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Article

Performance Comparison of Two-phase LP-based Heuristic Methods for Capacitated Vehicle Routing Problem with Three Objectives

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Abstract. This paper develops a two-phase LP-based heuristic for the Capacitated Vehicle Routing Problem (CVRP). It considers three objectives: (1) minimizing the total costs of fuel consumption and overtime, (2) maximizing the total personal relationships between customers and drivers, and (3) balancing the delivery weights of vehicles. The two-phase LP-based heuristic (cluster-first route-second) is proposed. First, in the clustering stage, three LP-based clustering models (denoted by C1, C2, and C3) are developed. Customers are grouped into clusters based on real distances between the customers for C1, personal relationships between the customers and drivers for C2, and the delivery weights of vehicles for C3. Second, in the routing stage, an LP-based traveling salesman problem model is used to form a route for each cluster, to minimize the total costs of fuel consumption and overtime labor. The experimental results from a case study of Thai SMEs show that when the C2 clustering model is applied, the performances are the best. Significant contributions of this paper include: (1) it is an original paper that proposes the C2 clustering model, and it has the best performances based on the experimental results, and (2) the proposed two-phase LP-based heuristic methods are suitable for practical use by SMEs since the required computational time is short, and it has multiple models with different objectives that can be selected to match a user's requirements.

Keywords: Capacitated vehicle routing problem, fuel and overtime costs, relationship between customers and drivers, balanced weights of vehicles, clustering-first route-second heuristic, linear programming.

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1. Introduction

The Capacitated Vehicle Routing Problem (CVRP) is a combinatorial optimization problem that aims to find the optimal set of routes for a fleet of vehicles from a central depot to supply goods to a set of customers with known demand such that the capacity of vehicles is not violated [1, 2]. Moreover, each customer is served exactly once by only one vehicle. Each vehicle should start and end its route at the depot. The literature related to the CVRP is rich due to its usefulness in real-life situations, especially for transportation and logistics (T&L) companies, such as logistics service providers and suppliers that own a fleet of vehicles. The objective of the classical CVRP is to minimize the total distance or time traveled by the vehicles [3, 4].

More objectives are introduced into the classical CVRP to handle real-life issues of T&L companies. In recent CVRP research, the objectives include economic, customer, and driver perspectives. The real-life issues are as follows. An economic issue is that T&L companies want to minimize fuel and overtime costs. Note that the salary is an irrelevant cost since all drivers are permanent employees and a fixed salary must be paid. Most customers need the driver to carry goods from the vehicle to storage spaces. Therefore, weight balancing among vehicles is important. Unbalanced weight means unfair and uneven workload allocation to the drivers. This issue affects the satisfaction of drivers. Customers prefer the same driver for the delivery because the driver already knows the special requirements of the customers and they have good relationships. This issue affects the satisfaction of customers. The classical CVRP can be modified into new CVRP variants with different objectives, to solve the real-life issues of T&L companies.

This paper is motivated by the needs of a Thai small-to medium-sized enterprise (SME) from a case study. The Thai SME considers three objectives for delivery route planning. First, since the Thai SME owns a fleet of pickup trucks and hires permanent drivers to operate the fleet, the company wants to minimize the total relevant costs for delivery route planning, including the fuel consumption cost and overtime cost, to satisfy the economic perspective. Second, the company considers relationships between customers and drivers. The company assigns customers to drivers who have good relationships with them, to satisfy the customer perspective. Third, when the drivers are permanent employees, the company needs to balance delivery weights assigned to vehicles to evenly distribute workloads to the drivers, to satisfy the driver perspective. This can also increase the lifespan of vehicles and is beneficial for the long-term use of vehicles. Besides considering different objectives, the company is also concerned about the computational time of planning. The company prefers a reasonable time that is not more than 10 minutes, to plan delivery routes for small- to medium-sized problems (i.e., a problem size of 30 customers and 4 vehicles).

This paper focuses on the three objectives that are considered by the Thai SME. The objectives include (1) minimizing the total costs of fuel consumption and overtime, (2) maximizing the total personal relationships between customers and drivers, and (3) balancing the delivery weights of vehicles, which are related to the economic, customer, and driver perspectives, respectively. This paper develops a route planning method that is suitable for Thai SMEs, to solve CVRPs with different objectives. This method can provide a high-quality solution within a reasonable time.

Since the classical CVRP is NP-hard [5], CVRP variants with new objectives that are extensions of the classical CVRP are also NP-hard. Optimal solutions from exact algorithms cannot be obtained within a reasonable time. Using heuristic approaches is necessary to obtain a near-optimal solution within a reasonable time. The Cluster-First Route-Second (CFRS) heuristic is a two-phase heuristic that is among several categories of classical heuristics [6, 7]. First, customers are grouped into clusters, and each cluster is assigned to a different vehicle. Then, the customers in each cluster are sequenced to form a route by solving the corresponding Traveling Salesman Problem (TSP). The main advantage of the CFRS heuristic is that problem sizes and computational times are significantly reduced, to obtain a near-optimal solution in a reasonable time.

This paper proposes Linear Programming-based (LP-based) CFRS heuristic methods for the CVRP variants with the objectives related to the satisfaction of the economic, customer, and driver perspectives. Based on the nature of the clustering technique, by assigning customers to vehicles, the total personal relationships between customers and drivers and the delivery weight of each vehicle can be directly considered. However, the total costs of fuel consumption and overtime can only be directly considered when the delivery routes are constructed using the routing technique. In this paper, the total personal relationships between customers and drivers are maximized, and the maximum delivery weight of vehicles is minimized in the clustering stage, to satisfy the customer and driver perspectives, respectively. Two LP-based clustering models are proposed for the two objectives. However, the total costs of fuel consumption and overtime that are the objective of the economic perspective cannot be directly minimized in the clustering stage. Therefore, another LP-based clustering model is used to minimize the maximum distance between any pair of customers in the same clusters, which indirectly minimizes the total cost in the clustering stage. Then, in the routing stage, a route is constructed by using an LP-based Traveling Salesman Problem (TSP) model to minimize the total costs of fuel consumption and overtime for each cluster. A branch-and-bound exact algorithm using ILOG CPLEX software is used to solve for the optimal solution of each model. The LP-based CFRS heuristic methods are combinations of three LP-based clustering models and an LP-based TSP model.

The three LP-based clustering models and the LP-based TSP model are described as follows.

- LP-based clustering model 1 clusters customers based on real distances (along an available road network) between customers. It minimizes the maximum distance between any pair of customers in the same clusters. This model is used to indirectly minimize the total costs of fuel consumption and overtime, which cannot be directly minimized in the clustering stage. Note that the fuel cost and overtime cost can be directly minimized during the routing stage.
- LP-based clustering model 2 clusters customers based on personal relationships between customers and drivers, to maximize the total personal relationships. The objective of this model is to satisfy the customer perspective.
- LP-based clustering model 3 clusters customers based on delivery weights carried by vehicles, balancing the delivery weights among the vehicles, to satisfy the driver perspective.
- LP-based TSP model sequences the customers to form a route, to minimize the total costs of fuel consumption and overtime. The objective is directly related to the economic perspective.

The three objectives, including the total costs of fuel consumption and overtime, total personal relationships between customers and drivers, and maximum delivery weight of vehicles, are the performance measures of the proposed heuristic methods for the economic, customer, and driver perspectives, respectively. However, they have different units/scales and cannot be directly compared. Therefore, the objective values are normalized into satisfaction levels with values from 0.0 to 1.0, for comparison.

The remainder of this paper is organized as follows. Related studies are reviewed in Section 2. Then, the characteristics of the CVRP variants with new objectives and the proposed two-phase LP-based heuristic are presented in Sections 3 and 4, respectively. Next, a real case study of a T&L company in Thailand is conducted in Section 5. After that, experimental results and discussion are provided in Section 6. Finally, conclusions and recommendations are presented in Section 7.

2. Relations between this Paper and Past Works

The relationships between this paper and past works focus on two main points. The first one involves the decision objectives related to the economic, customer, and driver perspectives. The second involves the solution methods for CVRPs.

Among the three perspectives, the objectives of the economic perspective are commonly found in the literature, as shown in Table 1. Note that Table 1 contains only closely related papers to this paper (not all cited papers appear in Table 1). In addition to the classical objective, the minimization of the total distance traveled by vehicles [1, 3, 8, 9], there are objectives related to routing costs. For the routing cost objectives, one objective is the minimization of the total fuel consumption of vehicles [10–12]. This objective is directly related to the additional cost to operate vehicles. Another routing cost objective is the minimization of the total routing costs, including the fuel consumption cost and fixed operating cost of vehicles [2, 13]. This objective is suitable when the total capacity of the internal vehicles is not enough, and the T&L companies have to rent and manage external vehicles to fulfill the capacity gap. It is also applied for heavy-load delivery when the drivers may require additional workers to help them in loading and unloading. In the study of [14], the fuel consumption cost, fixed operating cost, and carbon emission cost of vehicles are combined as a total cost objective for a low-carbon routing problem. When a company fully relies on external vehicles, the transportation unit cost is minimized [15]. The sum of depot opening cost and routing cost is minimized for the capacitated location-routing problem [16]. The sum of routing and handling costs is minimized for the two-echelon CVRP [17]. Overall cost (including facility opening cost, facility closing cost, and transportation cost) is minimized for the redesign of three-echelon multi-commodity distribution network [18]. This paper assumes that T&L companies own a fleet of vehicles with enough resources for distribution. For them, the fuel consumption and overtime costs are the only additional costs for route planning. Since the carbon emission is directly proportional to the amount of fuel consumption of the vehicles, the carbon emission cost is also reduced. Therefore, this paper considers the total routing costs that include only the fuel consumption cost and the overtime cost of drivers, for the economic perspective.

For the customer perspective, different objectives are proposed for different real-life situations. The total travel time to customers is minimized to provide a quick response to demands. It is crucial that rescuers arrive quickly in order to save lives and provide emergency supplies to survivors when natural disasters strike [19]. The total or average satisfaction of customers based on customer time windows is maximized while other cost objectives are minimized, to maintain customer satisfaction with delivery services [20–22]. The response time of ambulances is reduced to improve the emergency service [23]. In [24–26], the time window violations are converted into penalty costs incurred due to earliness and lateness of arrivals. Total costs of penalty and transportation are minimized. To the best of our knowledge, personal relationships between customers and drivers have never been considered for route planning. This paper introduces an objective based on the personal relationships between customers and drivers. The objective is to maximize the total personal relationships between customers and drivers, to satisfy the customer perspective.

For the driver perspective, the importance of workload balancing among vehicles is high, when the drivers are permanent employees. There are three categories of workload balancing: balancing the distances/durations of vehicles, balancing the delivery weights of vehicles, and balancing the numbers of customers of vehicles [27]. Normally, the objectives of workload balancing are considered in multi-objective problems together with other objectives. The total distance traveled by vehicles and the difference between the longest and the shortest route lengths are minimized for the CVRP with route balancing [28, 29]. The total routing cost and the difference between the largest and smallest route costs are minimized [30, 31]. The total routing cost and the maximum duration of routes are minimized [32]. In [33], the total distance traveled by vehicles is minimized and the imbalances of workloads in terms of distances traveled and weights carried by vehicles are also minimized. In real-life situations, however, overtime payments can compensate the driver of a vehicle with a long operation duration. Some customers are in the same area, but others are dispersed over a large area. Therefore, balancing the distances/durations and balancing the numbers of customers may be ineffective. This paper considers only balancing the delivery weights of vehicles, for the driver perspective. The maximum delivery weight of vehicles is minimized, to balance the delivery weights of vehicles.

For CVRPs, there are two groups of solution methods, including exact algorithms and approximate algorithms [6]. Branch-and-Bound Algorithm (BBA) and Branch-and-Cut-and-Price Algorithm (BCPA) are two exact algorithms that can find optimal solutions for CVRPs. In [2], Mixed Integer Linear Programming (MILP) models are formulated for a multiple-route Vehicle Routing Problem (VRP). The MILP models are solved by using ILOG CPLEX software with the BBA. The BCPA is a hybrid of the BBA, cut generation, and column generation. The BCPA is applied to solve different variants of CVRPs, including the VRP with stochastic demands [34], the cumulative CVRP [19], the energy minimization VRP [35], and the two-echelon CVRP [36]. However, the exact algorithms have a drawback. They can only solve small-sized problems and take long computational time for large-sized problems.

In contrast, the approximate algorithms that include classic heuristics and metaheuristics, can find near-optimal solutions for large-sized problems within a reasonable time. A popular classical heuristic is a two-phase algorithm, the CFRS heuristic [8, 11], that divides the CVRPs into two stages: clustering and routing. For clustering, customers are assigned to clusters, and each cluster is assigned to a different vehicle. For routing, a route is constructed for the customers in each cluster. This can significantly reduce problem sizes and computational times. In [37], a two-phase heuristic, route construction and vehicle dispatch, is developed for a dynamic vehicle routing problem with multiple depots. However, only the first phase, route construction, is considered as a static problem that is related to this paper. In the route construction phase, first, a modified Nearest Neighbor Procedure (NNP) is used to cluster a customer to a depot and assign the customer to a vehicle. Then, Sweeping and Reordering Procedures (SRPs) are applied to sequence the customers of the vehicle, to construct a feasible route. The NNP and SRPs are jointly iterated, to generate a good feasible route (i.e., initial route). Finally, an Insertion Procedure (IP) is applied to improve the initial route. A two-phase algorithm is also applied to solved large-sized general lot-sizing and scheduling problem that is commonly found in continuous production planning [38].

The metaheuristics are further categorized into two main types: local search and population search. Local search-based methods keep exploring the solution space by iteratively moving from the current solution to another promising solution in its neighborhood. In contrast, population search-based methods maintain a pool of good parent solutions by continually selecting parent solutions to produce promising offspring, so as to update the pool [6]. Two popular local search-based methods are Tabu Search Algorithms (TSAs) [4, 14, 24] and Simulated Annealing Algorithms (SAAs) [10, 13]. Population search-based methods include Genetic Algorithms (GAs) [20], Ant Colony Optimization Algorithms (ACOAs) [21], and Evolutionary Algorithms (EAs) [28, 31, 33].

In this paper, the CFRS heuristic methods are used to solve the CVRPs with three different objectives because of CFRS's advantage in reducing problem sizes and computational times, as well as its simplicity for implementation. Unlike [8, 11, 37] that use heuristic algorithms to find near-optimal solutions at the clustering stage, this paper uses ILOG CPLEX software with the BBA to solve the LP-models at both the clustering and routing stages. The proposed CFRS heuristic method can find the optimal solution for each stage. However, the decomposition of the entire problem into two sub-problems results in a suboptimal solution to the entire problem.

3. Characteristics of the CVRP Variant

In this paper, the characteristics of the CVRP variant are as follows. There is a set of customers supplied by a fleet of vehicles from a depot. Each customer has a known demand. Each vehicle has the same limited capacity. The travel time and distance between any pair of nodes (including the depot and the set of customers) are given according to actual road conditions provided by Google Maps. The personal relationships between customers and drivers are considered, based on how well they know each other. The customers prefer the drivers who have good personal relationships with them for delivery and assistance. There is a service time for the driver to finish a delivery task at each customer. Additionally, each customer is supplied exactly once by only one vehicle. Each vehicle starts and ends its route at the depot. When a vehicle is utilized for delivery, there is a fuel consumption cost of the vehicle. It depends on the unit fuel cost, fuel consumption rates for an empty vehicle and delivery weight, and the travel distance of the vehicle. Normally, the driver of a vehicle works from the morning to the evening (normal working hours), and during this

Table 1. Summary of relevant CVRP research subjected to the objective aspect.

Authors	**Perspectives**			**Solution methods**
	Economic	**Customer**	**Driver**	
2007 Dondo and Cerdá [7]	Total routing cost			Three-phase hybrid approach
2010 Kuo [10]	Fuel consumption			SAA
2012 Xiao *et al*. [13]	Fixed vehicle & fuel consumption costs			String-model-based SAA
2013 Baños *et al*. [33]	Travel distance		Travel distance & delivery weight of each vehicle	Pareto-based hybrid EA
2013 Gajanand and Narendran [2]	Fixed operating & fuel consumption costs			Exact algorithm: MILP model & BBA
2013 Yu *et al*. [3]	Travel distance			Three-phase hybrid approach
2014 Lysgaard and Wøhlk [19]		Total travel time		Exact algorithm: BCPA
2015 Zhang *et al*. [14]	Fixed vehicle, fuel consumption, & emission costs			Route splitting TSA
2016 Cinar *et al*. [11]	Fuel consumption			Two-phase algorithm: CFRS
2016 Halvorsen-Weare and Savelsbergh [29]	Total travel distance		Travel distance of each vehicle	Pareto optimal solutions: combine ε-constraint & lexicographic methods
2018 Comert *et al*. [8]	Travel distance			Two-phase heuristic: CFRS
2019 Ghannadpour and Zarrabi [20]	Travel distance, energy consumption, & number of vehicles	Total satisfaction		Pareto-based hybrid GA
2019 Zhang *et al*. [21]	Travel distance & fixed vehicle costs	Average satisfaction		Pareto-based hybrid ACOA
2020 Lehuédé *et al*. [32]	Total routing cost		Duration of each vehicle	Pareto optimal solutions: lexicographic minimax approach
This paper	Fuel consumption & overtime costs	Personal relationships	Delivery weight of each vehicle	Two-phase LP-based heuristic: CFRS

Notes: SAA = Simulated annealing algorithm. EA = Evolutionary algorithm. MILP = Mixed integer linear programming. BBA = Branch and bound algorithm. BCPA = Branch-and-cut-and-price algorithm. TSA = Tabu search algorithm. CFRS = Cluster-first route-second. GA = Genetic algorithm. ACOA = Ant colony optimization algorithm.

period the driver has a lunch break. When the driver works more than the normal working hours, there is an overtime cost of the driver. It depends on the unit overtime cost and the overtime duration.

Three objectives are considered for the economic, customer, and driver perspectives as follows. First, the total routing cost, including the fuel consumption cost and the overtime cost, is minimized, to satisfy the economic perspective. Second, the total personal relationships between customers and drivers are maximized, to satisfy the customer perspective. Third, the maximum delivery weight of vehicles is minimized to balance delivery weights among vehicles, to satisfy the driver perspective.

The notations used for model formulation are presented in the following subsections.

3.1. Indices and Sets

i, j Index of nodes

k Index of vehicles

C Set of customers; $C = \{1, 2, .., n\}$

K Set of vehicles; $K = \{1, 2, .., m\}$

N Set of nodes (including a depot denoted by 0 and the set of customers); $N = \{0, 1, 2, .., n\}$

3.2. Parameters

m Number of vehicles (vehicles)

n Number of customers (customers)

c^f Unit fuel cost (THB/L)

c^o Unit overtime cost (THB/h)

D^m Maximum distance between source and destination (km)

M Large positive time (min)

L_k Lunch duration for driver of vehicle k (min)

T Timespan (normal working hours) for delivery (h)

Q Capacity of vehicle (kg)

f_k^e Fuel consumption rate for empty vehicle k (L/km)

f^w Fuel consumption rate for carried weight (L/km•kg)

q_i Demand of customer i (kg)

s_i Service time at customer i (min)

r_{ik} Personal relationship between customer i and driver of vehicle k (unitless)

d_{ij} Travel distance from node i to node j (km)

t_{ij} Travel time from node i to node j (min)

3.3. Variables

x_{ijk} = 1, if vehicle k travels from node i to node j; 0 otherwise (binary)

y_{ik} = 1, if vehicle k visits node i; 0 otherwise (binary)

w_{ij} Delivery weight carried by a vehicle from node i to node j (kg)

W_k^t Total delivery weight assigned to vehicle k (kg)

C_k^t Total number of customers assigned to vehicle k (customers)

A_{ik} Arrival time of vehicle k at node i (min)

D_{ik} Departure time of vehicle k at node i (min)

O_k Overtime of vehicle k (h)

Z_1 Maximum distance between any pair of customers in the same cluster (km)

Z_2 Total personal relationships between customers and drivers (unitless)

Z_2^+ / Z_2^- Maximum and minimum values of Z_2 (unitless)

Z_3 Maximum delivery weight of vehicles (kg)

Z_3^+ / Z_3^- Maximum and minimum values of Z_3 (kg)

Z_4 Total travel distance of vehicles (km)

Z_5 Total routing cost, including fuel consumption and overtime costs (THB)

Z_5^+ / Z_5^- Maximum and minimum values of Z_5 (THB)

$SL(E)$ Satisfaction level of economic perspective (unitless)

$SL(C)$ Satisfaction level of customer perspective (unitless)

$SL(D)$ Satisfaction level of driver perspective (unitless)

4. Two-phase LP-based Heuristic

The two-phase LP-based heuristic used in this paper is the Cluster-First Route-Second (CFRS) heuristic that is divided into two stages: clustering and routing. In the clustering stage, customers are grouped into clusters, and each cluster is assigned to a vehicle. In the routing stage, the customers in each cluster are sequenced to form a route that starts and ends at the depot. Three LP-based clustering models and an LP-based TSP model are proposed for the clustering stage and routing stage, respectively. The first clustering model indirectly minimizes the objective of the economic perspective because the objective cannot be directly minimized in the clustering stage. The second clustering model directly maximizes the objective of the customer perspective. The third clustering model directly minimizes the objective of the driver perspective. The LP-based TSP model constructs a route for the customers in each cluster, and its objective is to minimize the total costs of fuel consumption and overtime for each cluster.

4.1. Clustering Stage

In the clustering stage, three LP-based clustering models are proposed. They are described as follows.

- LP-based clustering model 1, denoted by C1, groups customers into clusters based on real distances between the customers. The customers that have a relatively close distance to each other are assigned to the same cluster. The objective of C1 is to minimize the maximum distance between any pair of customers in the same cluster (see objective function (1) and inequality (2)). Because the total costs of fuel consumption and overtime cannot be directly minimized in the clustering stage, C1 is used to indirectly minimize the total cost (economic perspective).

- LP-based clustering model 2, denoted by C2, groups customers into clusters based on the personal relationships between customers and drivers. Customers are assigned to the vehicle that the driver has relatively good personal relationships with them. The objective of C2 is to maximize the total personal relationships between customers and drivers, as shown in objective function (3) and Eq. (4), to enhance customer satisfaction (customer perspective).
- LP-based clustering model 3, denoted by C3, groups customers by considering the delivery weights of vehicles. The objective of C3 is to minimize the maximum delivery weight of the vehicles, as shown in objective function (5) and inequality (6), to balance the delivery weights of vehicles (driver perspective). The concept of the min-max objective function in [39] is adapted for C1 and C3.

C1 is used to indirectly optimize the objective of the economic perspective. C2 and C3 are used to directly optimize the objectives of the customer and driver perspectives, respectively. The LP-based clustering models have common constraints, as shown in Constraints (7 to 11). Constraint (7) limits the total delivery weight assigned to each vehicle by the capacity of vehicles. Constraint (8) assigns each customer to only one vehicle to fulfill the demand. Constraint (9) calculates the maximum distance between customers (for all customers) as an input parameter, especially for C1. Constraints (10) and (11) compute the total delivery weight and the total number of customers assigned to each vehicle, respectively.

$$\text{minimize}\, Z_1 \tag{1}$$

$$Z_1 \geq d_{ij} + (y_{ik} + y_{jk} - 2)\cdot D^m; \quad \forall i \in C, \forall j \in C, \forall k \in K \tag{2}$$

$$\text{maximize}\, Z_2 \tag{3}$$

$$Z_2 = \sum_{i\in C}\sum_{k\in K} r_{ik}\cdot y_{ik} \tag{4}$$

$$\text{minimize}\, Z_3 \tag{5}$$

$$Z_3 \geq \sum_{i\in C} q_i \cdot y_{ik}; \quad \forall k \in K \tag{6}$$

$$\sum_{i\in C} q_i \cdot y_{ik} \leq Q; \quad \forall k \in K \tag{7}$$

$$\sum_{k\in K} y_{ik} = 1; \quad \forall i \in C \tag{8}$$

$$D^m \geq d_{ij}; \quad \forall i \in C, \forall j \in C \tag{9}$$

$$W_k^t = \sum_{i\in C} q_i \cdot y_{ik}; \quad \forall k \in K \tag{10}$$

$$C_k^t = \sum_{i\in C} y_{ik}; \quad \forall k \in K \tag{11}$$

4.2. Routing Stage

In the routing stage, an LP-based TSP model with a cost objective is proposed, to sequence the customers in each cluster to form a route. The proposed LP-based TSP model is compared to the classical TSP model with the distance objective, to show the proposed model's superiority over the classical TSP model. Therefore, two LP-based TSP models are formulated and solved for optimal routes. They are described as follows.

- Classical LP-based TSP model, denoted by R1, sequences the customers in each cluster to form a route, to minimize the total travel distance of vehicles (see objective function (12) and Eq. (13)).
- Proposed LP-based TSP model, denoted by R2, sequences the customers in each cluster, to minimize the total costs of fuel consumption and overtime, as shown in objective function (14) and Eq. (15). In Eq. (15), the first and second terms are the fuel consumption costs of vehicles determined by the travel distance and delivery weight of the vehicle, and the third term is the overtime cost of drivers. Note that the fuel consumption formula is adapted from [13].

The two LP-based TSP models have common constraints, as shown in Constraints (16 to 28). Constraint (16) allows a vehicle visit only once at each customer to fulfil its demand. Constraint (17) controls the path-flow of each vehicle. This ensures that the vehicle that visits a node, must depart from the node. Constraint (18) indicates the delivery weight reduction of the vehicle after it visits a customer, equaling to the demand of the customer. This also eliminate any illegal sub-tours to ensures that each vehicle route starts and ends at the depot [13]. Constraint (19) limits the delivery weight carried by each vehicle between two nodes by its capacity. Constraints (20 and 21) calculate the arrival time of each vehicle at each node. Constraint (22) calculates the departure time of each vehicle at each customer. This means that a vehicle can only depart from a customer after the driver finishes the delivery tasks at the customer. Constraint (23) calculates the overtime of the driver of each vehicle. Constraints (24 to 28) are binary and non-negativity constraints.

$$\text{minimize}\, Z_4 \tag{12}$$

$$Z_4 = \sum_{i\in N}\sum_{j\in N}\sum_{k\in K} d_{ij}\cdot x_{ijk} \quad (13)$$

$$\text{minimize}\, Z_5 \quad (14)$$

$$\begin{aligned} Z_5 = &\sum_{i\in N}\sum_{j\in N}\sum_{k\in K} c^f\cdot f_k^e\cdot d_{ij}\cdot x_{ijk} \\ &+\sum_{i\in N}\sum_{j\in N} c^f\cdot f^w\cdot d_{ij}\cdot w_{ij} \\ &+\sum_{k\in K} c^o\cdot O_k \end{aligned} \quad (15)$$

$$\sum_{j\in N, j\neq i, y_{jk}=1} x_{ijk} = 1; \quad \forall i\in N, \forall k\in K, y_{ik}=1 \quad (16)$$

$$\sum_{j\in N, j\neq i, y_{jk}=1} x_{jik} - \sum_{j\in N, j\neq i, y_{jk}=1} x_{ijk} = 0; \quad \forall i\in N, \forall k\in K, y_{ik}=1 \quad (17)$$

$$\sum_{j\in N, j\neq i, y_{jk}=1} w_{ji} - \sum_{j\in N, j\neq i, y_{jk}=1} w_{ij} = q_i; \quad \forall i\in C, \forall k\in K, y_{ik}=1 \quad (18)$$

$$w_{ij}\le Q\cdot x_{ijk}; \quad \forall i\in N, \forall j\in N, \forall k\in K, i\neq j, y_{ik}=y_{jk}=1 \quad (19)$$

$$A_{jk}\ge\left(D_{ik}+t_{ij}\right)-\left(1-x_{ijk}\right)\cdot M; \quad \forall i\in N, \forall j\in N, \forall k\in K, i\neq j, y_{ik}=y_{jk}=1 \quad (20)$$

$$A_{jk}\le\left(D_{ik}+t_{ij}\right)+\left(1-x_{ijk}\right)\cdot M; \quad \forall i\in N, \forall j\in N, \forall k\in K, i\neq j, y_{ik}=y_{jk}=1 \quad (21)$$

$$D_{ik}\ge A_{ik}+s_i; \quad \forall i\in C, \forall k\in K \quad (22)$$

$$O_k\ge A_{0k}/60-\left(T-L_k/60\right); \quad \forall k\in K \quad (23)$$

$$x_{ijk}\in\{0,1\}; \quad \forall i\in N, \forall j\in N, \forall k\in K \quad (24)$$

$$y_{ik}\in\{0,1\}; \quad \forall i\in N, \forall k\in K \quad (25)$$

$$w_{ij}\ge 0; \quad \forall i\in N, \forall j\in N \quad (26)$$

$$A_{ik}, D_{ik}\ge 0; \quad \forall i\in N, \forall k\in K \quad (27)$$

$$O_k, C_k^t, W_k^t\ge 0; \quad \forall k\in K \quad (28)$$

In this paper, there are three LP-based clustering models and two LP-based TSP models. A summary of the formulation for the five models is presented in Table 2. Thus, by combining the three and two models, there are six LP-based CFRS heuristic methods, including C1R1, C1R2, C2R1, C2R2, C3R1, and C3R2. Note that, only three methods (i.e., C1R2, C2R2, and C3R2) are proposed by this paper. Other three methods (including C1R1, C2R1, and C3R1) are used for comparison, to show the proposed TSP model's superiority over the classical TSP model for routing.

Table 2. Summary of three LP-based clustering models and two LP-based TSP models.

Models	Descriptions
C1	LP-based clustering model 1 - Objective function (1) - Subject to: Constraints (2, 7 – 11).
C2	LP-based clustering model 2 - Objective function (3) - Subject to: Constraints (4, 7 – 11).
C3	LP-based clustering model 3 - Objective function (5) - Subject to: Constraints (6 – 11).
R1	Classical LP-based TSP model - Objective function (12) - Subject to: Constraints (13, 16 – 28).
R2	Proposed LP-based TSP model - Objective function (14) - Subject to Constraints (15 – 28).

4.3. Performance Measures

Three objectives related to the economic, customer, and driver perspectives are used to evaluate the performances of the proposed LP-based CFRS heuristic methods. However, they cannot be directly used to compare the performances of the proposed methods because they have different units and scales. Thus, the objectives should be normalized into a common scale from 0.0 to 1.0, which is called a satisfaction level, for ease of comparison. The satisfaction levels of the three objectives are presented as follows.

- Satisfaction level of the economic perspective, denoted by $SL(E)$, is the satisfaction level of the total costs of fuel consumption and overtime (see Eq. (29)).
- Satisfaction level of the customer perspective, denoted by $SL(C)$, is the satisfaction level of the total personal relationships between customers and drivers (as shown in Eq. (30)).
- Satisfaction level of the driver perspective, denoted by $SL(D)$, is the satisfaction level of the maximum delivery weight of vehicles (as presented in Eq. (3)1).

$$SL(E)=\left(Z_5^+-Z_5\right)/\left(Z_5^+-Z_5^-\right) \quad (29)$$

$$SL(C)=\left(Z_2-Z_2^-\right)/\left(Z_2^+-Z_2^-\right) \quad (30)$$

$$SL(D) = \left(Z_3^+ - Z_3\right) / \left(Z_3^+ - Z_3^-\right) \tag{31}$$

For a given problem instance, there are six values of each objective from applying the six LP-based CFRS heuristic methods. The maximum and minimum values of each objective are determined from the set of six values. If the six values of an objective are the same, the value = 1 is given to the satisfaction level of the objective.

5. A Real Case Study in Thai SMEs

This section presents a real case study of applying the proposed two-phase LP-based heuristic to plan delivery routes for a fleet of vehicles of a Thai Small- to Medium-sized Enterprise (SME) located in Bangkok. The Thai SME produces adhesive products for construction and industrial uses.

The Thai SME owns a fleet of four pickup trucks with the same capacity (2,500 kg), to deliver products to customers located in Bangkok and the vicinity. Real travel times and distances between nodes are retrieved from a Google Maps API database. Based on historical delivery data, the service time at each customer is set to be 15 minutes (i.e., the average of historical service times).

The personal relationships between customers and drivers are divided into three types as follows. First, value = 0 is given when the customer is new for the driver. This means that they do not know each other. Second, value = 0.5 is given when the customer is familiar and has been served by the driver, but not frequently. Third, value = 1 is given when the customer and driver have a good relationship with each other.

The fuel consumption rate function presented by [13], $Y = 0.0000793X - 0.026$, is used to determine the fuel consumption rates for fuel consumption cost calculations. In this function, X is the weight (kg) of the vehicles including goods, and Y is the fuel consumption rate (L/km). Based on this function, the fuel consumption rate for the empty pickup trucks (with a curb weight of 2,000 kg) is approximately 0.1326 L/km, and the fuel consumption rate for the carried (additional) weight is 0.0000793 L/km•kg. The unit fuel cost is set to be 28 THB/L.

The overtime cost of drivers is calculated based on the following conditions. The drivers work from 8:00 AM to 5:00 PM and have a lunch break for 30 minutes. The system starts calculating the overtime cost after the drivers perform delivery tasks for 8 hours and 30 minutes. The unit overtime cost is 1.5 times the regular time labor cost, and it is approximately 130 THB/h.

To evaluate the performances of the proposed two-phase LP-based heuristic, six LP-based CFRS heuristic methods are tested with five datasets of 30 customers that are randomly selected from a set of 530 customers. The demand of each customer is randomly generated, based on a normal distribution with a mean of 200 kg and a standard deviation of 100 kg. When the generated weight is less than zero, it is assumed to be zero. When the delivery weight is zero, it is equivalent to a cheque collection from the customers (no delivery goods).

The LP-based clustering and routing models for the case study are solved by using IBM ILOG CPLEX 12.4 on a laptop computer with a 2.90 GHz Intel(R) Core(TM) i7-7500U CPU and 8.00 GB RAM, running on 64-bit Windows 10.

6. Experimental Results and Discussions

In this section, the experimental results are presented and discussed. Table 3 presents a part of data from a selected dataset of 30 customers that is used to evaluate the performances of the proposed LP-based CFRS heuristic methods. According to confidential policy of the company, real names of the Thai SME company and its customers are not disclosed. Therefore, the Thai SME company that produces and supplies adhesive products, is denoted by Depot. The set of 30 customers that place orders for adhesive products from the Thai SME company, are denoted by Customers 1 to 30. Note that the demands of Customers 1, 25, and 30 are 0. This means that the task is to collect cheques from these customers.

Table 4 presents a part of the results from the selected dataset of the six LP-based CFRS heuristic methods and the general CVRP model that minimizes the total travel distance. The results of the general CVRP model are provided by the IBM ILOG CPLEX solver with the time limit of 3600 seconds (1 hour). The total travel distance is 768.6 km, and it is 6.85% above the lower bound of the total travel distance. From this table, there are interesting points as follows.

First, the general CVRP model that directly minimizes the total travel distance (minimize TD) in a single stage, results in the lowest total travel distance (TD) compared with the six LP-based CFRS heuristic methods. However, the general CVRP model provides the lowest total personal relationship (PR) and the highest variation of delivery weights among vehicles (dW value is the highest). It provides higher total routing cost (TC) than C1R1, C1R2, C2R1, and C2R2 methods. This numerical example shows that the general CVRP model is inferior to the six LP-based CFRS heuristic methods in terms of computational time and quality of solutions when the economic, customer, and driver (employee) perspectives are considered. Therefore, only the six LP-based CFRS heuristic methods are further discussed.

Second, the clustering model C1, which minimizes the maximum distance between customers in the same cluster (minimize CD), results in the lowest total routing cost (TC) among the three clustering models. Thus, C1 is a clustering model that indirectly minimizes the total costs of fuel consumption and overtime. However, C1 has the highest variation of delivery weights among vehicles (the highest dW value among the three clustering models).

Third, the clustering model C2 that maximizes the total personal relationships between customers and drivers (maximize PR) results in the highest PR value among all clustering models. However, the total routing cost (TC) is higher than that of the C1 model. Note that the total travel distance (TD) and the total routing cost (TC) are calculated by using Eqs. (13) and (15), respectively. TC depends on travel distances, delivery weights, and durations of routes. This means that when TD is minimized, TC is not guaranteed minimum. For example, the TD and TC of C1R1 are 941 km and 5082.62 THB, respectively. The TD and TC of C2R1 are 926 km and 5252.05 THB, respectively. C2R1 has shorter TD but higher TC than those of C1R1.

Fourth, when the clustering model C3 that minimizes the maximum delivery weight of vehicles (minimize MW) is applied, the maximum delivery weight (MW) is the least among all clustering models, and weights are equally assigned to vehicles. However, the total personal relationships (PR) and the total routing cost (TC) are the worst, compared to the other clustering models. These interesting points indicate that all proposed clustering models are effective, to determine the optimal solutions based on their objectives. The clustering models have strong and weak points. A model may be good at an aspect but bad at other aspects.

Fifth, considering TSP (routing) models, when the R1 routing model is used with any clustering model, the total travel distance (TD) is lower than that of the R2 model. However, the R2 model has a lower total routing cost (TC), including fuel consumption and overtime costs. This indicates that the classical TSP model that minimizes the total travel distance (R1) is not suitable when users focus on the total costs of fuel consumption and overtime.

From the results in Table 4, the C2R2 method has relatively good performances since PR (personal relationship between drivers and customers) is the highest, TC (total cost) is the second best, and dW (difference between maximum and minimum weights) is moderate. Therefore, the delivery routes of the C2R2 method are selected to illustrate with graphical routes as shown in Fig. 1. There are four routes. The number of customers, delivery weight, total travel distance, and sequence of each route are also given (as shown in Figs. 1a, 1b, 1c, and 1d). From Fig. 1 and data in Table 3, it is possible to show that the solution of C2R2 method is good because of the reasons as follows. First, all routes have short distances since there is no backtracking and unnecessary U-turn. Second, each truck tends to visit customers that need products with relatively high weight as soon as possible to reduce carried weights and fuel consumption of the truck. The first and second points are occurred since the R2 routing model is effective. Third, from Table 4, the total personal relationships between customers and drivers (PR) of the C2R2 method is the highest, which is directly affected by the C2 clustering model that maximizes PR.

The objective values from five datasets are normalized into satisfaction levels to evaluate the performances of the six LP-based CFRS heuristic methods. The satisfaction levels of the economic, customer, and driver perspectives are averaged from the five datasets, and they are shown in Table 5. From this table, there is no clustering model that is the best for all performance measures. However, the methods that use the R2 routing model outperform the methods that use the R1 routing model for all perspectives. Thus, the R2 routing model is superior to the R1 routing model and should be selected for further analysis.

When the less-effective methods are eliminated, there are three methods left, which are C1R2, C2R2, and C3R2. The performances of these methods are plotted in a radar chart, as shown in Fig. 2. From this figure, C1R2 and C3R2 methods have a high satisfaction level for one perspective but low satisfaction levels for two perspectives. The C2R2 method has high satisfaction levels for two perspectives, which are $SL(E)$ and $SL(C)$, but a low satisfaction level for $SL(D)$. The company of this case study prefers the C2R2 method over the other methods since it has high satisfaction levels for two important perspectives, which are economic and customer perspectives. However, the C2R2 method has a low satisfaction level for the driver perspective, which is less important than the other two perspectives.

The mean and standard deviation of computational times (in seconds) of the proposed LP-based CFRS heuristic methods for 30 customers and 4 vehicles are presented in Table 6. The mean computational times of all methods are less than 5 minutes, which can practically be used by SMEs which have a medium (not too large) number of customers and fleet size.

From Table 6, C1R2 method has much higher mean and standard deviation of computational time than other methods because of the following reasons. First, R2 model that minimizes the total costs of fuel consumption and overtime is more complicated that R1 model that minimizes the total travel distance. Thus, any method that use the R2 model tends to have longer computational time than the method that uses the R1 model. Second, for some instances C1 model results in 14 customers in a cluster, which is the highest when compared with C2 and C3 models. Larger problems (the number of customers is higher) tend to have much longer computational times for the LP-based TSP model. Therefore, when C1 and R2 models are used together, the C1R2 method has much higher mean computational times than other methods. Third, when the MILP models are solved by branch-and-bound based algorithm using ILOG CPLEX software, more complicated and larger models (the R2 model that solve the routing problem with relatively high number of customers in a cluster that is obtained from C1 model) will have more variations of the computational times by nature of the branch-and-bound algorithm.

It is useful to discuss practical situations that are suitable for applications of the proposed LP-based CFRS heuristic methods (i.e., C1R2, C2R2, and C3R2) based on the results presented in Table 5. The C1R2 method is suitable for single-objective problems that T&L companies are interested in minimizing the total routing costs of fuel consumption and overtime (economic). However, the C2R2 and C3R2 methods are suitable for bi-objective problems, but one objective is more important than another. The C2R2 method is suitable for T&L companies that are concerned about maximizing the total personal relationships (customer) and minimizing the total routing costs (economic), and the customer perspective is more important than the economic perspective. The C3R2 method is applicable for T&L companies that focus on minimize the total routing costs (economic) and balancing delivery weights of vehicles (driver), and the driver perspective is more important than the economic perspective.

Table 3. Part of data from a selected dataset of 30 customers.

Nodes	**Names**	**Latitudes**	**Longitudes**	q_i	s_i	r_{ik} **(unitless)**			
				(kg)	**(min)**	**k=1**	**k=2**	**k=3**	**k=4**
0	Depot	13.843356	100.335792						
1	Customer 1	13.743923	100.399120	0	15	0	0	0	1
2	Customer 2	13.679702	100.528160	151	15	0	0	0	0.5
3	Customer 3	13.628968	100.360535	29	15	0	0	0	1
4	Customer 4	13.774270	100.364815	317	15	0	0	0	1
5	Customer 5	13.581803	100.763901	55	15	0	0	1	0
6	Customer 6	13.615710	100.641800	130	15	0.5	0.5	1	1
7	Customer 7	13.685065	100.442530	256	15	0	0	0.5	1
8	Customer 8	13.791658	100.080130	252	15	0.5	0	0	0.5
9	Customer 9	13.851172	100.620804	230	15	1	1	0.5	0.5
10	Customer 10	13.655090	100.545540	259	15	0	0	1	1
11	Customer 11	13.824422	100.553510	385	15	0	1	0	0
12	Customer 12	13.684373	100.403496	247	15	0	0	0	1
13	Customer 13	13.478756	101.003247	209	15	0	0	1	0
14	Customer 14	13.802288	100.449460	386	15	0	0	0	1
15	Customer 15	13.846124	100.708830	136	15	0	1	1	0
16	Customer 16	13.762935	100.689130	288	15	0	0	1	0
17	Customer 17	14.048130	100.743010	169	15	0	1	0	0
18	Customer 18	13.917327	100.543600	370	15	1	1	0.5	0
19	Customer 19	13.768828	100.808304	308	15	0	0	1	0
20	Customer 20	13.545637	100.158745	197	15	0	0	0	1
21	Customer 21	13.680292	100.719400	293	15	0	0	1	0
22	Customer 22	13.787612	100.312670	305	15	0.5	0	0	1
23	Customer 23	13.570677	100.794850	245	15	0	0	1	0
24	Customer 24	13.834238	100.413100	276	15	1	0	0	1
25	Customer 25	13.632894	100.430090	0	15	0	0	0	1
26	Customer 26	14.270525	101.119530	238	15	0	1	0	0
27	Customer 27	13.924322	100.393060	165	15	0	0	1	0
28	Customer 28	13.620698	100.653220	81	15	0	0	1	0
29	Customer 29	13.827508	100.538022	241	15	0.5	0.5	0.5	0.5
30	Customer 30	13.701434	100.524221	0	15	0.5	0.5	1	1

Notes: q_i = demand of customer i (kg). s_i = service time at customer i (min). r_{ik} = personal relationship between customer i and driver of vehicle k (unitless).

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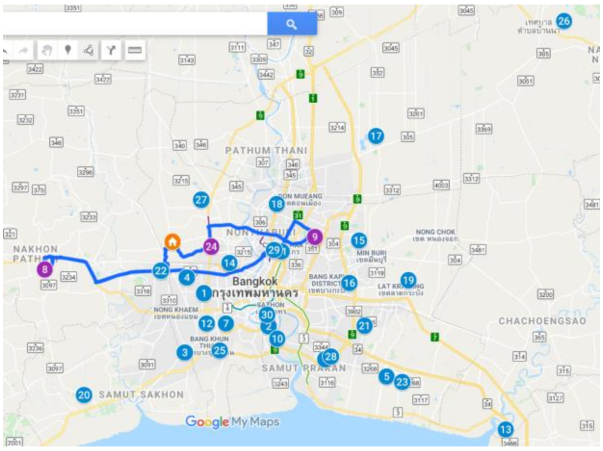
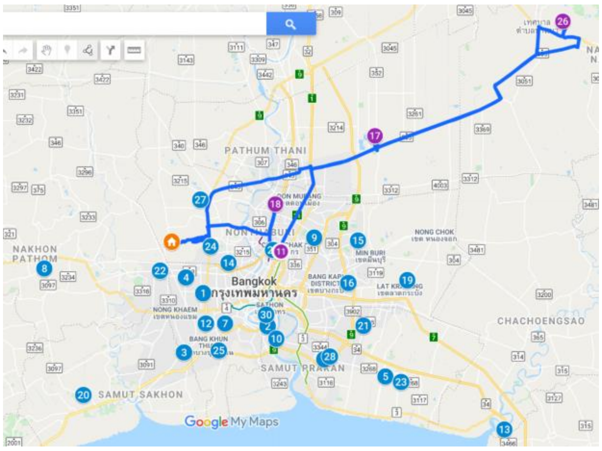
Table 4. Part of results for six LP-based CFRS heuristic methods and general CVRP model from the selected dataset of 30 customers.

Methods	CD	PR	MW	mW	dW	TD	TC	CPU
	(km)	-	(kg)	(kg)	(kg)	(km)	(THB)	(sec)
General CVRP model: minimize TD	126.9	7	2421	305	2116	*** 768.60**	5341.47	3600.00
C1R1: minimize CD + minimize TD	66.7	18	2477	407	2070	941.00	5082.62	32.25
C1R2: minimize CD + minimize TC	**66.7**	18	2477	407	2070	964.30	**4913.12**	45.58
C2R1: maximize PR + minimize TD	113	28.5	2151	758	1393	926.00	5252.05	33.50
C2R2: maximize PR + minimize TC	113	**28.5**	2151	758	1393	947.70	4970.23	67.68
C3R1: minimize MW + minimize TD	144	10	1555	1553	2	1143.20	6396.85	34.16
C3R2: minimize MW + minimize TC	144	10	**1555**	1553	2	1179.70	5915.23	41.93

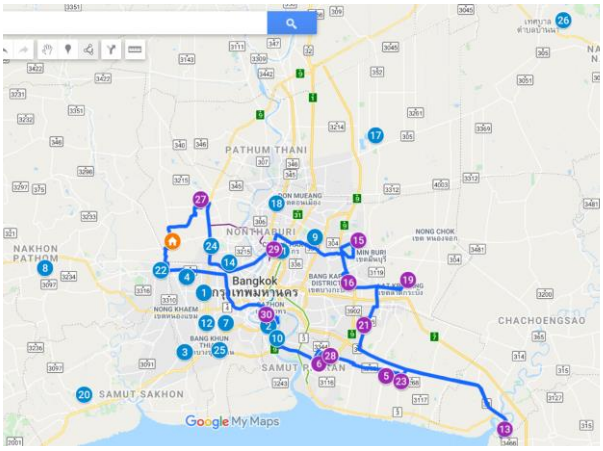
Notes: CD = maximum distance between customers in the same cluster. PR = total personal relationships between customers and drivers. MW/mW/dW = maximum/minimum/difference of delivery weight of vehicles. TD = total travel distance. TC = total routing costs (total costs of fuel and overtime). CPU = CPU time of the IBM ILOG CPLEX solver for solving the problem instance. * = total travel distance that is 6.85% above the lower bound of the total travel distance.



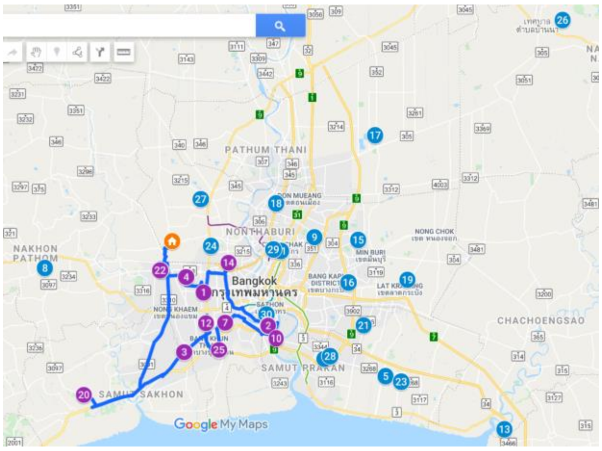
a) Truck 1's route: 3 customers, 758 kg, 160.5 km, Depot-24-9-8-Depot.



b) Truck 2's route: 4 customers, 1162 kg, 268.1 km, Depot-18-11-26-17-Depot.



c) Truck 3's route: 12 customers, 2151 kg, 310.9 km, Depot-27-29-15-16-19-21-13-23-5-28-6-30-Depot.



d) Truck 4's route: 11 customers, 2147 kg, 208.2 km, Depot-22-4-1-14-2-10-7-25-12-3-20-Depot.

Fig. 1. Delivery routes of trucks for C2R2 method from the selected dataset of 30 customers.

Table 5. Average satisfaction levels of economic, customer, and driver perspectives of five datasets.

Method	$SL(E)$	$SL(C)$	$SL(D)$
C1R1	0.857	0.106	0.141
C1R2	0.956	0.106	0.141
C2R1	0.818	1.000	0.292
C2R2	0.946	1.000	0.292
C3R1	0.000	0.104	1.000
C3R2	0.233	0.104	1.000

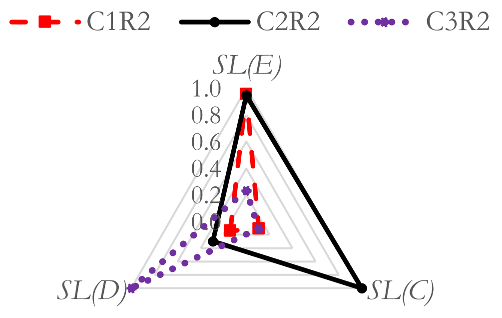


Fig. 2. Radar chart for three methods that use the total routing cost objective for the TSP models.

Table 6. Computational times of proposed LP-based CFRS heuristic methods for 30 customers and 4 vehicles.

Methods	Computational times (sec)	
	Mean	SD
C1R1	34.84	2.77
C1R2	273.57	519.70
C2R1	33.20	2.26
C2R2	43.21	14.05
C3R1	33.82	1.78
C3R2	39.05	2.39

7. Conclusions and recommendations

This paper proposes an LP-based cluster-first route-second heuristic to solve the CVRPs with different objectives. Three objectives related to the economic, customer, and driver perspectives are considered for route planning. They include the minimization of the total costs of fuel consumption and overtime (economic), the maximization of the total personal relationships between customers and drivers (customer), and the minimization of the maximum delivery weight of vehicles (driver).

Three LP-based clustering models are proposed to group customers into clusters. LP-based clustering model 1 indirectly minimizes the total costs of fuel consumption and overtime. LP-based clustering models 2 and 3 directly maximize the total personal relationships between customers and drivers and minimize the maximum delivery weight of vehicles, respectively. Then, an LP-based TSP (routing) model that minimizes the total costs of fuel consumption and overtime sequences the customer in each cluster to form a route.

The proposed two-phase heuristic methods are tested, and their performances are evaluated by using five datasets of 30 customers from a real case study of a Thai SME. Based on the experimental results, there is no clustering model that performs well for all perspectives. However, the clustering model based on personal relationships between the customers and drivers provides better performances among the three clustering models. The LP-based routing model that minimizes the total routing costs (fuel and overtime costs) is better than the model that minimizes the total travel distance.

This paper has significant contributions as follows. First, it is an original paper that considers personal relationships between customers and drivers for route planning. Second, the proposed LP-based CFRS heuristic methods are suitable for practical use by SMEs since the required computational time is short enough and it has multiple models with different objectives to be selected, matching the user requirements. Third, the proposed methods are tested using a real case study in a Thai SME with real data, for example, the locations of the depot and all customers, truck capacity, service time, fuel consumption rate, unit fuel cost, and overtime cost. Moreover, the travel distance and time between nodes are retrieved from a Google Maps API database, which is more accurate than a Euclidean distance. Fourth, the experimental results indicate that among the three LP-based clustering models, there is no model that can achieve good performances for all perspectives. There is a strong need to develop a clustering model that compromises among conflicting perspectives.

This paper has some limitations as follows. First, each proposed clustering model is good for one perspective but inadequate for other perspectives. The models cannot compromise among all perspectives. Second, environmental awareness of climate change and global warming caused by excessive carbon dioxide emission may inspire further research on environmental issues for route planning. However, these issues are not included in this paper.

Further research is recommended as follows. The environmental issues related to carbon dioxide emissions should be considered. A compromise-solution method, such as maximizing the weighted average of satisfaction levels for all perspectives, should be used for a trade-off among the objectives, for route planning. Moreover, Pareto-based approaches should be considered for multi-objective optimization to determine Pareto-optimal solutions.

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