Multi-objective Heterogeneous Capacitated Vehicle Routing Problem with Time Windows and Simultaneous Pickup and Delivery for Urban Last Mile Logistics

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Abstract. The Urban Last Mile Logistics (LML) is known to be the most expensive, least efficient and most polluting section of the supply chain. To that extent, a multi-objective heterogeneous capacitated vehicle routing problem with time windows and simultaneous pickup and delivery (MoHCVRP-TWSPD) is formulated and solved to cater to this section of the supply chain. The proposed model is solved through two proposed methods that are based on exact methods. A small benchmark was adopted from the current literature to test the proposed methods and computational results are reported. Based on the computational results, a number of insights into the MoHCVRP-TWSPD problem are provided.

Keywords: last mile, vehicle routing, time window, simultaneous pickup and delivery, capacitated, heterogeneous, logistics.

1 Introduction

The Vehicle Routing Problem (VRP) was first introduced by Dantzig and Ramser [1]. Throughout the years, various variations of VRP have been studied, each variation having different or multiple attributes. An attribute is defined as the feature considered in the problem such as heterogeneous fleet or customers' time windows.

The Urban LML; the last leg of the supply chain of much concern to logistics service providers (LSPs), is known to be the most expensive, least efficient and most polluting section of the supply chain. The LSPs typically have a mixed fleet of vehicles with differing capacities to handle day to day operations that include criteria such as customer requirements for pickup and delivery and customers' preferred times. Despite the maturity in the study of VRP, according to our literature review, there has yet to be work that directly addresses all of the aforementioned concerns. In order to cater to the multi-objective nature of the Urban LML problem faced by LSPs, in this paper, we present a VRP variant referred to as Multi-objective Heterogeneous Capacitated Vehicle Routing Problem with Time Windows and Simultaneous Pickup and

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Delivery (MoHCVRP-TWSPD). To our best knowledge, there has yet to be work in this multi-objective multi-attribute VRP problem.

The MoHCVRP-TWSPD is a problem of finding optimal heterogeneous fleet routes to serve pickup and delivery orders of customers according to the customers' preferred time windows, departing from the depot and returning to the depot once serving all of their assigned customers. During the course of execution, each of the vehicle's capacity cannot be exceeded and the time window of the depot cannot be violated as well. Optimality of vehicle routes is defined as per the objective function values. In our study, we attempt to optimise the total travelling distance, total travel time and the total emission caused by the execution of the fleet routes.

Our contributions in this paper are three folds. First, we present a mixed integer formulation of MoHCVRP-TWSPD. Second, we present two solving methods based on exact methodologies; a One-step method that provides a more realistic solution through the discretisation of vehicle speed and a Two-step method that provides a glimpse of the consequences of the current industry practice of prioritizing minimization of distance over other objectives such as emission. Finally, we provide a few insights gained from the results of our computations. Section 2 will provide the reader with an overview of related works in this variant of VRP. Section 3 will present the reader with our formulation of the problem and the proposed solving methods. Section 4 houses the computational results obtained by us and insights into the meaning of the results. Finally, Section 5 is where we will conclude the paper and their findings.

2 Related Works

In line with the aim to better fit research work to real world problems, there has been a surge in VRPs with multiple attributes such as Capacitated VRP with Time Window and Simultaneous Pickup and Delivery (CVRPTWSPD)[2-6] and Capacitated VRP with Time Window and Pickup and Delivery(CVRPTWPD)[7].

As mentioned in the introduction, to our best knowledge, there hasn't been any works in MoHCVRP-TWSPD. The closest variant that has been discovered in the literature review is CVRPTWSPD which only considers a single objective as opposed to the problem being studied in this paper. We first present the reader with a brief literature review of CVRPTWSPD. The reader will then be provided with an overview of works in Green VRP, Multi-Objective VRP and truckload factor considerations in VRP.

CVRPTWSPD is one of the multi-attribute problems that has been increasingly studied over the years. In 2002, Angelelli and Marsini[2] presented a set covering formulation for CVRPTWSPD and solved the problem using branch-and-price and branch-and-bound algorithms. The benchmark from Solomon[8] was modified to test their algorithms. Chang et al.[3] looked into real time CVRPTWSPD and solved it by iteratively solving a mixed integer programming model on a rolling time horizon.

The methodology employed by them consisted of route construction and improvement heuristics and TS. They tested their algorithm by adopting a benchmark from Gelinas et al.[9]. More recently, Gutiérrez-Jarpa et al.[4] presented a branch-and-price algorithm and Mingyong and Erbao[5] studied a minimization of total travel distance and employed differential evolution algorithm, both to solve the CVRPTWSPD problem. In 2012, Wang and Chen [6] designed a coevolution genetic algorithm to solve the problem and adopted the Solomon[8] benchmark to test their algorithm.

Given recent initiatives taken by governments all over the world to improve the environment, number of studies in Green VRP has been picking up over the years. Bektaş and Laporte [10] looked into the Pollution Routing Problem (PRP) in 2011, an extension of VRP that considers other factors such as greenhouse emissions. They considered fuel consumption and greenhouse gas emission as their eco-indicators. In order to solve for the solution, they employed CPLEX 12.1 with its default settings and tested their model with three classes of problems with varying number of cities as nodes. Interested readers may refer to a survey done by Lin et al.[11].

Jozefowiez et al.[12] presented a review on Multi-objective VRP (Mo-VRP). According to the review, some of the most studied objectives include minimization of travel distance[13], travel time[14], number of vehicles[15], waiting times of vehicles[15], makespan of routing solution[16], deviation from or number of violations of constraints such as time window constraints[17] and risk in transporting of hazardous materials[18]. There have also been studies on optimizing the balance of travel time between vehicles[13], load balance between the various vehicles in the fleet[19] and balance of tour lengths between the various vehicles[20].

According to our literature review, research on active optimization of truckload factor in VRP is scarce. The search terms used by us in Google Scholar are inclusive of ‘truckload factor vehicle routing problem’, ‘capacity utilization vehicle routing problem’, ‘balance capacity vehicle routing problem’, ‘balance load vehicle routing problem’, ‘balance load factor vehicle routing problem’, ‘resource utilization vehicle routing problem’, ‘resource maximization vehicle routing problem’, ‘deadhead vehicle routing’ and ‘volume utilization vehicle routing problem’. Among all the results obtained by the author, only a few works were found to have focused on maximizing truckload factor of vehicles. Tavakkoli-Moghaddam[21] considered maximizing vehicle utilization in a variant of Capacitated Vehicle Routing Problem (CVRP). In the field of Mo-VRP, Sutcliffe and Board[13] considered maximization of vehicle utilization in their paper besides minimization of travel distance while Moura[22] considered the objective in the VRPTW with Loading Problem.

From the literature review performed by us, it can be concluded that the literature on MoHCVRP-TWSPD is scarce. Therefore, this paper attempts to bridge the gap between the current literature and the needs of the industry through the analysis of the MoHCVRP-TWSPD problem. For an example, one of the major gaps concerns with the balance between objectives such as total travelled distance and total emission which is looked into in this paper.

3 Problem Definition and Formulation

In order to tackle the MoHCVRP-TWSPD problem, we modified and extended the formulation presented by Cordeau et al.[23] and produced the following mixed integer programming formulation as follows:

We assume that there is only one depot and a set of customers where the number of customers and number of vehicles are assumed to be at least two. The capacities of the vehicles are assumed to be non-homogeneous, that is there exists at least two vehicles where their capacities are different from each other. The vehicles are assumed to be of heavy duty with weights in between 3500 kg and 7500 kg. It is also assumed that the vehicles depart from the depot at the start of their trip and return to the depot upon completion of their trip. Finally, each customer is assumed to be visited only once by one vehicle and has a time period of which they can only be served within this time period. In this paper, we are going to focus on several objectives inclusive of minimization of travel distance, travel time and emission while maintaining a certain level of vehicle utilization.

Sets

- $V = \{0, 1, 2, \ldots, n+1\}$
  - Set of nodes of G (0: index of node representing departure of depot, 1 ~ n: indices of nodes representing customers, $n+1$: index of node representing destination of depot)
- $N = V \backslash \{0, n+1\}$
  - Set of customers
- $K = \{1, \ldots, k\}$
  - Set of vehicles
- $A = \{(i,j) \mid i,\ j \in V,\ i \neq j\}$
  - Set of arcs of G

Parameters

- $c_{i,j}$: Travel cost or distance from node i to node j
- d_i: Delivery demand of customer i
- p_i: Pickup demand of customer i
- $[a_i, b_i]$: Time window for node $i \in N$
- $[a_0, b_0]$: Time window for the depot
- s_i: Service time for node i
- Ca^k: Capacity of vehicle k
- V_{ij}^{max} : Maximum speed limit travelling from node i to node j
- V_{ij}^{min} : Minimum speed limit travelling from node i to node j
- TF: Minimum desired truckload factor
- M: A large constant

Variables

- $x_{i,j}^k$: Binary variable, 1 if arc $(i,j) \in A$ belongs to the optimal routes by vehicle k, 0 otherwise
- $l_{i,j}^k$: Load of vehicle k travelling from node i to node j
- $v_{i,j}^k$: Vehicle k's speed travelling from node i to node j
- w_i^k: Start time of vehicle k at node i

$$\text{Min} \quad \sum_{k\in K}\sum_{(i,j)\in A} c_{i,j}x_{i,j}^k \tag{1a}$$

$$\text{Min } \sum_{k\in K}\sum_{(i,j)\in A}\left(\frac{-8.8125\times10^{-7}}{{v_{ij}^k}^2}\left(v_{ij}^k-539.376\right)\left(v_{ij}^k-1.04928\right)\left({v_{ij}^k}^2-100.34v_{ij}^k+6495.77\right)\left({v_{ij}^k}^2+100.34v_{ij}^k+3572.38\right)\right)c_{i,j}\,x_{i,j}^k \tag{1b}$$

$$s.t. \quad \sum_{k\in K}\sum_{j\in V} x_{i,j}^k = 1, \forall i \in N, \tag{2}$$

$$\sum_{j\in V} x_{0,j}^k = 1, \forall k \in K, \tag{3}$$

$$\sum_{i\in V} x_{i,n+1}^k = 1, \forall k \in K, \tag{4}$$

$$\sum_{i\in V} x_{i,h}^k - \sum_{j\in V} x_{h,j}^k = 0, \forall h \in N, \forall k \in K, \tag{5}$$

$$\sum_{i\in V} l_{0,i}^k = \sum_{i\in N} d_i \sum_{j\in V} x_{i,j}^k, \forall k \in K, \tag{6}$$

$$\sum_{i\in V} l_{i,n+1}^k = \sum_{i\in N} p_i \sum_{j\in V} x_{i,j}^k, \forall k \in K \tag{7}$$

$$l_{j,i}^k + p_i - d_i - Ca^k\left(1-x_{i,j}^k\right) \le l_{i,m}^k, \forall i \in N, \forall j,m \in V, \forall k \in K, \tag{8}$$

$$w_i^k + s_i + \frac{c_{ij}}{v_{ij}^k} - w_j^k \le \left(1-x_{i,j}^k\right)M, \forall (i,j) \in A, \forall k \in K, \tag{9}$$

$$a_i \le w_i^k \le b_i, \forall i \in V, \forall k \in K, \tag{10}$$

$$l_{i,j}^k \le Ca^k x_{i,j}^k, \forall i,j \in V, \forall k \in K \tag{11}$$

$$x_{i,j}^{k} \in \{0,1\}, \forall i,j \in V, \forall k \in K \quad (12)$$

$$l_{i,j}^{k} \geq 0, \forall i,j \in V, \forall k \in K \quad (13)$$

$$V_{ij}^{\min} \leq v_{ij}^{k} \leq V_{ij}^{\max} \quad (14)$$

$$\frac{\sum_{(i,j)\in A} c_{i,j} \frac{l_{i,j}^{k}}{Ca^{k}} x_{i,j}^{k}}{\sum_{(i,j)\in A} c_{i,j} x_{i,j}^{k}} \geq TF \quad (15)$$

The objective functions of the formulation above are represented by 1a and 1b. 1a represents the total travel distance of the fleet. 1b represents the total emission produced by the fleet. Our emission formula is adopted from the formula presented by Hickman[24]. It is of utmost importance to note that travel time is decided by the speed of the vehicle and distance covered by the vehicle. Through the relationship between the 3 variables, it follows that travel time and travel distance are positively proportional to each other i.e. optimization of travel distance implies optimization of travel time and vice versa. Constraint 2 specifies that each customer is served by exactly one vehicle. Constraint 3 necessitates that each vehicle will leave node 0 for a total of one time while constraint 4 ensures that each vehicle returns to node n+1. Constraint 5 specifies that each vehicle that enters a customer node has to leave the customer node. Constraint 6 specifies that each vehicle leaves the depot with the total delivery load assigned to it. Constraint 7 ensures that each vehicle returns to the depot with the total pickup load assigned to it. Constraint 8 is the load balance constraint. Constraint 9 ensures that the start time of the service at the next node is not earlier than the earliest time possible given the start time of the current node. Constraint 10 is the time window constraint. Constraint 11 is the vehicle capacity constraint. Constraint 12 is the binary variable constraint while constraint 13 is a non-negativity constraint. Constraint 14 is the speed limit constraint on each arc. Constraint 15 specifies that the weighted average of the utilization of the vehicle is at least of the desired minimum truckload factor. Note that Constraint 15 is an ε-constraint method to optimise the utilization of each vehicle in the fleet.

Note that the formulation can be easily altered to only consider a subset of the attributes considered in this formulation. The reader is reminded to note that the formulation provided above is non-linear.

4 Solution of MoHCVRP-TWSPD

In order to solve the aforementioned problem in CPLEX, the formulation above is solved using two methods which are explained below.

4.1 One-Step Optimisation

Assume that the speed variables of the vehicles on each arc are discrete variables. Using linearization methods provided by Bisschop [25], objective 1b, constraint 9 and constraint 15 are linearised. The outcome of the linearization is as provided below. Unless otherwise stated, the variables, parameters and sets in the following expressions, equations and inequalities are defined as before.

Sets

- $speed = \{10,20,\ldots,80\}$: Set of discrete speeds for each vehicle on each arc where $speed_u$ refers to element u of the set $speed$.
- $SL = \{1,2,\ldots,8\}$: Set of indices of the set $speed$

Parameters

- M': A large constant

Variables

- $v_{i,j}^u$: Binary indicator specifying whether the vehicle transversing arc (i,j) is travelling at $speed_u$
- $y_{i,j}^k$: $x_{i,j}^k \times l_{i,j}^k$

$$\text{Min } \sum_{u\in SL}\sum_{(i,j)\in A}\Bigg(\frac{-8.8125\times10^{-7}}{{speed_u}^2}(speed_u - 539.376)(speed_u - 1.04928)\left({speed_u}^2 - 100.34 speed_u + 6495.77\right)\left({speed_u}^2 + 100.34 speed_u + 3572.38\right)\Bigg)c_{i,j}\, v_{i,j}^u \tag{1c}$$

$$w_i^k + s_i + \frac{c_{ij}}{speed_u} - w_j^k - \left(1 - x_{i,j}^k\right)M \le \sum_{z\in SL, z\ne u} M' v_{i,j}^z,\ \forall (i,j)\in A, \forall k\in K, \forall u \in SL \tag{16}$$

$$\sum_{u\in SL} v_{i,j}^u - \sum_{k\in K} x_{i,j}^k = 0,\ \forall (i,j)\in A,\ \forall k\in K, \forall u\in SL \tag{17}$$

$$\frac{\sum_{(i,j)\in A} c_{i,j}\frac{y_{i,j}^k}{Ca^k}}{\sum_{(i,j)\in A} c_{i,j} x_{i,j}^k} \ge TF \tag{18}$$

$$y_{i,j}^k \le \min\left\{Ca^k x_{i,j}^k, l_{i,j}^k\right\},\ \forall (i,j)\in A,\ \forall k\in K, \tag{19}$$

$$y_{i,j}^k \ge \max\left\{0, l_{i,j}^k - Ca^k\left(1 - x_{i,j}^k\right)\right\},\ \forall (i,j)\in A,\ \forall k \in K, \tag{20}$$

Objective 1b is linearised into objective 1c while Constraint 9 is linearised into constraint 16 and constraint 17. Finally, constraint 9 is linearised into constraint 18-20. A new objective 1d is then formed through the summation of objective 1a and 1c.

$$\text{Min } \sum_{k\in K}\sum_{(i,j)\in A} c_{i,j}x_{i,j}^{k} + \sum_{u\in SL}\sum_{(i,j)\in A}\left(\frac{-8.8125\times 10^{-7}}{{speed_u}^2}(speed_u - 539.376)(speed_u - 1.04928)\left({speed_u}^2 - 100.34 speed_u + 6495.77\right)\left({speed_u}^2 + 100.34 speed_u + 3572.38\right)\right) c_{i,j}\, v_{i,j}^{u} \tag{1d}$$

The resultant formulation is solved using CPLEX.

4.2 Two-Step Optimisation

Using linearization methods provided by Bisschop [25], constraint 15 is linearised into constraint 18-20. The first step involves solving a HCVRPTWSPD formulation with minimization of total travel distance as the objective. A new travel time matrix is formed through the normalization of the distance matrix. The formulation is then simplified to a HCVRPTWSPD formulation through the replacement of the speed variable by the corresponding travel time parameter and removal of constraint 14. This results in constraint 9 being formulated into constraint 21 as given below. Unless otherwise stated, the variables, parameters and sets in the following expressions, equations and inequalities are defined as before.

Parameters:

- $t_{i,j}$: Travel time from node i to node j

$$w_i^k + s_i + t_{ij} - w_j^k \le \left(1 - x_{i,j}^k\right)M, \forall (i,j) \in A, \forall k \in K, \tag{21}$$

The resultant simplified problem is then solved using CPLEX to obtain an initial solution.

The second step involves the optimisation of emission of the initial solution through the optimisation of travel speed on each arc. Note that the solution produced by step 2 will have total distance value corresponding to the one provided by step 1. Given that the emission function (objective 1b) is a convex function from 10km/h to 100km/h, it can be obtained that the optimal speed for minimal emission without any constraints is approximately 55.1771km/h. Through the employment of goal programming, a new formulation is formed as provided below. Unless otherwise stated, the variables, parameters and sets in the following expressions, equations and inequalities are defined as before.

$$\text{Min} \quad \sum_{k\in K}\sum_{(i,j)\in A} c_{i,j} \times \max\left(55.1771 \times t_{ij} - c_{i,j}, c_{i,j} - 55.1771 \times t_{ij}\right) \tag{1e}$$

$$s.t. \quad w_i^k + s_i + t_{ij} - w_j^k \le \left(1 - x_{i,j}^k\right)M, \forall (i,j) \in A, \forall k \in K, \tag{21}$$

$$a_i \leq w_i^k \leq b_i, \forall i \in V, \forall k \in K, \tag{10}$$

$$V_{ij}^{\min} \times t_{ij} \leq c_{i,j} \leq V_{ij}^{\max} \times t_{ij} \tag{22}$$

The objective is to minimize the deviation of optimal feasible speed on each arc from the aforementioned value while ensuring that constraint 9, 10 and 14 are satisfied. Note that constraint 9 and 14 is represented by constraint 21 and constraint 22 respectively as time based constraints. The resultant formulation is solved through CPLEX again.

5 Computational Results and Discussions

In order to test the methods proposed, we modified the benchmark provided by Mingyong and Erbao [5]. CPLEX was run on a 64-bit Windows 7 computer with a 2.7Ghz quad core processor and 4Gb of RAM. We tested both methods at TF = 0, TF = 0.3 and TF = 0.8 respectively to represent negligence, low and high requirement in truckload factor. Note that we assume the objectives considered in this paper are unitless.

Table 1. Objective Values and Computation Time

Settings	Objective Values & Computation Time	Single Step Optimisation	Two-Step Optimisation
TF = 0.8	Distance	795	795
	Emission	≈295686.65	≈293468.685
	Computation Time(seconds)	6.46	1.21(Step 1)
			0.50(Step 2)
TF = 0.3	Distance	795	790
	Emission	≈295686.65	≈313441.06
	Computation Time(seconds)	8.66	1.23(Step 1)
			0.51(Step 2)
TF = 0	Distance	795	790
	Emission	≈295686.65	≈313441.06
	Computation Time(seconds)	10.49	1.27(Step 1)
			0.63(Step 2)

Table 1 shows the computational results obtained by us. A notable observation from the results would be the drastic increase in the number of units of emission as a tradeoff with a small decrease in unit distance in the case of using Two-step optimisation method to solve the problem with the setting TF = 0.3 and TF = 0. This implies that a prioritization of minimisation of distance in solving the MoHCVRP-TWSPD might lead to a drastic increase in emission. The observation also suggests that a low truckload factor requirement might lead to a solution with high emission. Given the results above, we have summarised the advantages and disadvantages of the suggested methods as provided in Table 2.

Table 2. Advantages and disadvantages of proposed methods

	One-Step Optimisation	Two-step Optimisation
Advantages	• Optimise all the 3 objectives on the same level of priority • A more granular discretisation leads to more optimal solution	• Fast computation
Disadvantages	• Slow computation • Discretisation of velocity decision variable generates more constraints	• Possibly less optimal than single step optimisation • Emission as secondary objective

Table 2 shows a comparison of both methods presented in this paper in terms of the advantages and disadvantages. From our analysis, even though the Single step optimisation method optimizes all the considered objectives with equal priority, it should be noted that a more optimal solution in objective 1b would necessitate more constraints which would lead to slower computation time. On the other hand, Two-step optimisation shows a relatively shorter computation time compared to Single step optimisation at the possible expense of a less optimal objective value for objective 1b.

6 Conclusion and Further Research

In this paper, we have presented a formulation for MoHCVRP-TWSPD to address complexity of urban last mile logistics and presented 2 approaches based on exact methods to show that the problem is solvable. The One-step method provides a more realistic solution through the discretisation of vehicle speed. The Two-step method on the other hand provides a glimpse of the consequences of the current industry practice of prioritizing minimization of distance over other objectives such as emission. The results indicate that a prioritisation of minimization of travel distance might lead to a solution with substantially higher emission and a possible inverse relationship between truckload factor and emission level.

For further research, a number of promising directions can be pursued. In order to better serve the logistics industry, the inclusion of total waiting time into the total travel time of the objective will serve to make the problem more realistic. Inclusion of other objectives such as balance of load or travel time or maximization of customer satisfaction will bolster the usefulness of the study of this problem to the real world. Finally, research on more efficient multi-objective evolutionary algorithms is our next research effort.

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