quad (8)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N}(E_{ij} * X_{ijk}) = DIS_k \quad \forall_k \in \{1, \ldots K\} \quad (9)$$

$$\sum_{i=1}^{N} TD_i * (Y_{ik} - LT_{ik}) \geq MO \qquad \forall_k \in \{1, \ldots K\} \quad (10)$$

$$\sum_{i=1}^{N}(TD_i * (Y_{ik} - LT_{ik})) - MO = BO_k \forall_k \in \{1, \ldots K\} \quad (11)$$

$$\sum_{i=1}^{N}\sum_{p=1}^{N}(d_{ip} * Y_{ik}) \leq Q_k \qquad \forall_k \in \{1, \ldots K\} \quad (12)$$

$$Q_k - \sum_{i=1}^{N}\sum_{p=1}^{N}(d_{ip} * Y_{ik}) = Add_k \qquad \forall_k \in \{1, \ldots K\} \quad (13)$$

$$TO_{ik} + (E_{ij} * TPK_k) - M * \big(1 - X_{ijk}\big) \leq TA_{jk} \quad \forall_i \in \{1, \ldots N\}, \forall_j \in \{1, \ldots N\}, \forall_k \in \{1, \ldots K\} \quad (14)$$

$$TA_{ik} + S_i * (Y_{ik} - LT_{ik}) = TO_{ik} \qquad \forall_i \in \{1, \ldots N\}, \ \forall_k \in \{1, \ldots K\} \quad (15)$$

$$TA_{jk} \leq a_j \qquad \forall_j \in \{1, \ldots N\}, \forall_k \in \{1, \ldots K\} \quad (16)$$

$$TA_{jk} \leq (b_j * Y_{jk}) + (MP * LT_{jk}) \qquad \forall_j \in \{1, \ldots N\}, \ \forall_k \in \{1, \ldots K\} \quad (17)$$

$$-M * LT_{jk} + TA_{jk} \leq b_j \qquad \forall_j \in \{1, \ldots N\}, \forall_k \in \{1, \ldots K\} \quad (18)$$

$$M * (1 - LT_{jk}) + TA_{jk} > b_j \qquad \forall_j \in \{1, \ldots N\}, \ \forall_k \in \{1, \ldots K\} \quad (19)$$

$$\sum_{j=1}^{N} X_{jik} \geq LT_{ik}, \forall_i \in \{1, \ldots N\}, \forall_k \in \{1, \ldots K\} \quad (20)$$

$$TO_{ik} + (E_{i0} * TPK_k * X_{i0k}) \leq TMAX \qquad \forall_i \in \{1, \ldots N\}, \forall_k \in \{1, \ldots K\} \quad (21)$$

The objective function (1) aims to minimize the total cost, which includes fuel costs, standard and bonus driver costs, missed deliveries costs, and costs associated with the quality preservation strategy. Constraints (2) and (3) ensure that the vehicle starts and ends at the depot. Constraint (4) limits the number of active vehicles to the number of vehicles available. Constraint (5) ensures that if a vehicle visits a specific customer, it will also leave that customer. Constraint (6) certifies that a vehicle traveling from customer i to customer j has only one destination. Constraint (7) ascertains that each customer is visited only once by a vehicle. Constraint (8) specifies that a vehicle k can travel to customer i only if it follows a route through customer j. Constraint (9) calculates the total distance traveled by vehicle k. Constraint (10) ensures that each vehicle used must deliver more goods than the specified minimum standard quantity. Constraint (11) calculates the number of products eligible for a bonus value of vehicle k. Constraint (12) specifies that the total product carried by the vehicle does not exceed its capacity. Constraint (13) indicates the quantity of additional goods included as part of the strategy to maintain the product quality for the vehicle k. Constraint (14) calculates the arrival time of vehicle k at the customer. Constraint (15) eatimates the departure time of vehicle k from customer i. Constraint (16) certifies that vehicles can reach customers before the earliest time without incurring additional costs. Constraint (17) guarantees that vehicles arrive at the customer within the latest time for service, and if not, they must pass the customer within a specified extended period. Constraints (18) and (19) determine the implications of vehicle k arriving at the customer later than the latest allowed time, resulting in missed deliveries. Constraint (20) determines that vehicle k must pass customer i even if no service is provided to prevent permanent customer loss. Constraint (21) ensures that the total vehicle travel time does not exceed the maximum distribution time.

B. Hierarchical Cluster-First-Route-Second approach

The cluster-first-route-second is a hierarchical method that simplifies complex problems by breaking them down into more manageable subproblems. This approach is employed to deal with the large-scale VRPTW problem. In the first phase, customers are grouped deploying the capacitated K-means clustering method. In the second phase, a mathematical model is applied for route optimization using MILP, employing a branch-and-bound algorithm. The steps for solving this hierarchical approach are:

- Step 1 - Input customer data: Relevant data for clustering customers, including total demand, latitude and longitude coordinates, and the distance matrix, are collected and generated.
- Step 2 - Determine the number of clusters: The K-means clustering algorithm has no specific rules for determining the number of clusters. The number of clusters (k) usually depends on the data characteristics. In general, classical clustering methods use the distance between members and center points. However, for VRPTW, vehicle capacity must be considered. As suggested in [38, 39], the appropriate number of clusters (k) is determined based on the total demand and the vehicle capacity, utilizing a specific formula:

$$number\ of\ cluster\ (k) = \frac{Total\ demand}{vehicle\ capacity} \tag{22}$$

The number of clusters is rounded up to the nearest integer. For instance, for a total demand of 968 units and a vehicle capacity of 150 units, the number of clusters is 7.

- Step 3 - Apply the K-means algorithm: The K-means algorithm partitions data into k clusters to maximize similarity within each cluster. This is determined by the average distance between the data point and the centroid of each cluster.

```
Algorithm 1 The steps of K-Means algorithm
1. Initialize a set of K centers through
random
   sampling.
2. Determine cluster membership by
calculating the
   distance between each data point and
the center
   point, assigning each member to the
closest
   set.
3. Calculate the new center point for each
set
   using the mean values.
4. Repeat steps 2 and 3 until the center
points no
   longer change.
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- Step 4 - Verify cluster constraints: After clustering customers based on location, each cluster's demand is verified to ensure that it meets the vehicle's capacity and the worker's standard rate (70 to 150 units). Clusters that satisfy both constraints are considered acceptable. The system relocates customers to the nearest cluster that can accommodate their demand if their demand within a cluster exceeds the capacity constraint. This process is repeated iteratively until all customers are part of a single cluster that satisfies the capacity condition.
- Step 5 - Prioritize clusters by distance from the depot: Given the utilization of homogeneous vehicles with varying ages, which consequently exhibit different fuel consumption rates, the arrangement of vehicles within each cluster has a significant impact on transportation costs. Thus, this study arranges the sequence of clusters for vehicle selection based on the distance from the depot and the centroid center of each cluster. Vehicle assignment is prioritized for the cluster farthest from the depot, followed by clusters in descending order of distance.
- Step 6 - Apply a mathematical optimization model: Route optimization and vehicle assignment for each cluster are carried out using an MILP with a branch and bound algorithm.

C. Differential Evolution (DE) Algorithm

DE consists of four main steps. This study employed a DE-based metaheuristic to find optimal solutions to complex and large-scale problems. The DE procedure includes the following operations: solution initialization, mutation, recombination, and selection.

1) Step 1: Solution Initialization

Generating the initial vector population is crucial in DE, as a well-designed initial population significantly affects the quality of the solution. The encoding and decoding procedures below outline the population design and parameters.

- Encoding solution: An initial vector population comprises a set of parameters that define a proposed solution to the problem. This population is generated by randomly selecting uniform numbers in the range [0,1). Each vector comprises a customer sequence $C = \{C_n \in J | n = 1, \ldots, N\}$ and a vehicle sequence $V = \{V_k \in J | k = 1, \ldots, K\}$. The vector represents defined customer and vehicle positions based on C and V coordinate system, as shown in Figure 2. The first iteration initializes each position in the vector with randomly generated real numbers. Subsequent iterations update these position values using DE operations (mutation and recombination).

- Decoding solution: In Figure 2, the position values of both C and V in vectors are sorted, with smaller values being given higher priority according to the ROV rule. Therefore, the customer and vehicle positions are rearranged based on their sorted values. The conceptual procedure for decoding is illustrated in Figure. 3.

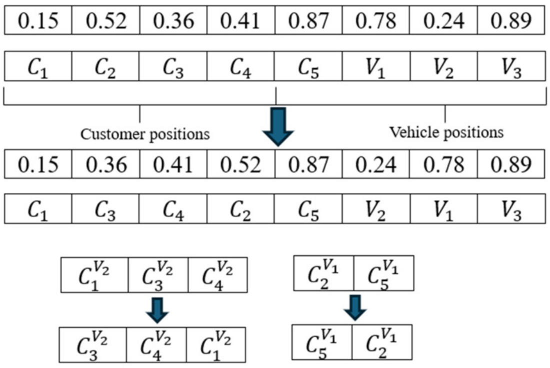

Fig. 2. Example of randomly generated encoding and decoding.

```
Procedure Decoding of the problem
For each vehicle V_k from V_1 to V_K:
  // Assign customer to vehicle V_K
  For each customer C_n from C_1 to C_N:
    If Cumulative total demand + demand of C_n ≤
       Capacity of V_K
      Assign Customers C_n to V_k as (C_n^{V_k})
      Update cumulative total demand
      Update demand of C_n to 0
    Else
      Break the customer loop and move to the next
      vehicle V_{K+1}
  // Routing process for each vehicle
  Rearrange assigned customers (C_n^{V_k}) by ROV
  earlies time
  For each customer in assigned customers for
  vehicle:
    Consider the time window constraints
    Update departure time, total distance,
    cumulative demand
    Calculate objective function and update total
    costs for the vehicle
// After completely assigning all customers to
// vehicles, check minimum served constraints
Return objective function
```

2) Step 2: Mutation Operation

The mutation operation generates a new solution different from the initial population. The mutation vector $V_{ji,G+1}$ is calculated using (23), combining three randomly selected vectors from the initial solution $(X_{r1,G}, X_{r2,G}, X_{r3,G})$. The scaling factor F is a constraint from [0, 2].

$$V_{ji,G+1} = X_{r1,G} + F(X_{r2,G} - X_{r3,G}) \tag{23}$$

3) Step 3: Recombination Operation

This operation generates the trial vectors $U_{ji,G+1}$ through crossover between the mutant vector $V_{ji,G+1}$ and the target vector $X_{ji,G+1}$, as obtained from (24). The position value of the vector can be either a trial or a target value, depending on a random number $rand_j$ and a crossover rate $CR \in [0,1]$.

$$U_{ji,G+1} = \begin{cases} V_{ji,G+1}\ if rand_j \leq CR \\ X_{ji,G+1}\ if\ rand_j > CR \end{cases} \tag{24}$$

4) Step 4: Selection Operation

The final operation selects the vector that will become the initial solution for the next generation $G+1$. This is achieved by comparing the objective function values of the trial and target vectors one-to-one. The vector with the lowest value of the objective function is chosen as the new target vector for the next generation, according to (25). In subsequent iterations, the best solution is determined by comparing the objective function of the target vector.

$$X_{j,G} = \begin{cases} U_{j,G}\ if\ \ f(U_{j,G}) \leq f(X_{j,G-1}) \\ X_{j,G-1}\ otherwise \end{cases} \tag{25}$$

IV. RESULTS AND DISCUSSION

This section presents a case study that evaluates the effectiveness of the solutions acquired using the exact model, the hierarchical cluster-first-route-second approach, and the DE algorithm. Initially, a mathematical model was developed to address the VRPTW for ice distribution, to determine the most efficient ice distribution routes while minimizing total costs. This study generated 35 test instances, dividing them into three sizes: 1) a small problem with 10, 20, and 30 customers, 2) a medium problem with 40 and 50 customers, and 3) a large problem with 60 and 70 customers. Real data from a case study consisting of 83 customers were also deployed. The distance matrix for all locations was calculated using latitudes and longitudes retrieved from Google Maps.

The company's eight-hour planning time constraint limits the scenarios it can solve. Each problem was tested under five scenarios based on customer demand and time windows. The Lingo 19 software was applied for the exact model, whereas DE was implemented using Python in Google Colab. The two-phase approach utilized Google Colab for the first phase and Lingo 19 for the second phase. Table I presents the best solution for each scenario, solved in five iterations, showing the objective results and computation times obtained from MILP, the two-phase approach, and DE. The last two columns provide the efficiency in determining the objective results of cluster-first-route-second and DE methods. Table II depicts the percentage differences between the objective results and CPU times among the three methods.

The results demonstrate that the exact model could achieve the global optimal solution for small problems with up to 30 customers (instances 1-15). The efficiency of the cluster-first-route-second method and DE was assessed by comparing their objective solutions with the global optimal solution. The cluster-first-route-second provided an objective solution very close to the global optimal, with an average efficiency of 99.50%. The DE method achieved an average efficiency of 91.72%, indicating that both methods can provide acceptable solutions for small problems. However, DE required significantly less computation time compared to the cluster-first-route-second.

For medium problems with 40 customers (instances 16-20), the exact model could not provide a global optimal solution within the limited computation time, making it more challenging to obtain feasible solutions. Both the cluster-first-route-second and DE methods consistently delivered feasible solutions. The cluster-first-route-second method provided the objective solution with an average cost that was 10.21% lower than that of the optimal solution and required a shorter computation time. DE resulted in higher costs, averaging 2.67% above the optimal solution, although it also required a shorter computation time compared to both the optimal solution and the cluster-first-route-second method.

For problems with more than 40 customers (medium and large problems), the exact model could not find optimal solutions due to the increased complexity of larger-size problems in VRPTW. Both the cluster-first-route-second approach and the DE provided feasible solutions. However, the cluster-first-route-second method delivered an objective solution with a 24.40% lower average cost than that of DE. Even though it required slightly more computation time, this is acceptable given the significant cost savings. This makes the cluster-first-route-second approach more suitable, as it offers feasible solutions with much lower costs and reasonable computation times. In the real case with 83 customers, the cluster-first-route-second approach was proved again more practical, delivering significantly lower costs by 58.59% and acceptable computation times compared to those of DE.

TABLE I. RESULTS COMPARISON FROM EXACT MODEL, CLUSTERING-FIRST-ROUTE-SECOND, AND DE ALGORITHMS

Test instance	Number of customers	Exact model			Cluster-first route-second		DE		Cluster-first route-second _EF (%)	DE-EF (%)
		State	Total costs (baht)	CPU time (sec)	Total costs (baht)	CPU time (sec)	Total costs (baht)	CPU time (sec)		
1	10	Global	1,102.00	28.89	1,102.00	630.89	1,102.00	152.77	100	100
2	10	Global	1,583.75	42.88	1,583.75	650.35	1,768.50	154.34	100	89.55
3	10	Global	1,041.25	14.32	1,041.25	620.12	1,390.75	144.62	100	95.43
4	10	Global	1,100.00	26.86	1,100.00	630.52	1,100.00	152.26	100	100
5	10	Global	1,076.00	20.04	1,076.00	620.69	1,076.00	149.45	100	100
6	20	Global	1,412.50	115.80	1,412.50	620.85	1,714.75	286.26	100	82.37
7	20	Global	1,472.37	169.92	1,410.00	614.39	1,546.50	293.24	100	91.17
8	20	Global	1,436.00	136.76	1,436.00	614.61	1,436.00	285.91	100	100
9	20	Global	1,406.75	213.16	1,406.75	611.27	1,406.75	286.17	100	100
10	20	Global	1,425.50	91.25	1,428.75	615.25	1,425.50	263.61	99.77	100
11	30	Global	2,174.50	9,146.84	2,203.75	623.39	2,577.50	341.26	98.67	84.36
12	30	Global	2,221.50	5,307.45	2,234.50	618.96	2,491.25	428.17	99.42	89.17
13	30	Global	2,586.00	28,800	2,614.25	621.47	2,907.75	371.45	98.92	88.93
14	30	Global	2,463.32	28,800	2,520.25	623.23	2,949.50	407.18	97.74	83.52
15	30	Global	2,444.40	28,800	2,494.25	615.41	3,429.25	365.13	98.00	71.28
16	40	Feasible	4,294.11	28,800	3,770.60	683.45	5,402.01	505.67	113.88	79.49
17	40	Feasible	4,288.08	28,800	4,548.43	691.89	4,501.77	486.39	94.28	95.25
18	40	Feasible	5,144.91	28,800	4,591.75	693.92	4,933.71	522.21	112.05	104.28
19	40	Feasible	4,959.92	28,800	4,292.60	660.54	4,586.71	474.33	115.55	108.14
20	40	Feasible	4,754.27	28,800	3,768.60	665.29	4,479.34	510.10	126.15	106.14
21	50	N/A	N/A	-	3,915.73	643.99	5,237.87	576.41	-	-
22	50	N/A	N/A	-	4,207.53	663.73	5,431.10	610.94	-	-
23	50	N/A	N/A	-	4,484.94	670.08	5,334.09	559.24	-	-
24	50	N/A	N/A	-	5,398.08	681.97	5,920.80	526.05	-	-
25	50	N/A	N/A	-	4,207.73	669.70	5,463.33	609.23	-	-
26	60	N/A	N/A	-	4,194.01	670.56	7,036.70	657.49	-	-
27	60	N/A	N/A	-	4,607.28	667.08	5,436.15	673.92	-	-
28	60	N/A	N/A	-	5,842.02	642.42	7,335.61	674.52	-	-
29	60	N/A	N/A	-	6,333.52	653.53	7,155.63	672.84	-	-
30	60	N/A	N/A	-	4,717.49	679.08	6,061.80	692.56	-	-
31	70	N/A	N/A	-	4,947.82	673.33	8,640.28	796.35	-	-
32	70	N/A	N/A	-	4,924.26	700.62	7,775.67	768.30	-	-
33	70	N/A	N/A	-	5,530.08	692.52	8,715.66	796.12	-	-
34	70	N/A	N/A	-	5,217.82	684.77	9,030.35	752.46	-	-
35	70	N/A	N/A	-	5,183.78	680.91	8,574.97	793.33	-	-
Real case	83	N/A	N/A	-	6,193.50	704.16	9,822.24	945.128	-	-

The exact model could provide efficient solutions for small-size problems. However, for the larger cases, the hierarchical cluster-first-route-second approach demonstrated superior efficiency, cost-effectiveness, and scalability. This method is particularly suitable for real-world applications in the ice distribution industry, especially in competitive market environments where time and cost optimization are crucial. Meanwhile, the metaheuristic DE method is also popular and effective for solving VRPTW. Its performance depends on the problem's complexity, solution encoding and decoding, and the software used.

TABLE II. DIFFERENCES OF OBJECTIVE RESULTS AND CPU TIME

Test instance	Difference of total cost (%)			Difference of CPU time (sec)		
	OP_K	OP_DE	K_DE	OP_K	OP_DE	K_DE
1	0.00	0.00	0.00	-602.00	-123.88	478.12
2	0.00	-11.67	-11.67	-607.47	- 111.46	496.01
3	0.00	-4.78	-4.78	-605.80	-130.30	475.50
4	0.00	0.00	0.00	-603.66	-125.40	478.26
5	0.00	0.00	0.00	-600.65	-129.41	471.24
6	0.00	-21.40	-21.40	-505.05	-170.46	334.59
7	0.00	-9.68	-9.68	-444.47	-123.32	321.15
8	0.00	0.00	0.00	-477.85	-149.15	328.70
9	0.00	0.00	0.00	-398.11	73.01	325.10
10	- 0.23	0.00	0.23	-524.00	-172.36	351.64
11	- 1.35	-18.53	-16.96	8,523.45	8,805.58	282.13
12	- 0.59	-12.14	-11.49	4,688.49	4,879.28	190.79
13	- 1.09	-12.44	-11.23	28,178.53	28,428.55	250.02
14	- 2.31	-19.74	-17.03	28,176.77	28,392.82	216.05
15	- 2.04	-40.29	-37.49	28,184.59	28,434.87	250.28
16	12.19	-25.80	-43.27	28,116.55	28,294.33	177.78
17	- 6.07	-4.98	1.03	28,108.11	28,313.61	205.50
18	10.75	4.11	-7.45	28,106.08	28,277.79	171.71
19	13.45	7.52	-6.85	28,139.46	28,325.68	186.22
20	20.73	5.78	-18.86	28,134.71	28,289.90	155.19
21	-	-	-33.76	-	-	67.59
22	-	-	-29.08	-	-	52.79
23	-	-	-18.93	-	-	110.85
24	-	-	-9.68	-	-	155.92
25	-	-	-29.84	-	-	60.47
26	-	-	-67.78	-	-	13.07
27	-	-	-17.99	-	-	-6.84
28	-	-	-25.57	-	-	-32.10
29	-	-	-12.98	-	-	-19.31
30	-	-	-28.50	-	-	-13.48
31	-	-	-74.63	-	-	-123.02
32	-	-	-57.91	-	-	- 67.68
33	-	-	-57.60	-	-	-103.60
34	-	-	-73.07	-	-	- 67.69
35	-	-	-65.42	-	-	-112.97
Real case	-	-	-58.59	-	-	-240.97

In the real-world case study, involving 83 customers and a total demand of 968 units, clustering resulted in seven distinct clusters, as evidenced in Figure 3. These clusters were prioritized based on the distance from the depot to each cluster's centroid to optimize vehicle routing. MILP was then applied to each cluster to determine the optimal routes, appropriate vehicle types, and associated total costs. Table IV outlines the details of the computational results. The proposed approach resulted in a total cost of 6,193.50 baht per day and required approximately 704.16 s overall computation time. Compared to the company's current transportation costs, this method could potentially reduce monthly costs by 54,195 baht, equivalent to a 23% decrease. The results disclose that the two-phase algorithm, which uses the cluster-first-route-second approach, effectively addresses the ice distribution problem by providing optimal vehicle routing without missing customers. Its total costs are lower than those of the current ice company, indicating a potential for significant cost savings and operational efficiency improvements.

The results from the exact model reveal that solving times utilizing the branch-and-bound method in Lingo software depends not only on the problem size, but also on the dataset's complexity. As problems become more complex with a larger number of variables, they require further computation time, making conventional methods unsuitable. The cluster-first-route-second approach and the DE algorithm are capable of tackling large-scale VRPTW problems, with the cluster-first-route-second approach achieving the best balance between solution quality and computational efficiency. Although the proposed algorithm, which combines capacitated K-means clustering and branch-and-bound, does not guarantee optimization, it provides solutions close to optimal within practical solving times. This approach demonstrates the potential for real-world application in the ice industry and similar contexts, particularly those with dynamic delivery times and varying data, such as daily customer demands. In such cases, effective planning must deliver solutions within a reasonable timeframe and with a limited set of configurations.

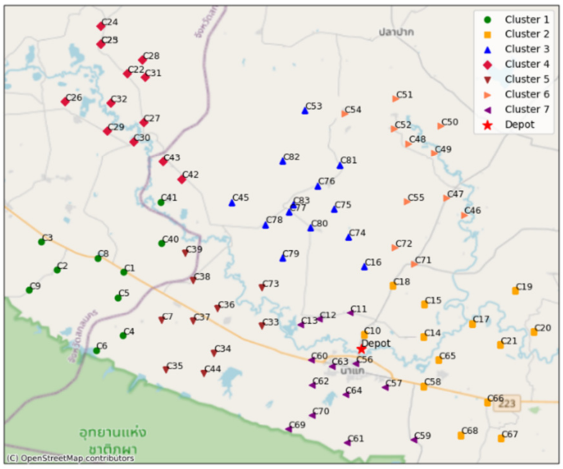

Fig. 3. Depot and customer locations of seven clusters.

V. THEORETICAL AND PRACTICAL IMPLICATIONS

This study provides resources for researchers and practitioners aiming to optimize VRPTW solutions in the context of perishable goods distribution. From a theoretical perspective, this study introduces new practical constraints in ice distribution in VRPTW, such as a customer retention strategy and a quality preservation method. This extension of traditional VRPTW models aligns the problem more closely with real-world applications, offering a more comprehensive theoretical framework. Future models for other distributions of perishable goods can explore and integrate this extension. This work can be extended by incorporating these constraints into different contexts, potentially leading to more comprehensive models. Furthermore, the use of the hierarchical cluster-first-route-second approach to handle VRPTW can be adapted and expanded in future research by combining different algorithms and techniques to address similar complex logistics problems more effectively. Finally, by comparing the performance of the exact method, hierarchical approaches, and metaheuristics, this comparative analysis improves the understanding of the strengths and limitations of various optimization techniques in different problem scenarios.

TABLE III. COMPUTATIONAL RESULT OF THE CASE STUDY

Cluster	Vehicle type	Number of customers	Sequence	Total demand (units)	Total costs (baht)	CPU time (s)
1	New	10	0-4-40-6-5-8-1-41-2-9-3-0	139	782.25	18.86
2	Old	13	0-10-14-17-20-68-18-66-67-19-21-58-65-15-0	140	1,238.00	11.72
3	Mid	13	0-80-79-45-83-78-16-81-75-77-53-82-74-76-0	139	860.00	16.87
4	New	13	0-43-27-22-23-31-28-32-24-25-26-29-30-42-0	149	749.00	8.37
5	Mid	10	0-36-7-34-33-44-35-39-37-38-73-0	115	876.00	13.47
6	New	11	0-55-49-52-51-54-48-46-72-71-47-50-0	136	729.75	19.81
7	Old	13	0-56-60-13-11-70-62-61-69-64-59-63-12-57-0	150	958.50	15.06

For practitioners, the study offers practical tools to enhance distribution strategies, reduce costs, and improve service efficiency in the competitive ice distribution market. The proposed methods help in strategic decision-making regarding vehicle allocation and route planning. The study's methodology, which uses real-world data and addresses practical constraints, ensures that the proposed solutions are directly applicable to current industry practices. This study provides a practical approach to maintaining customer satisfaction and loyalty by ensuring timely deliveries within specified windows and incorporating strategies for handling late arrivals to retain customers, even when service time windows are missed. This study also includes a strategy to maintain ice quality, which provides a holistic approach to ice distribution. Practitioners can utilize these insights to refine their delivery strategies, enhance service quality, and ascertain that their products maintain quality throughout the distribution process, thus reducing losses and improving customer satisfaction. In addition, this study provides a clear approach to managing vehicle routes and schedules more efficiently. The proposed hierarchical approach is scalable and can be adapted to various sizes of distribution problems. Practitioners in different industries can adopt and tailor these methods and strategies to their specific needs to streamline their operations, certifying optimal use of resources and time.

VI. CONCLUSIONS

This study addresses the VRPTW specific to the ice distribution industry, which faces challenges in a competitive market, by introducing new conditions critical to operating in such an environment. The purpose is to improve the efficiency of ice distribution operations by incorporating real-world constraints to cope with the increasingly competitive conditions in the ice market. This contributes to the development of a novel and comprehensive mathematical model that incorporates previously unexplored practical constraints. These constraints include delivery time windows, varying fuel consumption rates based on vehicle age, vehicle capacity constraints, different product types, bonus costs to incentivize employee performance, and distribution strategy requirements. A key customer retention strategy implemented is that even if a customer does not receive service within the specified time window, the vehicle must still pass by within an extended time frame to avoid permanent customer loss. This guarantees that customers perceive the ice delivery service as reliable, thus maintaining retention. Quality preservation methods are also considered to ensure customer satisfaction.

Real-world data from an ice company in Thailand provide a robust framework to optimize distribution routes while minimizing total costs. The results demonstrate that the exact model effectively solves small problems, while the hierarchical cluster-first-route-second approach and the DE algorithm offer scalable and efficient solutions for larger problems. The hierarchical method, particularly when using capacitated K-means clustering followed by branch-and-bound optimization, is proved to be highly effective in balancing solution quality and computational efficiency. The hierarchical cluster-first-route-second approach is well-suited for real-world applications, providing significant cost savings and operational efficiencies. This method outperforms the traditional exact method and the DE algorithm in terms of both solution quality and computation time, especially for medium- to large-sized problems. As a result, the company can efficiently strategize its distribution by managing the required number of vehicles, organizing optimal delivery routes to adhere to specified timeframes, and determining customer retention for late arrivals, as well as product quality, at the lowest possible cost. These contributions enhance customer satisfaction and strengthen the company's competitiveness in today's dynamic market environment.

Although this study presents a robust framework, there are limitations related to model complexity, single-depot configurations, and deterministic parameters. Future research should investigate multi-depot configurations, split deliveries, and variable vehicle speeds to further enhance model applicability and solution efficiency. Additionally, exploring hybrid methods could yield further improvements in solving complex logistics problems. In conclusion, this study offers significant theoretical and practical contributions to VRPTW in the ice distribution industry, providing scalable, efficient, and cost-effective solutions that are adaptable and extendable to other perishable goods distribution contexts.

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