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Optimizing the Vehicle Routes of End Devices Installation for Internet Speed Test Platform Using the Hybrid OVRP-TSP Model

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ABSTRACT

The National Broadcasting and Telecommunications Commission (NBTC) Thailand has implemented a policy to evaluate the quality of Fixed Broadband (FBB) internet in response to numerous customer complaints across the country. One of the proposed solutions for assessing FBB internet quality involves installing end devices to test internet speeds with various internet service providers in the experimental area. However, due to the presence of many providers within the area, planning the vehicle routes for this mission is challenging, particularly given resource limitations. This paper proposes an approach to optimize the vehicle routes for the installation of internet speed test devices. The objective is to minimize the total transportation time, thereby reducing overall costs and carbon emissions. A hybrid OVRP-TSP (Open Vehicle Routing Problem - Traveling Salesman Problem) approach is introduced to address this challenge and is compared with the Clake-Wright Savings Heuristic, the Nearest Neighbor Heuristic, and existing methods. Furthermore, the hybrid OVRP-TSP is tested on 30 provider locations in the eastern region of Thailand. The results demonstrate that the hybrid OVRP-TSP provides the best solution across all measures (Total Time, Total Cost, and Total Emissions), while the other methods also yield efficient solutions compared to existing approaches.

Article information:

Keywords: Hybrid OVRP-TSP, Vehicle Routing Problem, Clarke-Wright Saving, Nearest Neighbor Heuristic, Internet Speed Test Devices

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1. INTRODUCTION

The number of fixed broadband internet users in Thailand has increased since the COVID-19 pandemic began in 2020. Fixed broadband internet aims to make internet usage more convenient for home offices and remote work, which have recently become the most popular working trend. However, the NBTC of Thailand has received numerous complaints about broadband internet services from customers. The organization is actively working to resolve these service issues, addressing concerns from both the private and public sectors. The NBTC currently lacks in-depth information about internet usage from customers and Internet Service Providers (ISPs), making it challenging to propose effective policies and guidelines for the ISPs [1].

In response to this, NBTC has provided research funding to develop a quality assessment system for fixed broadband internet across all service providers in Thailand. An internet speed test platform will be implemented to measure the quality of fixed broadband internet for customers, including metrics such as upload/download speed, ping/latency, jitter, ISP, internet package, and the location (latitude/longitude) of the testing internet service users. The collected data will be analyzed to identify issues with internet usage. Moreover, the findings will contribute to improving ISP standards and establishing appropriate regulations to ensure consistent service quality for all customers. The eastern region of Thailand has been selected for validating internet speed performance and usage quality. The target group includes 30 internet speed test devices (referred to as end devices) that are installed and connected to the

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internet network across four major ISPs, serving 200 customers in the region.

Regarding the implementation plan for the internet speed test platform, several key processes are required to ensure its successful deployment. One of the most crucial processes involves installing the end devices of the internet speed test platform at 30 designated ISP locations in the eastern region. Given the limitations in available drivers, vehicles, time, and installation budget, it is essential to manage resources efficiently for the installation of these end devices at each ISP. Initially, our research team devised a set of vehicle routes for the installation process based on the driver's experience. However, we have encountered challenges related to the high transportation costs associated with these installations. As a result, we are seeking alternative solutions to reduce the total transportation cost for this mission. Several approaches have been proposed to optimize these costs [2]–[5], with one promising solution involving the creation of a list of optimal vehicle routes for end-device installations at each ISP in the eastern region using relevant transportation models. However, there are still some limitations to focusing on only one solving solution, such as longer computational time, disconnected points between vehicle routes, and suboptimal routing solutions.

To address the aforementioned gap, we propose a hybrid OVRP-TSP model, which integrates the Open Vehicle Routing Problem (OVRP) and the Traveling Salesman Problem (TSP), to determine the most efficient vehicle routes with seamless connections among all routes. The installation of end devices in the eastern region serves as a case study for implementing this proposed hybrid model, with three main objectives:

- Firstly, identifying the optimal vehicle routes for installing end devices in the eastern region.
- Secondly, improving resource utilization during the installation process through the application of this model.
- Lastly, comparing the performance outcomes of the hybrid OVRP-TSP with existing vehicle routing solutions based on driver experience.

This paper is divided into five sections. The first section introduces the background, identifies the problem statement, and outlines the main contribution of this work. Section 2 reviews the literature on exact and heuristic methods for establishing vehicle routes, as well as relevant works on vehicle routing problems. Section 3 provides details about the methodology and the implementation of the hybrid OVRP-TSP model. Section 4 presents the results of the proposed model and compares them with the existing solution. Finally, section 5 summarizes the key findings and offers suggestions for future research.

2. LITERATURE REVIEWS

This section provides an overview of the Vehicle Routing Problem (VRP) theories and related existing works. We discuss the Traveling Salesman Problem (TSP), Open Vehicle Routing Problem (OVRP), Clake-Wright Saving Heuristic, and Nearest Neighbor Heuristic. We introduce an overview of each method, some related studies, and comparisons, and define the applied approach used in this study.

2.1 Traveling Salesman Problem (TSP)

The Traveling Salesman Problem (TSP) has garnered significant attention from mathematicians and computer scientists due to its simple description yet complex solution. The problem is defined as follows: A traveling salesman must visit each of m cities exactly once, with travel costs from city i to city j denoted as c_{ij}. The objective is to determine the least costly route that allows the salesman to visit all cities and then return to the starting city [3].

In the paper by [6], a novel approach to TSP was introduced, which minimizes the sum of latencies to cities instead of the total distance traveled. The paper also presented the Travelling Maintainer Problem (TMP), which integrates prognostics from Condition-based Maintenance (CBM) with TSP to optimize maintenance scheduling. Genetic Algorithm and Particle Swarm Optimization solutions for TMP are compared in a case study.

In recent years, Unmanned Aerial Vehicles (UAVs), commonly known as drones, have revolutionized logistics, particularly in last-mile delivery for commercial sectors. The paper [7] integrated drones with trucks to enhance service quality and reduce transportation costs for direct-to-customer deliveries. This innovation led to a variant of the TSP known as the TSP with Drones (TSP-D). Previous studies, such as those by [8], focused on minimizing completion times for both trucks and drones to improve service efficiency. In contrast, Ha et al.'s paper introduced a new formulation of TSP-D aimed at minimizing total operational costs, including transportation expenses and idle waiting times between vehicles. The paper presented two algorithms: TSP-LS, which adapts Murray and Chu's method to convert optimal TSP solutions into feasible TSP-D solutions via local searches, and GRASP, which uses a novel split procedure to optimize any TSP tour into a TSP-D solution, followed by refinement using local search operators. Numerical experiments across various problem sizes and scenarios demonstrate that GRASP consistently outperforms TSP-LS in terms of solution quality, while manageable computation times.

In response to the growing need to reduce greenhouse gas emissions, the logistics sector has increasingly adopted electric vehicles, presenting new computational challenges in distribution planning. The paper [9] focused on the Electric Traveling Salesman

Problem with Time Windows (E-TSPTW). They introduced a mixed-integer linear formulation capable of efficiently solving instances with up to 20 customers within short computing times. Additionally, they proposed a Three-Phase Heuristic algorithm that integrated General Variable Neighborhood Search (GVNS) and Dynamic Programming (DP). Computational experiments demonstrated the heuristic's effectiveness: it consistently identifies optimal solutions for small instances within milliseconds and delivers competitive solutions for larger scenarios involving up to 200 customers. This research provided valuable insights into addressing environmental concerns while optimizing logistical operations through advanced computational techniques tailored to electric vehicle routing challenges. The insights gained from these studies are relevant to the vehicle routing plan proposed in this study.

2.2 Open Vehicle Routing Problem (OVRP)

The Open Vehicle Routing Problem (OVRP), first introduced by Linus Schrage [10], differs from traditional vehicle routing problems in that, once the last customer on a route is serviced, the driver does not necessarily return to the depot. Instead, the route may conclude at a designated car park or even at the driver's home, depending on operational constraints and logistics requirements.

With the rapid expansion of the sharing economy, outsourcing logistics operations to third-party logistics providers has emerged as a cost-effective strategy in freight transportation. This study [11] effectively modeled a variant of the OVRP, where vehicles do not return to the depot after serving customers. Despite its relevance, there has been limited research addressing fuel consumption within the context of third-party logistics. This study introduced the Green Open Vehicle Routing Problem with Time Windows (GOVRPTW), integrating a mathematical model based on the Comprehensive Modal Emission Model (CMEM). To solve this complex problem, a hybrid Tabu Search algorithm incorporating multiple neighborhood search strategies was developed. Computational experiments were conducted using realistic instances reflecting the road conditions in Beijing, China. The analysis highlights the impact of empty kilometers by comparing various cost components. Results demonstrated that adopting open routes instead of closed routes reduced total costs by 20%, with fuel and CO2 emissions costs declining by nearly 30%. However, in scenarios involving congested nodes, fuel and emissions costs increased by 12.3%, while driver costs rose sharply by 31.3%. This research contributes valuable insights into optimizing logistics operations under environmental constraints, emphasizing the benefits and challenges of adopting open vehicle routing strategies in urban logistics contexts.

Another example, the Open Vehicle Routing Problem with Decoupling Points (OVRP-DP) [12] addressed a critical logistical challenge where companies seek to optimize freight transportation over large territories by leveraging multiple carriers efficiently. Unlike traditional routing problems where each route is handled by a single carrier, OVRP-DP allows for the strategic use of decoupling points. At these points, one carrier completes part of the deliveries before transferring the remaining load to another carrier to continue the route, thereby maximizing operational efficiency and minimizing costs. This problem was modeled using a sophisticated cost function tailored for multi-drop less-than-truckload scenarios, incorporating nonlinear transportation costs, detour penalties, and drop-off expenses. The development of a specialized Iterated Local Search (ILS) algorithm demonstrated its effectiveness in solving OVRP-DP instances, achieving optimal solutions across varied scenarios, and improving upon existing solutions for specific instances. Real-world validations with industrial data underscore the significant cost-saving benefits of implementing decoupling points in logistics planning, showcasing the algorithm's superiority over commercial solvers in terms of solution quality and robust performance. The main ideas from these studies align with the vehicle route construction approach used in this study.

2.3 Clake-Wright Savings Heuristics

The Savings heuristic was proposed by Clake and Wright. This algorithm constructs a list of vehicle routes with a simple technique and short computational time [13]. It builds vehicle routes based on the saving score, calculated from the difference between the direct freight distance and the freight distance combined between two customers. Several research works have examined and implemented the concept of Clake-Wright Saving.

For example, this study [4] introduced a new heuristic approach based on the Clarke-Wright Savings algorithm to address the OVRP. The researchers modified the Clarke-Wright Savings through three specific procedures: Clarke-Wright formula modification, open-route construction, and a two-phase selection process. These were combined with a route post-improvement procedure utilizing neighborhood structures including shift, swap, and λ-opt move operators to refine the best solutions. Experiments conducted using six well-known OVRP data sets, encompassing 62 instances from the literature, demonstrated the competitiveness of this approach. The numerical results revealed that this new method consistently outperformed the original Clarke-Wright solutions and generated the best-known solutions in 97% of instances. The study also highlighted areas for further exploration, such as developing a more robust post-improvement procedure and extending the modified Clarke-Wright algorithm to address other problem variants like the Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD) and the Vehicle Routing Problem with Time Windows (VRPTW).

The VRP is a versatile tool widely applied in logistics, but its adaptation to agricultural field operations, where machine paths must efficiently cover entire fields, presents unique challenges. The study [14] addressed this by formulating field path allocation and sequencing into a VRP aimed at optimizing overall field completion times. They employed a basic heuristic algorithm based on a modified Savings method and a more advanced meta-heuristic, Tabu Search. Despite Tabu Search requiring significantly more computational time than the heuristic approach, it consistently yields superior solutions by reducing field completion times and increasing effective field capacity. The Savings method presents an interesting alternative solution applicable to various problem scenarios. Two additional papers have studied how to solve VRP routes using Savings heuristics. For example, the authors in [15] applied this heuristic method to optimize vehicle routes for the distribution of medical devices in Medan City, Indonesia. The results revealed that the Clake-Wright Savings method provides the shortest distance with multiple trips. Another paper [16] implemented the Savings heuristic to determine the optimal distribution routes for reducing ATM operational costs. The results showed that relevant operational costs, such as fuel and toll fees, decreased when compared to the initial solution.

2.4 Nearest Neighbor Heuristic

The Nearest Neighbor (NN) heuristic is another straightforward method for planning vehicle routes in various case studies, including the Traveling Salesman Problem (TSP). The NN selects the next node based on the closest distance between the current node and the subsequent node[17]. Several studies have implemented the NN paradigm.

For instance, the study [18] proposed three modifications to the NN algorithm—PNN, DNN, and DDNN—aimed at reducing data delivery latency without significantly increasing computational time. Analytical and simulation results reveal that these new algorithms outperform the traditional NN algorithm, particularly in scenarios with densely deployed nodes and larger transmission ranges.

The VRP seeks to determine a vehicle route that minimizes mileage while meeting customer demands at their respective locations. A variant of VRP is the Capacitated Vehicle Routing Problem (CVRP), which includes constraints on vehicle capacity. The study [5] demonstrated how the CVRP can be addressed using the NN and Tabu Search algorithms. The Tabu Search Algorithm process begins with an initial solution determined by the NN method, followed by generating alternative solutions through exchanges, where two points in the solution are swapped. These alternatives are then evaluated using a Tabu list, and the best solution is selected and refined as the optimal solution. The Tabu list is subsequently updated, and the process continues until the termination criteria are met. If the criteria are not satisfied, the algorithm returns to generating alternative solutions. Calculations showed that using the Tabu Search algorithm results in a travel distance approximately 10.01% shorter than that achieved by the NN method.

2.5 Existing works summary

Based on the details from Sections 2.1-2.4, we have compiled a list of relevant publications that explore Vehicle Routing and Traveling Salesman problems over the past 10 years. All relevant publications are shown below in Table 1.

Table 1: *Summary of solving solution of the VRP.*

List of existing publications	Problem Type	Solving Solution
Pichpibul and Kawtummachai, 2013 [4]	OVRP	Savings Heuristic
Camci, 2014 [6]	TSP	Genetic Algorithm (GA), Particle Swarm Optimization (PSO)
Roberti and Wen, 2016 [9]	TSP	General Variable Neighborhood Search (GVNS), Dynamic Programming (DP)
Alemayehu and Kim, 2017 [18]	TSP	Nearest Neighbor Heuristics (NN)
Seyyedhasani, and Dvorak, 2017 [14]	VRP	Tabu Search (TS), Savings Heuristic
Mostafa and Eltawil, 2017 [19]	VRP	K-Means, Mixed Integer Programming (MIP)
Atefi *et al.*, 2018 [12]	OVRP	Iterated Local Search (ILS)
Ha *et al.*, 2018 [7]	TSP	TSP-LS, GRASP
Masudin *et al.*, 2019 [5]	VRP	Tabu Search (TS), Nearest Neighbor Heuristics (NN)
Jaradat and Diabat, 2019 [20]	TSP	K-Means, Firefly Algorithm (FA)
Sánchez *et al.*, 2022 [21]	VRP	K-Means, Mixed Integer Linear Programming (MILP)
Kantasa-ard *et al.*, 2023 [22]	OVRP	Mixed Integer Programming (MIP), Random Local

		Search (RLS), Simulated Annealing (SA)
Cipta and Hasibuan, 2023 [15]	VRP	Savings Heuristic
Nurcahyo *et al.*, 2023 [16]	VRP	Savings Heuristic

OVRP: Open Vehicle Routing Problem
TSP: Traveling Salesman Problem
VRP: Vehicle Routing Problem

From the literature review above, most studies focus on only a single problem type (OVRP or TSP). However, few studies combine these two problems. To address the research gaps mentioned, we propose the integration of the Open Vehicle Routing Problem (OVRP) with the Traveling Salesman Problem (TSP) approach to construct vehicle routes for the installation of internet test devices in the eastern region of Thailand. Heuristic algorithms are more popular than exact algorithms, highlighting the need for a new solution that increases efficiency.

3. METHODOLOGY

This section provides an overview of the problem statement, assumptions, and solution approach of this study. All details are described below.

3.1 Problem statement and assumptions

In this study, we focus on increasing the efficiency of device installation routing management in the eastern region of Thailand. The problem involves 30 points spread across 7 provinces. Please refer to Table 2 for more details.

Table 2: *The device installation points for the internet speed test platform in the eastern region of Thailand.*

Point Name	Location	Point Name	Location
ISP-A1	Muang, Chonburi	ISP-C1	Aranyaprathet, Sa Kaeo
ISP-A2	Bang Lamung, Chonburi	ISP-C2	Muang, Chachoengsao
ISP-A3	Muang, Chachoengsao	ISP-C3	Muang, Chanthaburi
ISP-A4	Aranyaprathet, Sa Kaeo	ISP-C4	Muang, Trat
ISP-A5	Muang, Rayong	ISP-C5	Muang, Chonburi
ISP-A6	Muang, Trat	ISP-C6	Sriracha, Chonburi
ISP-A7	Muang, Chanthaburi	ISP-C7	Muang, Rayong
ISP-A8	Muang, Rayong	ISP-C8	Bang Lamung, Chonburi
ISP-B1	Muang, Prachinburi	ISP-D1	Plaeng Yao, Chachoengsao
ISP-B2	Khao Saming, Trat	ISP-D2	Sriracha, Chonburi
ISP-B3	Aranyaprathet, Sa Kaeo	ISP-D3	Bang Lamung, Chonburi
ISP-B4	Muang, Chonburi	ISP-D4	Sattahip, Chonburi
ISP-B5	Bang Lamung, Chonburi	ISP-D5	Muang, Chonburi
ISP-B6	Muang, Rayong	ISP-D6	Muang, Chonburi
ISP-B7	Muang, Chanthaburi	ISP-D7	Pluak Daeng, Chonburi

ISP-A: Internet Service Provider Company A
ISP-B: Internet Service Provider Company B
ISP-C: Internet Service Provider Company C
ISP-D: Internet Service Provider Company D

Initially, the existing plan for end-device installation was established based on the driver's experience. It involved 30 points over 11 days, covering 3,088.63 kilometers. This plan included a single trip with overnight stays. The transportation cost was 8.25 Thai Baht (THB) per kilometer, and the accommodation cost was 500 THB per day. The transportation cost amounted to approximately 25,481.22 THB, and the accommodation cost for 6 nights was around 3,000 THB, bringing the total cost to 28,481.22 THB. The route allowed travel through various cities on the same day without the need to return to the depot. The existing plan is outlined in Table 3.

Table 3: *The existing plan for device installation.*

Day	Vehicle Route	Distance (KM)	Travel Time (Minute)
1	ISP-B4 > ISP-B5 > ISP-C7	126.74	174.50
2	ISP-C3 > ISP-D1 > ISP-D5	383.71	375.81
3	ISP-D6 > ISP-B6 > ISP-B7	222.57	238.38
4	ISP-B2 > ISP-B3 > ISP-B1	512.74	461.89
5	ISP-D2 > ISP-D3 > ISP-D4	194.94	249.96
6	ISP-C5 > ISP-C6 > ISP-C8	103.88	189.24
7	ISP-A1 > ISP-A2 > ISP-A5	128.58	175.72
8	ISP-D7 > ISP-A8 > ISP-A7	199.75	223.17
9	ISP-A6 > ISP-C4	339.44	316.30
10	ISP-A3 > ISP-A4	453.01	392.01
11	ISP-C1 > ISP-C2	423.27	372.18
Total		3,088.63	3,169.16

However, there are several issues with the current plan. Firstly, the decision-making process relies solely on the driver's experience, which may not always yield optimal results. Secondly, while this method may be effective for smaller datasets, it becomes inefficient when expanding to larger regions with more points. Lastly, there is a lack of consistency in the routing strategy. For example, the plan does not prioritize visiting all nodes within the same city before moving to the next. This inconsistency leads to increased transportation costs and longer travel times.

Based on the issues identified with the existing plan above, we conducted an experimented to develop a new route for installing end devices in the eastern region of Thailand. We compared the results using three solutions: the hybrid OVRP-TSP model, the Savings heuristic, and the Nearest Neighbor heuristic. The assumptions for this problem are as follows:

- The depot serves as the starting and ending points after completing the installation of all end devices in the eastern region.
- Each point will be visited exactly once.
- The endpoint from the previous day becomes the starting point for the current day.
- The total installation time for all end devices in one day must not exceed 500 minutes.
- Each route will be free of sub-tours.
- Perturbation situations, such as road closures, traffic jams during rush hours, and temporary one-way streets, are not included in this study.

3.2 Solution approach

3.2.1 The hybrid OVRP-TSP model

The formulation of the hybrid OVRP-TSP model is adapted from the VRP model [2].

Indices

$i = set\ of\ point\ i\ by\ i = 0, 1, 2, \ldots, N$
$j = set\ of\ point\ j\ by\ j = 0, 1, 2, \ldots, N$
$k = set\ of\ route\ k\ by\ k = 1, 2, \ldots, M$
$q = the\ last\ point\ of\ the\ last\ route$
$S = number\ of\ assigned\ point$
$N = number\ of\ points$
$M = number\ of\ routes$

Parameters

$T_{ij} = Total\ time\ from\ point\ i\ to\ j$
$C_k = Maximum\ working\ time\ for\ route\ k$
$Starting_k = the\ first\ point\ of\ route\ k$
$Ending_k = the\ last\ point\ of\ route\ k$

Decision Variables

$$X_{ijk} = 1,\ if\ route\ k\ had\ point\ i\ to\ j;\ 0, otherwise$$

Objective Function

$$Min = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} T_{ij} X_{ijk} \quad (1)$$

Constraints

$$\sum_{j=0}^{N} \sum_{k=0}^{N} X_{ijk} = 1, \forall i = 0, 1, 2, \ldots, N \quad (2)$$

$$\sum_{i=0}^{N} \sum_{k=0}^{N} X_{ijk} = 1, \forall i = 0, 1, 2, \ldots, N \quad (3)$$

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

$$\sum_{i=0}^{N} \sum_{j=0}^{N} T_{ij} X_{ijk} \leq C_k, \forall k = 0, 1, 2, \ldots, M \quad (5)$$

$$Min = \sum_{j=0}^{N} X_{0j1} = 1 \quad (6)$$

$$Starting_{k=1} = X_{0j1} \quad (7)$$

$$\sum_{i=1}^{N} X_{i0kq} = 1 \quad (8)$$

$$Ending_{k_q} = X_{i0k_q} \quad (9)$$

$$Starting_{k+1} = Ending_k, \forall k = 1, 2, 3, \ldots, M \quad (10)$$

$$X_{ijk} \in \{0, 1\} \quad (11)$$

In the hybrid OVRP-TSP model, equation (1) represents the objective function, which minimizes the total time for all routes by calculating the total distance divided by the average speed of the vehicle. This objective function includes both transport time and device installation time, starting from the depot, traveling to all points, and returning to the depot after completing all installations. Equations (2) and (3) are constraints ensuring that each point serves as an arrival and departure point only once. Equation (4) is a constraint to avoid subtour problems (Laporte, 1992), while equation (5) sets the maximum working time per day. If the last point of a route is not the depot, the plan incurs an accommodation cost for overnight stays. Equations (6) and (7) set the first point of the first route as the depot, and equations (8) and (9) set the last point of the last route as the depot. This model requires starting and ending at the depot but does not necessitate returning every day. In cases of overnight stays, equation (10) ensures that the last point of the previous route is the same as the first point of the next route. Equation (11) defines a binary variable.

The hybrid OVRP-TSP model in this research was implemented using Google OR-Tools on Google Colab. As illustrated in Figure 1, the procedure begins by creating the data model for the problem, which involves setting up the distance matrix between points, the number of vehicles, and the depot as the starting point. This step is essential because it provides the fundamental data required by the routing algorithm to solve the Traveling Salesman Problem (TSP). The total number of points, N, represents the number of cities or locations involved in the TSP. The starting point is set to the depot, which is the initial location from where the route will begin and typically end.

```
Start Procedure
    Create data model for the problem
    Define total_points = N
    Define first_point = depot
    Create routing model with OVRP-TSP
    Define distance callback function
        Convert from_index and to_index to actual points
        Return distance between these points
    Set arc cost evaluator for all vehicles to use the distance callback
    Set search parameters for the first solution strategy to "PATH_CHEAPEST_ARC"
    Solve the problem with the search parameters
    If a solution is found:
        Print the solution with the route
End Procedure
```

Fig.1: *The hybrid OVRP-TSP Model pseudo code using Google OR-Tools.*

A routing model for the Open Vehicle Routing Problem with a Traveling Salesman Problem formulation (OVRP-TSP) is then created using Google OR-Tools, a powerful optimization library[23]. The Cheapest Arc heuristic from Google OR-Tools was chosen to construct vehicle routes in this study. This model is responsible for finding the optimal route that minimizes the total travel distance while visiting all points exactly once. Next, a distance callback function is defined to calculate the distance between two points. This function is crucial as it provides the routing model with the necessary information to evaluate the cost of traveling from one point to another. The function converts the indices used in the routing model to actual points (cities) and returns the corresponding distance from the distance matrix.

The routing model is then configured to use this distance callback function to evaluate travel costs. This is achieved by setting the arc cost evaluator for all vehicles to use the distance callback. This setup ensures that the routing model correctly calculates the travel distance between points, which is essential for finding the optimal route. Search parameters are set for the first solution strategy, specifically "PATH_CHEAPEST_ARC." This strategy constructs the initial solution by always choosing the Nearest Neighbor, which is a common heuristic for solving TSP as it provides a good starting point for further optimization.

The problem is then solved using these search parameters. Google OR-Tools employs sophisticated algorithms to explore different possible routes and find the one with the minimum total travel distance. If a solution is found, the solution is printed, displaying the route and potentially the total distance. This output is valuable as it shows the optimal path that the vehicle should take to visit all points with the least travel cost. The procedure concludes with the end of the main process, marking the completion of the TSP solution using Google OR Tools with Python. This structured approach ensures that the TSP is efficiently solved, leveraging the capabilities of OR Tools to handle complex routing problems.

3.2.2 Clake-Wright Savings Heuristics

Figure 2 shows an algorithm for solving a routing problem, likely related to the Vehicle Routing Problem (VRP) or similar logistics optimization tasks. The process begins with setting all points and the depot, followed by computing and storing a matrix of savings between each pair of points. This matrix is then sorted in descending order to prioritize the most beneficial connections. The algorithm starts routing from the depot and selects the next point with the highest saving from the depot. It checks if the total time of the current route is within the maximum allowed time. If the time exceeds the limit, a new route is added, and the process repeats. If the time is within the limit, the selected point is added to the current route, and the next highest saving point, which is not the depot, is chosen. The algorithm continues to add points to the route while checking the total time until all points have been chosen. If all points are chosen, the depot is set as the ending point for the last route. The algorithm concludes by ensuring all routes are efficient and within the specified constraints. This approach systematically constructs routes by maximizing savings between points, ensuring that the routes adhere to the constraints, such as the maximum allowed time per day.

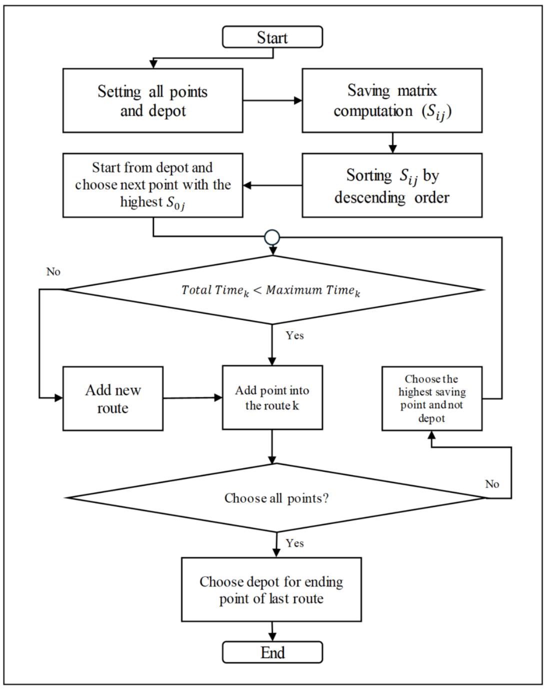

Fig.2: *The Clake-Wright Savings Heuristics Process.*

3.2.3 Nearest Neighbor Heuristics

Figure 3 shows an algorithm for solving a routing problem using the Nearest Neighbor (NN) method. The process begins by setting all points and the depot. Starting from the depot, the algorithm selects the next nearest unvisited point. It then checks if the total time for the current route is within the maximum allowable time. If the time exceeds the limit, a new route is added, and the process restarts from step 3. If the time is within the limit, the nearest point is added to the current route. The method continues by choosing the nearest unvisited point that is not the depot and adding it to the route. This process repeats, checking if the total route time is within the limit and adding new routes as necessary until all points are visited. Once all points are included, the depot is selected as the ending point for the last route, concluding the algorithm. This systematic approach aims to build efficient routes by continuously selecting the nearest unvisited point, ensuring the routes adhere to specified time constraints.

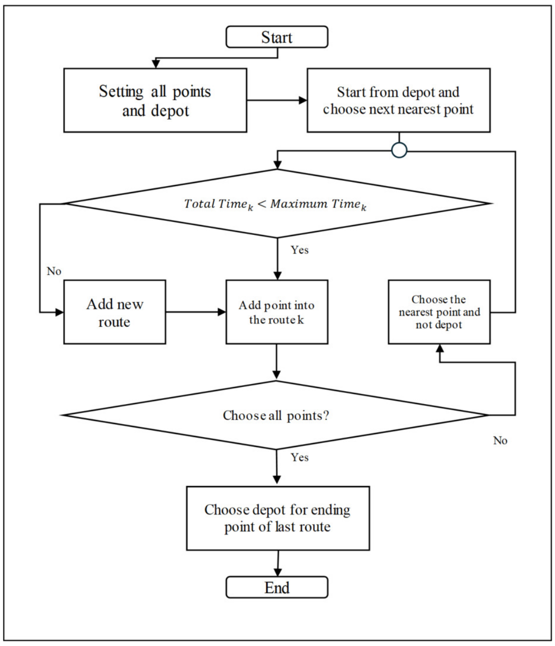

Fig.3: *The Nearest Neighbor Heuristics Process.*

4. RESULTS AND DISCUSSION

In this research, we experimented to plan the route for installing devices in the eastern region of Thailand. We compared the existing plan with three solutions: the hybrid OVRP-TSP model, the Savings heuristic, and the Nearest Neighbor heuristic. Our focus was on three measures: Total Time, Total Cost, and Total Emission. The formula of total emissions was inspired by [24] and adapted from [22]:

$$EM_{total} = FE * FC * D \tag{12}$$

The fuel emission rate (FE) was 2621 g/l, and the fuel consumption rate (FC) was 0.3462 l/km based on a 70% to 80% load in rural areas [24]. The total distance (D) was the main input factor to calculate total carbon emissions. In this study, the total distance was the sum of the total distance from the depot to points and points to points.

4.1 Experimental Results: the hybrid OVRP-TSP model

In the field of logistics and route planning, optimizing the sequence of locations for device installations is crucial for efficiency and cost-effectiveness. This research explores the application of the Open Vehicle Routing Problem (OVRP) combined with the Traveling Salesman Problem (TSP) to determine the optimal route for a device installation itinerary across Eastern Thailand. The itinerary includes various cities and towns, focusing on minimizing travel distance and time while ensuring that all required locations are covered. All route details are displayed in Table 4 and Figure 4, with descriptions provided below.

On the first day, the route begins at the Depot and ends at ISP-B6, Muang, Rayong. The route is optimized to cover 209.33 kilometers in 499.55 minutes, passing through 12 nodes. The model efficiently sequences the travel through various parts of Chonburi and Rayong. On the second day, the route starts in Muang, Rayong, and ends in Aranyaprathet, Sa Kaeo, beginning at ISP-B6 in Muang, Rayong, and concluding at ISP-A4 in Aranyaprathet, Sa Kaeo. The journey covers 420.05 kilometers in 490.03 minutes across seven nodes. On the third day, the route extends from Aranyaprathet, Sa Kaeo, to Muang, Chonburi, covering 349.79 kilometers and consisting of eight nodes completed in 473.20 minutes. The final day's route starts at ISP-A1 in Muang, Chonburi ,and concludes back at the Depot, covering 23.42 kilometers in 135.62 minutes across four nodes.

The use of OVRP combined with TSP for route optimization in device installation demonstrates significant improvements in efficiency and cost-effectiveness. Over four days, the itinerary covers 1,002.59 kilometers in 1,598.40 minutes (approximately 26 hours and 38 minutes) across 31 nodes. This optimized route not only reduces travel distance and time but also ensures comprehensive coverage of all required locations.

4.2 Comparison Experimental Results

Route optimization is crucial for achieving logistical efficiency, cost-effectiveness, and timely delivery across various sectors, including device installation. This comparative analysis evaluates three different methods: the Open Vehicle Routing Problem (OVRP) combined with the Traveling Salesman Problem (TSP), the Savings Method, and the Nearest Neighbor (NN) method. The performance of

Table 4: *The vehicle routes by the hybrid OVRP-TSP model.*

Day	Vehicle Route	Distance (KM)	Travel Time (Minute)
1	Depot > ISP-C6 > ISP-D2 > ISP-C8 > ISP-D3 > ISP-B5 > ISP-A2 > ISP-D4 > ISP-D7 > ISP-C7 > ISP-A5 > ISP-A8 > ISP-B6	209.33	499.55
2	ISP-B6 > ISP-A7 > ISP-C3 > ISP-B7 > ISP-A6 > ISP-C4 > ISP-B2 > ISP-A4	420.05	490.03
3	ISP-A4 > ISP-B3 > ISP-C1 > ISP-B1 > ISP-D1 > ISP-A3 > ISP-C2 > ISP-B4 > ISP-A1	349.79	473.20
4	ISP-A1 > ISP-D5 > ISP-D6 > ISP-C5 > Depot	23.42	135.62
Total		1,002.59	1,598.40

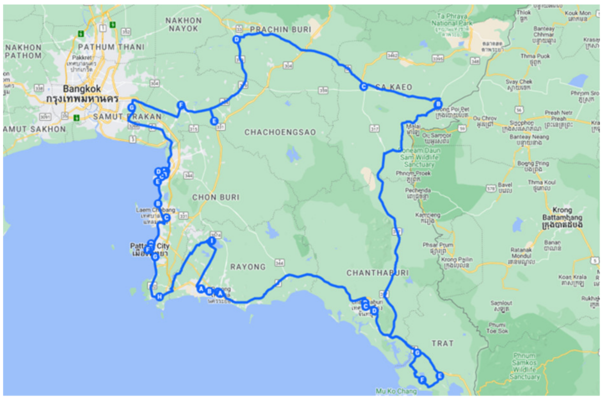

Fig.4: *The overall routes from the OVRP-TSP method.*

these methods is assessed based on total time, total distance, number of operational days, overnight stays, transport costs, accommodation costs, and total costs.

Table 5 compares four different routing methods—Existing, OVRP-TSP, Savings, and Nearest Neighbor (NN)—across various measures, highlighting their respective efficiencies and costs in device installation.

The total time required for installation varies significantly across the methods. The Existing method takes the longest time, requiring 3,169.16 minutes. In contrast, the OVRP-TSP model dramatically reduces this time to 1,598.40 minutes, a reduction of 49.56%. The Savings method requires 1,919.60 minutes, while the NN method takes 1,703.50 minutes. These reductions indicate that all three methods are more time-efficient than the existing method, with OVRP-TSP

Table 5: *Comparison of Experimental Results with three models.*

Factor	Existing	OVRP-TSP	Savings	NN
Total Time (Mins)	3,169.16	1,598.40	1,919.60	1,703.50
Total Distance (KM)	3,088.63	1,002.59	1,394.70	1,160.27
Total Day	11	6	5	4
Overnight	6	3	2	3
Transport Cost (THB)	25,481.22	8,271.39	11,506.28	9,572.22
Accommo dation Cost (THB)	3,000.00	1,500.00	1,000.00	1,500.00
Total Cost (THB)	28,481.22	9,771.39	12,506.28	11,072.22
Total Emission (Kg)	2,802.60	909.74	1,256.54	1,052.82

being the most effective. The total time reductions are detailed in Figure 5.

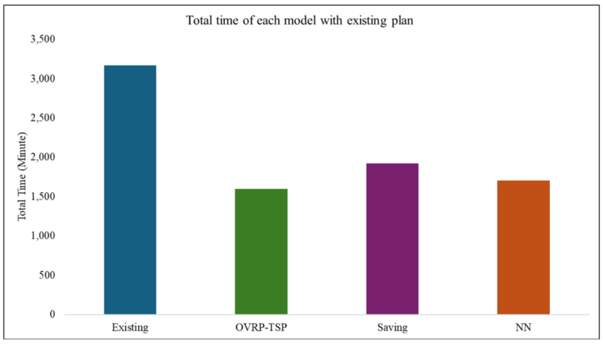

Fig.5: *Total time of each model compared to the existing plan.*

The total distance covered also varies. The Existing method covers the most distance at 3,088.63 kilometers. The OVRP-TSP model is the most efficient, reducing the distance to 1,002.59 kilometers. The Savings method covers 1,394.70 kilometers, and the NN method covers 1,160.27 kilometers. All three alternative methods cover significantly less distance than the Existing method.

Next, we consider the number of days required for installation. The Existing method takes 11 days. The OVRP-TSP model reduces this to 6 days. The Savings method further reduces it to 5 days, while the NN method requires only 4 days. This highlights a significant improvement in the time needed for installation when using alternative methods.

Another key measure is the number of overnight stays required. The Existing method requires 6 overnight stays. The OVRP-TSP model reduces this to 3 stays, while the Savings method requires only 2. The NN method also requires 3 overnight stays. This indicates that both OVRP-TSP and NN methods are more efficient in this aspect compared to the existing method.

Transportation costs associated with each method vary widely. The Existing method incurs a high cost of 25,481.22 Thai Baht (THB). The OVRP-TSP model significantly reduces this cost to 8,271.39 THB. The Savings method incurs a cost of 11,506.28 THB, while the NN method costs 9,572.22 THB. These alternative methods, particularly OVRP-TSP, show substantial cost savings.

Accommodation costs also differ. The Existing method incurs a cost of 3,000 THB. The OVRP-TSP model reduces this to 1,500 THB, with the Savings method lowering it further to 1,000 THB. The NN method also incurs 1,500 THB in accommodation costs, indicating that both OVRP-TSP and NN are more cost-effective than the Existing method.

The combined total cost of transportation and accommodation highlights the overall financial efficiency of each method. The Existing method has the highest total cost at 28,481.22 THB. The OVRP-TSP model significantly reduces the total cost to 9,771.39 THB, achieving a 65.69% reduction compared to the existing method. The Savings method follows closely with a total cost of 12,506.28 THB (a 61.12% reduction), while the NN method costs 11,072.22 THB, marking a 56.09% reduction. These figures demonstrate substantial cost savings with the alternative methods, especially the OVRP-TSP model. The details of transport cost reductions are shown in Figure 6.

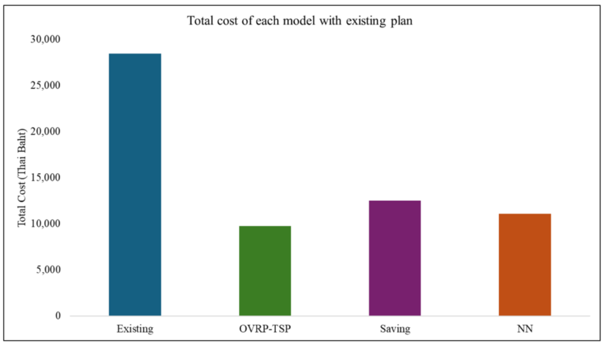

Fig. 6: *Total cost of each model compared to the existing plan.*

Finally, total emissions vary across the methods. The Existing method results in the highest emissions at 2,802.60 kilograms. The OVRP-TSP model is the most efficient, reducing emissions to 909.74 kilograms, which represents a 67.54% reduction compared to the Existing method. The Savings method results in emissions of 1,256.54 kilograms, achieving a 62.43% reduction. The NN method results in emissions of 1,052.82 kilograms, marking a 54.84% reduction. These findings indicate that the alternative methods significantly reduce the environmental impact compared to the Existing method, with the OVRP-TSP model being the most environmentally friendly. The details of emission reductions are shown in Figure 7.

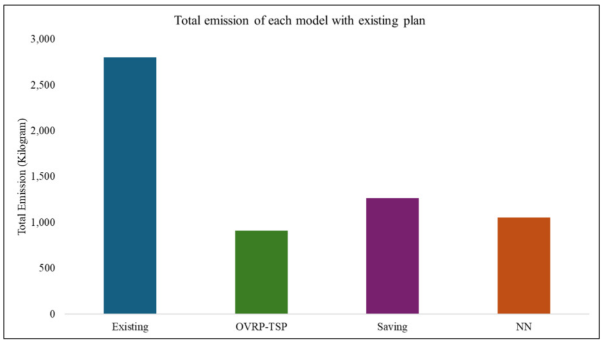

Fig. 7: *Total emission of each model compared to the existing plan.*

4.3 Discussion with existing works

Regarding the comparison results in Section 4.2, we can see that the hybrid OVRP-TSP model provides the best performance when compared to the Savings and Nearest Neighbor (NN) methods. All indicators, such as total travel times, travel costs, and carbon emissions, are drastically reduced by approximately 49.5-67.5%.

In addition, we also compare the performance of this hybrid model with some relevant existing studies on the vehicle routing problem. The results reveal that the hybrid OVRP-TSP model provides the shortest distribution routes in all existing studies. Although one of these studies uses the maximum capacity to choose customers on the route instead of travel time, our proposed hybrid model can be modified to work well with the capacity constraint. Furthermore, the performance of the proposed hybrid model is equal to the best performance of the mentioned solutions in all existing studies.

All performance comparison details are demonstrated in Table 6.

Table 6: *Comparison of the distribution performance between the hybrid OVRP-TSP and other methods in existing studies.*

Existing study	Indicator	OVRP-TSP	Savings	NN
Cipta and Hasibuan, 2023 [15]	Distance (KM)	**32.5**	**32.5**	32.6
Nurcahyo *et al.*, 2023 [16]	Distance (KM)	**47.3**	52.6	**47.3**

5. CONCLUSION

The comparative analysis of the four routing methods—Existing, OVRP-TSP, Savings, and Nearest Neighbor (NN)—demonstrates significant improvements in logistical efficiency, cost-effectiveness, and environmental impact when using alternative methods for device installation. The Existing method proves to be the least efficient, with the highest total time, costs, and emissions.

Among the alternative methods, the OVRP-TSP model consistently outperforms the others across all metrics. It reduces total installation time by 49.56% and total costs by 65.69%, while achieving the lowest emissions, with a reduction of 67.54%. These substantial improvements make the OVRP-TSP model the most effective solution for optimizing routing management. The NN method also shows considerable efficiency gains, with a 46.25% reduction in total time, a 62.43% reduction in total emissions, and a 61.12% reduction in total costs. The Savings method, while less effective than the OVRP-TSP and NN methods, still provides significant benefits, including a 39.43% reduction in total time, a 54.84% reduction in total emissions, and a 56.09% reduction in total costs. Additionally, the hybrid OVRP-TSP outperforms other heuristic methods in the relevant studies proposed, as mentioned in Section 4.3. The results from all experiments, which include 30 installation points from our study and five different locations from each existing study in Section 4.3, verify the robustness and complexity of our hybrid OVRP-TSP model's performance.

In summary, adopting any of the three alternative routing methods—OVRP-TSP, Savings, or NN—offers marked improvements over the Existing method in terms of operational efficiency, cost savings, and environmental sustainability. The OVRP-TSP method stands out as the most effective and comprehensive solution, making it highly recommended for optimizing route management in device installation projects. However, the NN and Savings methods also present viable options, contributing to enhanced operational performance and reduced environmental impact.

For future perspectives, we plan to add more constraints to the model, such as vehicle capacity and time windows for installations, to better reflect real-world situations. Furthermore, we will explore scenarios with multiple vehicles, which would be relevant for larger-scale installation projects. The effects of increasing the number of endpoints on the performance of the routing methods will also be investigated. Finally, we will evaluate and compare the effectiveness of other routing models and optimization techniques against the hybrid OVRP-TSP model.

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AUTHOR CONTRIBUTIONS

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