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Driver helper dispatching problems: Three essays

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by

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ABSTRACT

The driver helper dispatching problems (DHDPs) have received scant research attention in past literature. In this three essay format dissertation, we proposed two ideas: 1) minimizing of the total cost as the new objective function to replace minimizing the total distance cost that is mostly used in past traveling salesman problem (TSP) and vehicle routing problem (VRP) algorithms and 2) dispatching vehicle either with a helper or not as part of the routing decision. The first study shows that simply separating a single with-helper route into two different types of sub-routes can significantly reduce total costs. It also proposes a new dependent driver helper (DDH) model to boost the utilization rate of the helpers to higher levels. In the second study, a new hybrid driver helper (HDH) model is proposed to solve DHDPs. The proposed HDH model provides the flexibility to relax the constraints that a helper can only work at one predetermined location in current-practice independent driver helper (IDH) model and that a helper always travels with the vehicle in the current-practice DDH model. We conducted a series of full-factorial experiments to prove that the proposed HDH model performs better than both two current solutions in terms of savings in both cost and time. The last study proposes a mathematical model to solve the VRPTW version of DHDPs and conducts a series of full factorial computational experiments. The results show that the proposed model can achieve more cost savings while reducing a similar level of dispatched vehicles as the current-practice DDH solution. All these three studies also investigate the conditions under which the proposed models would work most, or least, effectively.

CHAPTER 1. GENERAL INTRODUCTION

Introduction

In the US, the winter holiday shopping season from Black Friday to Christmas holidays accounts for around 30% of the total US annual retail sales (National Retail Federation, 2014). However, as more and more people prefer to shop online and take advantage of delivery service convenience, shipment during holiday shopping seasons becomes a big challenge to parcel delivery service providers. Last minute shoppers, higher than expected e-commerce volume, retailers with increasingly later delivery cut-off times, and harsh winter weather are all sources of logistic service challenges (Soltes, 2014). As a result, shipment delays during shopping seasons have occurred many times in the past few years. While some domestic companies service only tens or hundreds of customers every day, international companies such as United Parcel Service (UPS), Federal Express (FedEx), and Deutsche Post (DHL) are servicing millions of customers daily all over the world. Those companies always look for methods to find the most cost-efficient way to distribute parcels across the logistic network.

The volume from one origin to one destination is typically too small to justify direct transport. The shipments of the same neighborhood area (e.g., city) are typically consolidated into a facility known as a station. In most of the cases, each station has a predetermined service area, which covers an appropriate geographic size with a sufficient customer base. The primary objective of a station is to ensure that all delivery and pickups shipments are accomplished in a timely and efficient manner. Ideally, the daily delivery capacity of one station should be larger than the daily customer demand in the service area. Therefore, all the customers can receive their parcels on time.

Typically, a station is equipped with one or more trucks and drivers. Each driver has on average 8 to 12 hours of daily work. The need for drivers to work overtime is the industry normal. Working overtime, however, has many drawbacks. First, from companies' perspectives, based on the Fair Labor Standards Act (FLSA) in the US, employees must receive overtime payment for hours worked over 40 in a given workweek at a rate not less than one and a half of their regular rates. That is, letting drivers work overtime will increase direct labor costs. Second, from drivers' perspectives, even with overtime payment, not every driver is willing and able to work overtime especially if it involves significant time during the entire winter shopping season. This unpleasant employment condition can not only put pressure on the drivers' physical or mental well-being, but also increase driver turnover. This in turn can increase indirect labor cost, such as hiring and training. Last and most importantly, even though FLSA does not limit the total working hours in a period, for employees aged 16 years and older can be required to work, there is still a physical limitation on the drivers' daily work time. If delivery capacity cannot cover the delivery demand of the day, some customers would be unable to receive their packages by the promised time. This potential failure in service turns out to be a more serious problem for the parcel delivery companies. Moreover, the trend shows that home delivery volumes during peak seasons keep increasing (National Retail Federation, 2014). Thus, a parcel delivery company that is unable to implement useful solutions to deal with the increasing demand, is likely to face increasing operation costs and worsening delay issues from year-to-year.

Hiring seasonal employees is one widely used method by parcel delivery companies. For example, in the year 2015, UPS and FedEx announced a plan to hire 95,000 and 55,000 seasonal employees respectively to support the anticipated increase in package volume from November through January (Schlangenstein, 2015). A significant number of those seasonal employees work as driver helpers, who assist drivers in the delivery of packages. Driver helpers are not required to drive the delivery vehicle and usually meet the drivers at a mutually agreed upon time and location.

This dissertation focuses on investigating the enhanced ways of utilizing driver helpers to reduce costs, and the design of mathematical models to support the decision-making of driver helper dispatching problems in various scenarios. Modeling the driver-helper dispatching problem provides researchers a further understanding of this new type of transportation problem, and may trigger creative ideas to solve related issues. It also provides value to practitioners by seeking methods to avoid drivers working overtime, in addition to providing better customer service, in terms of on-time delivery, during the peak holiday seasons. In essence, this study proposes a novel framework that shapes the way the increasing package delivery challenges that occur in the e-commerce era are dealt with. Computational experiments show that simultaneously analyzing driver helper scheduling and vehicle routing can significantly improve the efficiency of a firm's shipping pattern. This study also shows that the utilization performance of driver helpers is enhanced considerably by using the proposed models.

Dissertation Organization

Utilizing the three-essay format, this dissertation's main chapters follow journal article formatting to separate distinct but related models to driver helper dispatching problems. In Chapter 2, the focus is on the first type of helpers named dependent driver helpers (DDHs). Mathematical models for helper dispatching are developed to simulate current solutions in which a predetermined shortest route must be followed either with or without a helper. This is then followed by an assessment of the opportunities to enhance the current solutions, resulting in the proposal of a new model to realize the saving opportunities. In Chapter 3, the focus is shifted to the second type of helpers called independent driver helpers (IDHs). A new hybrid model to consider a helper, who works as either a DDH or an IDH in each node, is introduced. In Chapter 4, the research topics is extended to a large-scale vehicle routing problem (VRP) which considers routing multiple vehicles and scheduling multiple helpers. This results in the design of a metaheuristic algorithm to tackle the problem. In each of the main chapters, computational simulation experiments are conducted to evaluate the savings in cost, driver time, and numbers of dispatched vehicles for the proposed ideas. Chapter 5 will summarize all the important findings from these three essays and provide comprehensive academic and practical suggestions.

CHAPTER 2. DEPENDENT DRIVER HELPER DISPATCHING MODEL

Abstract

The driver helper-related issues in dispatching problems have received scant research attention in past literature. This study shows that simply separating a single with-helper route into two different types of sub-routes can significantly reduce total costs and proposes a new DDH model to boost the utilization rate of the helpers to higher levels. Three main contributions are provided by the current research. First, it introduces a new transportation problem, DHDPs, which had never been studied before. Second, the results of the experiment show that the proposed DDH model provides a higher cost savings percentage than the current-practice DDH solutions. Finally, it conducts a series of experiments to investigate the conditions under which the proposed DDH model would work most and least effectively.

Introduction

Hiring seasonal driver helpers is a widely used method to temporarily boost the service capacity by parcel delivery companies. To date, parcel delivery companies have primarily utilized two types of driver helpers (Rhodes et. al., 2007). The first is dependent driver helpers (DDHs) who travel with delivery trucks (in the passenger seat) but work separately from drivers to deliver packages. The second type is independent driver helpers (IDH), who do not travel with delivery trucks but work at a predetermined local distribution point which typically covers a high customer density area. In this chapter, we focus on driver helper dispatching problem (DHDP) while considering only the DDH strategy, and will shift the focus to both types of helpers in DHDPs in the next chapter.

DDH strategy is designed to reduce drivers' workloads at locations with more than one customer. While a driver delivers packages on one street, the paired helper can deliver packages on another street. With the assistance from a helper, the driver can share the delivery workload. However, current vehicle routing tools are designed for finding the shortest routes to reduce the total travel cost without considering the scheduling helper. We believe that such shortest route can be a drawback when pursuing DHDP solutions. Therefore, we propose a new DDH model that relaxes the shortest route assumption and includes both travel and service cost in its objective function. A mixed integer linear programming algorithm was used to solve the problem and conduct a series of full-factorial computational experiments to evaluate the savings that can be achieved with these proposed ideas.

Literature Review

In this section, literature focused on DHDPs and other similar or related topics are reviewed.

Driver helper dispatching problem (DHDP)

To the best of our knowledge, Rhodes et al. (2007) is the only previous study that has focused on the DHDP. Rhodes and colleagues proposed an idea about a helper dispatch tool for UPS's delivery system to find out the optimal driver-helper dispatch combination based on a cost-benefit analysis. The drivers' pay rate is higher than the helpers' pay rate, with the drivers' overtime rate being even higher. By replacing drivers' overtime with helpers' regular work time, the decision tool could save on direct labor costs and provide a more efficient delivery solution.

In Rhodes et al. (2007), the authors did not mention any routing decision. Therefore, it is believed that their helper decision tool does not affect the vehicle routing decision, but rather focuses on answering the strategic level questions of 1) how many helpers should be deployed, 2) which routes need dependent helpers, and 3) which locations need independent helpers. In contrast to Rhodes et al. (2007), the scope of the decision was extended to include routing which can further improve cost savings. In other words, the study focuses on the operational level problem of finding the optimal driver-helper routing and scheduling decisions based on calculations of work time in each node and travel distance among them.

Last mile logistics problems and solutions

Last mile logistics refers to the last portion of transit in supply chains, where goods are delivered from the last transit point to the final drop point of the delivery chain, or called door-to-door (D2D) delivery (Lee and Whang, 2001). This part of logistics often involves routing a fleet of vehicles for physical distribution, and plays a crucial role in ensuring that consignments are distributed in correct quantities and within the timing limits promised to the customers. It also can be regarded as one of the most expensive and least efficient segments in the supply chain field (Gevaers et al., 2011). The vehicle operational decisions by the logistics providers can significantly affect costs in various ways including fuel consumption and labor costs (via the methods used to load, unload, and provide delivery service), and so on.

Another less obvious but also important issue is that of the information and communication technology used. Parcel delivery companies, such as UPS, Fedex, DHL, US Postal Service, etc. have long maintained records to be able to verify deliveries. Typically, a driver leaves the vehicle with one or more parcels and a portable data acquisition device. The device may be able to collect data for further tracking and forecasting analysis, such as the travel time from one location to another and the service time at each customer node. Our proposed model is built around the concept of using such historical data to estimate the service time at each node for making better-combined routing and helper scheduling decisions.

Traveling salesman problem (TSP) and vehicle routing problem (VRP)

We consider DHDP as a new type of last mile logistics problem. Last mile logistics problems were frequently solved as a traveling salesman problem (TSP) or a vehicle routing problem (VRP). If a delivery company considers the problem scope as using only one vehicle to visit all customer nodes in one route (without capacity limitation), the problem can be modeled as a TSP. TSP is a popular research topic that has received much attention from researchers, because it is so easy to describe but so difficult to solve (Hoffman et al., 2013). The basics of this problem can be simply described as finding the shortest travel path that visits each city once and only once and then back to the origin (Applegate et al., 2011).

The TSP has received considerable attention over the past few decades and various methods based on deterministic or probabilistic heuristics have been proposed to solve the problem, such as branch-and-bound, simulated annealing, genetic algorithms, tabu search, and ant colony optimization. (Lin, 1965; Lawler and Wood, 1966; Held and Karp, 1970; Lin and Kernighan, 1973; Christofides, 1976; Kirkpatrick et al., 1983; Glover, 1989; Reinelt,1991; Dorigo and Gambardella, 1997; Dorigo and Gambardella, 2016). Readers interested in discussions of various TSP studies are referred to Laporte (1992a), and Applegate et al. (2011).

If a parcel delivery company considers using more than one vehicle routes to serve all customers, then the problem should be modeled as a VRP. VRP aims to select an optimal set of routes for a fleet of vehicles on a network to serve a set of customers given specified constraints. Traditional objectives typically entail minimizing the total distance traveled by all vehicles or minimizing the total travel cost. Dantzig and Ramser (1959) first introduced VRP where they described a real-world problem considering the delivery of gasoline to service stations and proposed the first mathematical algorithm to solve the problem. Clarke and Wright (1964) proposed an effective saving heuristic that made an improvement on the Dantzig and Ramser (1959) approach.

To date, many variants of VRPs have been investigated in both academia and industry. Classification schemes are available in Desrochers et al. (1990) and Laporte et al. (2000). Other important VRP surveys studies include Magnati (1981), Raff, (1983), Laporte (1992b), Osman (1993), Desrosiers et al. (1995), and Fisher (1995). Readers that are interested in recent detailed reviews of various VRP studies are referred to Golden et al. (2008) and Toth and Vigo (2014).

Model Formulation

Keeping the delivery peak season challenge and the driver helper concept in mind, we first provide an illustration of our proposed ideas and then construct the mathematical models for both the current and proposed solutions. The current driver helper solution follows traditional TSP and VRP approaches, which seek to optimize routes to reduce the overall traveling costs and meet customer requirements. In order to improve the current solution, a more complete objective function was incorporated that includes both costs from travel time and service time in our proposed model.

Problem definition and illustration

The problem of DHDP in a one vehicle scenario may be viewed as a variant of the TSP, which allows companies considering using a DDH to reduce the drivers' work time at nodes with more than one customers. With this approach, it is assumed that all customer nodes must be visited by the vehicle once and only once, and the delivery service can be handled by either only the driver or shared by the driver and the helper. Since the driver's pay rate is higher than the helper's pay rate, it provides cost savings to use the helper's time to replace the driver's time.

Consider a route where there exist one depot and four customer nodes (denoted A, B, C, and D). In this example, we assume the visiting sequence "Depot – A – B – C– D – Depot" is the shortest path calculated by standard routing software. The travel time between customer nodes are all 5 minutes, and those between the depot and customer nodes are all 4 minutes. We also assume that the driver's pay rate is three times that of the helper's pay rate. Each node may have one or more customers. To simplify this demonstration problem, we assume that each customer needs 5 minutes for delivery service. If a node has more than one customer then, the driver and the helper will equally share the service time. If a node has only one customer, utilization of DDH will be unable to reduce the service time. Table 1 shows the service time in each node done by the driver alone or with a helper's assistance. In both nodes A and B, where there is more than one customer, the service time in both nodes is reduced by half if using a helper. In nodes C and D, because each of these nodes has only one customer, using a helper does not reduce the service time.

Table 1: Expected service time of each node in the example problem

	A	B	C	D
Expected Service time without a helper (minute)	60	30	5	5
Expected Service time with a helper (minute)	30	15	5	5

Base on the results of interviews with practitioners, in peak seasons, parcel delivery companies typically consider two ways to deal with the customer demand surge. Namely, either letting the driver work alone (in most of these cases the driver needs to work overtime, referred to as no-helper solution) or assigning a helper to the driver (referred to as current-practice DDH solution).

Here is a demonstration of the proposed solution. The proposed solution has two core concepts. The first is assigning a helper to assist with delivery in only a part of the driver's route. Therefore, the company can separate the original route into two sub-routes, one without a helper and the other with a helper. The second is to relax the shortest one route assumption, and therefore re-route for these two sub-routes. Figure 1 below demonstrates the first two solutions, and Figure 2 demonstrates the proposed DDH solution.

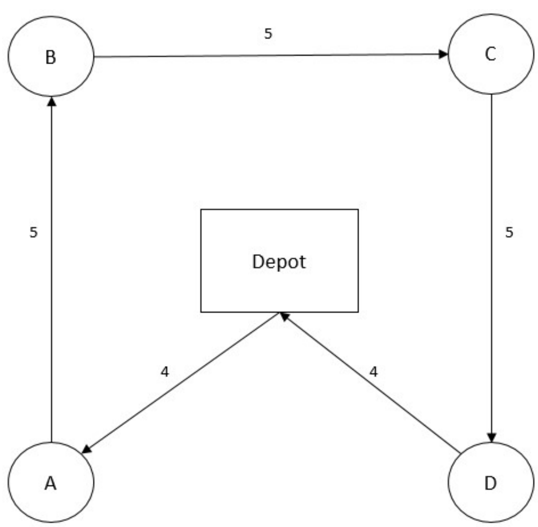

Figure 1: Example problem solved by no-helper solution and current-practice DDH solution
(*All figures are in minutes)

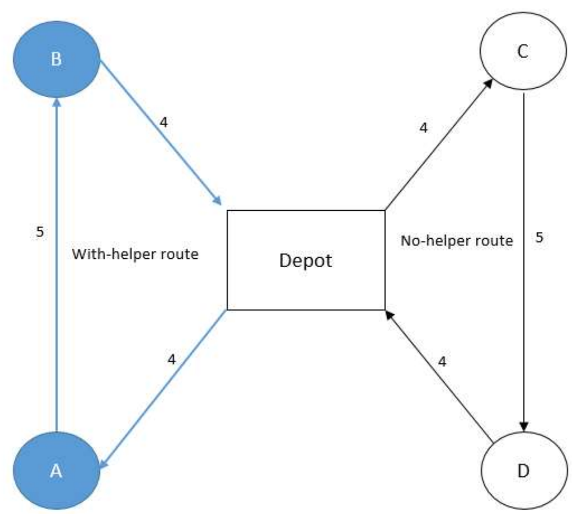

Figure 2: Example problem solved by proposed DDH solution
(*All figures are in minutes)

If the driver does not use a helper (Figure 1) then the total time of the entire route will be 123 minutes. If a helper accompanies the driver on the entire route, the total time will be 78 minutes. By using a helper, it saves 45 minutes of driver's time with the cost of 78 minutes of the helper's time. It is worth noting that, in the current-practice DDH solution, the helper does not actually provide help in node C and D. Therefore the helper's time, spent at nodes C and D along with the time spent traveling to and from both nodes, is unnecessary.

The proposed solution, shown in Figure 2, separates the service schedule into two sub-routes. The first one is a with-helper route "Depot – A – B – Depot"; the second is a no-helper route "Depot – C – D – Depot". Table 2 shows the comparison of the proposed DDH solution to that of the two current standard solutions. Since it was assumed that the driver's pay rate is three times that of the helper's pay rate, the proposed DDH solution is the most cost-efficient among these three solutions.

Table 2: Comparison of the no-help, current-practice DDH, and proposed DDH solutions

	No-Helper solution	Current-practice DDH solution	Proposed DDH solution
Driver's Time	123	78	81
Helper's Time	0	78	58

The goal of the proposed model is to help parcel delivery companies to make cost efficient driver helper dispatching decisions. It is worth noting that the helper's time spent on visiting nodes with only one customer provides no value to the delivery process. When a helper travels with a vehicle, a good solution should let the vehicle continuously visit high customer density nodes and avoid those nodes with only one customer. Therefore, the helper can spend the bulk of their work time on customer service to a sufficient level and replace a large amount of the driver's work time.

Current-practice DDH model

Based on information collected from interviews with practitioners, current drivers usually have a fixed service route called "routing," which typically provides a near-shortest (if not exactly the shortest) route. Therefore, it is reasonable to simulate the current solution by first finding the shortest route and then assigning to that route.

This is the notation used to describe the mathematical model.

- N= {1, 2, …, n}: set of all customer nodes;
- V= {0, 1, 2, …, n, n+1}: set of all nodes;
- t_{ij} : travel time from node i to node j;
- x_{ij} : binary decision variable that equals 1 if the vehicle travels from node i to node j;
- u_i : auxiliary integer variable that specifies the travel sequence of node i on the vehicle's path.
- M: an arbitrarily large number;

Given the notation, the current solution model is expressed as the following two steps.

Step 1: The following standard TSP algorithm is used to simulate the initial shortest route-finding process made by standard routing tools.

$$\text{Minimize} \sum t_{ij} x_{ij} \tag{1}$$

Subject to:

$$\sum_{j \in V \setminus \{i\}} x_{ij} = 1 \qquad \forall i \in V \tag{2}$$

$$\sum_{q \in V \setminus \{i\}} x_{qi} = 1 \qquad \forall i \in V \tag{3}$$

$$u_i - u_j + 1 \leq M(1 - x_{ij}) \qquad \forall i \in V \setminus \{0\}, \forall j \in V \setminus \{0\} \tag{4}$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in V, \forall j \in V, j \neq i \tag{5}$$

$$1 \leq u_i \leq n \qquad \forall i \in V \setminus \{0\} \tag{6}$$

The objective function (1) aims to minimize the total travel time. Constraint (2) serves to make sure each customer node will be visited once and only once. Constraint (3) ensures that for each node the inflow equals to the outflow. Constraint (4) is the sub-tour elimination constraint. Constraint (5) and (6) specify the domains for decision variables.

Step 2: Given the visiting sequence with the shortest travel distance from Step 1, the total work time for the driver and the helper can be collected and the total cost of the current-practice DDH solution can be calculated. Note that the same procedures were followed to get the no-helper solution from the same model with the only change that the driver must do all the service work individually.

Proposed model

It is worth noting that in the current-practice DDH model the helper may be forced to visit nodes with only one customer and provide no help there. The shortest route setting, while minimizing the travel distance, may unnecessarily increase unnecessary helper work time when pursuing an optimal DDH dispatch solution. Therefore, eliminating the shortest route assumption and pursuing a minimal total cost objective function in the proposed model to test how much savings can be achieved with this change.

By relaxing the shortest route assumption, our model separates the customer nodes into two routes. On the first route, all customer nodes have only one or very few customers, where the helper can't provide sufficient help. Therefore, the driver is better of working alone on this route (referred to as *no-helper route*). On the second route, the majority of nodes have a large number of customers, where the helper can efficiently help (referred to as *with-helper route*). Therefore, it is better for the driver better to work along with a helper on this route. The notations used to describe the mathematical model are aligned to those in section 2.3.3. The redefined and additional notations are presented as follows.

- x_{ij} : binary decision variable that equals 1 if the no-helper route includes a travel from node i to node j;
- y_{ij} : binary decision variable that equals 1 if the with-helper route includes a travel from node i to node j;
- u_i : auxiliary integer variable that specifies the travel sequence of node i on the no-helper route;

- v_i : auxiliary integer variable that specifies the travel sequence of node i on the with-helper route;
- s_i^1 : work time at node i if all the workload is done by the driver;
- s_i^2: work time at node i if all the workload is shared by the driver and the helper;
- DT: driver's total work time, which equals to the sum of driver's service time and driver's travel time;
- HT: helper's total work time, which equals to the sum of helper's service time and helper's travel time;
- DC : driver's pay rate;
- HC : helper's pay rate;
- TD : total traveled distance of the vehicle;
- FC : fuel cost per distance unit of the vehicle;
- VS : vehicle speed.

Thus, the proposed solution is expressed as follows.

$$\text{Minimize } DT \times DC + HT \times HC + TD \times FC \tag{7}$$

$$\text{Where } DT = \sum_{i \in V} \sum_{j \in V} x_{ij}(t_{ij} + s_i^1) + \sum_{i \in V} \sum_{j \in V} y_{ij}(t_{ij} + s_i^2)$$

$$HT = \sum_{i \in V} \sum_{j \in V} y_{ij}(t_{ij} + s_i^2)$$

$$TD = \sum_{i \in V} \sum_{j \in V} t_{ij}(x_{ij} + y_{ij}) \times VS$$

Subject to:

$$\sum_{j \in V \setminus \{i\}} x_{0j} <= 1 \tag{8}$$

$$\sum_{j \in V \setminus \{i\}} y_{0j} <= 1 \tag{9}$$

$$\sum_{j \in V \setminus \{i\}} (x_{ij} + y_{ij}) = 1 \qquad \forall i \in V \setminus \{0\} \tag{10}$$

$$\sum_{q \in V \setminus \{i\}} x_{qi} - \sum_{j \in V \setminus \{i\}} x_{ij} = 0 \qquad \forall i \in V \tag{11}$$

$$\sum_{q \in V \setminus \{i\}} y_{qi} - \sum_{j \in V \setminus \{i\}} y_{ij} = 0 \qquad \forall i \in V \tag{12}$$

$$u_i - u_j + 1 \le M(1 - x_{ij}) \qquad \forall i \in V \setminus \{0\}, \forall j \in V \setminus \{0\} \tag{13}$$

$$v_i - v_j + 1 \le M(1 - y_{ij}) \qquad \forall i \in V \setminus \{0\}, \forall j \in V \setminus \{0\} \tag{14}$$

$$x_{ij} \in \{0,1\} \qquad \forall i, j \in V \tag{15}$$

$$y_{ij} \in \{0,1\} \qquad \forall i, j \in V \tag{16}$$

$$1 \le u_i \le c \qquad \forall i \in V \setminus \{0\} \tag{17}$$

$$1 \le v_i \le c \qquad \forall i \in V \setminus \{0\} \tag{18}$$

The objective function (7) aims to minimize the total direct labor cost and fuel cost. Where the first and second term for DT in the objective function represents the sum of travel and work times on the no-helper route and with-helper route, respectively. The numerator in the TD term represents the total travel time of the vehicle.

Constraints (8) to (10) serve to make sure that each customer node will be visited once and only once on either route. Constraints (11) and (12) ensure that for each node the inflow equals to the outflow. Constraints (13) and (14) work as the sub-tour elimination constraints. Constraints (15) and (16) specify the domains for decision variables. Constraint (17) and (18) specify the ranges for travel sequence variables.

Computational Experiments

In this section, a series of experiments were conducted to investigate the conditions under which the proposed DDH solution works most, or least, effectively.

Experimental factors and their ranges

How the cost-saving potential of the solution is affected by the following four experimental factors was tested: 1) the total number of customer nodes, 2) the size of the service network, 3) the percentage of multiple-customer nodes, and 4) driver pay rates.

To obtain realistic results and implications, the experiment and specified model parameters were carefully designed by referring to a variety of reliable data sources. The sources include the following: 1) inputs from a global retail corporation with online shopping and delivery service, 2) expert opinions obtained from a global parcel delivery company, and 3) a public postal service database based in the US. The selected parameters are provided in Table 3.

Table 3: Selected parameters

Parameter	Symbol	Value or Range
Total number of customer nodes	N	{5, 10, 15, 20}
Service area size (miles x miles)	$L(.)$	{4x4, 6x6, 8x8, 10x10, 12x12}
Percentage of multiple-customer nodes	p	{10%, 30%, 50%, 70%, 90%}
Driver pay rate (dollars per hour)	DC	{24, 30, 36}
Helper pay rate (dollars per hour)	HC	12
Fuel cost (dollars per mile)	TC	0.17
Vehicle speed (miles per hour)	VS	30

The range of total number of customer nodes was set at four levels: 5, 10, 15, and 20. To set a realistic range for this factor, a pilot test was conducted under the experimental settings and found that the average total work time of the no-helper route with 10 to 15 customer nodes is the segment most close to a driver's regular 8-hour work shift in the US. Therefore, 10 customer nodes were used as the base level and 50% decrease, 50% increase, and 100% increase as the other three levels to represent the demands variances.

For the size of the service network, the size of one service area varies from an urban high-density area to a rural low-density area. The higher the population density in one area, the smaller the size of a network a driver can serve in one day. Expert opinions were consulted and the following five levels were set: 16 $mile^2$, 36 $mile^2$, 64 $mile^2$, 100 $mile^2$, and 144 $mile^2$. Note that service area shape is not considered as a factor (i.e., a square shape was assumed in all service networks).

For service time in each node, we set the distribution percentage of the multiple-customer nodes (i.e., p) at five levels: 10%, 30%, 50%, 70%, and 90%. If a node has only one customer, both the service time by a driver alone (s_i^1) and that by a driver and a helper together (s_i^2) are 5 minutes. For each multiple-customer node, s_i^1 follows a uniform distribution between 10 and 120 minutes, and s_i^2 is a half of s_i^1.

For drivers pay rate, the inputs obtained from industry experts were adopted along with the publicly available driver wages database and set a three-level range (i.e., 24, 30, and 36 dollars per hour), which are also 2, 2.5, and 3 times that of the helpers pay rate in the experiment (12 dollars per hour). It is assumed that time saved from the solution can be employed elsewhere, and can be converted to cost savings via the pay rate structure. Finally, yet importantly, overtime pay structure is not include in the research to present a more conservative result. The main reason is that the threshold of overtime may vary by companies and shift schedules. For example, under a 40 work hours per week regulation, some parcel delivery companies require that their drivers work only 4 days a week and 10 hours each day instead of 5 days a week and 8 hours each day. However, it should be readily apparent that the inclusion of an overtime pay structure would result in cost savings that are at minimum as high as those from the proposed solution are.

Design of experiments

The simulation experiments randomly generate and solve several hypothetical DHDP instances under a variety of factorial combinations, and compare the costs of proposed solutions to those of the current-practice DDH solutions of the no-helper solutions (i.e., current practices). We use Visual Basic .NET (2012) to generate instances, and use CPLEX (12.5) to solve instances.

A full factorial design was employed of the four factors specified earlier. Each simulation trial was repeated ten times by executing the following steps. First, a depot and n ∈{5, 10, 15, 20}customer nodes in a service area L(.) were randomly generated, where the size of L(.) is assigned as one of the five levels 16, 36, 64, 100, and 144 in mile^2. The distance unit as set at 0.1 miles; for example, a 16 mile^2 service area converts to a 40 (distance unit) x 40 (distance unit) network with 1600 possible locations for each randomly decided location. After randomly generating the locations, each customer node was assigned a set of service time either without helper (s_i^1) or with a helper(s_i^2). Note that the service times are decided by the distribution of customers in nodes. There are $p * n$ of multiple-customer nodes and $(1 - p)$*n of single-customer nodes, where p ∈{10%, 30%, 50%, 70%, 90%}.

Second, each of the problems was solved using the two current solution methods along with the proposed DDH model to obtain three different solutions. The above simulation trial (i.e., generation of 300 problem versions, and 900 solutions) was repeated 10 times. In total, the experiment generated 4 x 5 x 5 x 3 x 10 =3,000 instances, and 3,000 × 3 = 9,000 solutions. Finally, after all the trials are completed, for each instance, the percentage cost saving and time saving attained by the current-practice DDH solutions over the no-helper solutions were computed, which is used as the benchmark to evaluate the performance of our proposed DDH solutions. The same computation for the proposed DDH solutions over current-practice DDH solutions was then repeated.

Results

Computational results are summarized in the following tables. Table 4 shows the cost-savings frequency count percentage and the average impacts on cost, driver time, and distance of using two DDH strategies over the no-helper solutions. Table 5 focuses on the paired comparisons between the current-practice DDH solutions and that of the proposed DDH solutions. Table 6 reports the sensitivity of the model's effectiveness to changes in the experimental factors.

Table 4: Improvement over the no-helper model

	Current-practice DDH Model			Proposed DDH Model		
	Better	Worse*	Overall	Better	Same*	Overall
Probability	75.07%	24.93%	-	82.40%	17.60%	-
Cost	-16.82%	18.98%	-7.89%	-16.20%	0%	-13.34%
Driver time	-41.02%	-15.24%	-34.59%	-38.02%	0%	-31.32%
Helper time	58.98%	84.76%	65.41%	52.54%	0%	43.29%
Distance	0%	0%	0%	5.77%	0%	4.76%

* the current-practice DDH solution has 0% to get the same cost as that from no-helper solution, while the proposed DDH solution has 0% to get a worse result as compare to the no-helper solution.

In Table 4, the analysis focuses on performance improving frequency and the average improvement in each dimension. First, in all instances, the frequency counts of the current-practice DDH solution and that of the proposed model were calculated, finding better, the same, or worse results (based on total cost), respectively. Second, in each instance, the cost saving, driver time saving, and increased distance were calculated and reported the average percentage values over all instances among the paired comparisons.

The results show that both the current-practice DDH solution and proposed model can help parcel service companies archive cost savings by using helpers' time to replace drivers' time. On average, the current-practice DDH solution can save 7.89%, while the proposed DDH model can enhance the figure to 13.34%. Specifically, with respect to the current-practice DDH solution, companies have a 75.07% chance to find a more cost-efficient solution with 16.82%

cost reductions through replacing 41.02% of the drivers' time by helpers' time. However, 24.93% of the results show that using current-practice DDH solutions may not always lead to a cost saving solution. In those worse results, although the drivers' time still reduces by 15.24%, the total cost increases by 18.98%. The lower driver-time replacement rate provides the major explanation these phenomena.

When switching from the no-helper solution to the proposed DDH solution, companies have an 82.40% chance of finding a cost saving opportunity with an average total cost reduction of 16.20% while replacing 38.02% of the drivers' time with helpers' time on average. In terms of time-savings, the proposed DDH solution eliminates the wasted time for helpers' at single-customer nodes by separating the route into two, one with a helper, and the other without a helper. Although this strategy slightly increased the travel distance (4.76% on average) and the driver time (3.27% on average), it provided the tradeoff opportunity to use less of the helpers' time (22.12% on average) while gaining higher total cost savings (5.45% on average).

Table 5: Improvement over the current-practice DDH model

	Proposed DDH Model		
	Better	Same	Overall
Probability	46.97%	53.03%	-
Cost	-9.40%	0%	-4.42%
Driver time	9.46%	0%	4.44%
Helper time	-57.05%	0%	-26.81%
Distance	10.13%	0%	4.76%

In Table 5, the current-practice DDH solution was used as the benchmark to evaluate the proposed DDH solution. The results in Table 5 illustrate that a company who has already adapted the current-practice DDH solution still has a 46.97% chance of achieving a cost reduction by switching to the proposed DDH model. If such a company does so, it can have an average reduction in total costs of 4.42% by using 26.81% less of helpers' time. Moreover, the probability of the company getting a worse result by switching to the proposed DDH solution is zero. That is because the proposed DDH model provides the flexibility of using either a pure no-helper route or a pure with-helper route to service all customers. In other words, the proposed DDH model will always find either better or the same quality solutions as the approaches used in current practice. However, it is also worth noting that the savings come with the following drawbacks: 1) the average drivers work time is 4.44% longer than that in the current-practice DDH solutions, and 2) the travel distance is 4.76% longer than that in current-practice DDH solutions.

Table 6: Impact of individual factor

Factor	Current-practice DDH Model over No-helper Model		Proposed DDH Model over No-helper Model		Proposed DDH Model over Current-practice DDH Model	
	Cost	Time*	Cost	Time*	Cost	Time*
Customer nodes						
5	-2.18%	-30.30%	-10.34%	-26.13%	-6.35%	4.16%
10	-8.16%	-34.81%	-13.11%	-31.53%	-4.03%	3.28%
15	-10.06%	-36.24%	-14.50%	-33.41%	-3.67%	2.83%
20	-11.18%	-37.03%	-15.42%	-34.20%	-3.61%	2.83%
Service area (miles^2)						
4 x 4	-10.84%	-36.72%	-16.34%	-34.55%	-4.55%	2.18%
6 x 6	-9.87%	-36.05%	-14.89%	-33.23%	-4.11%	2.82%
8 x 8	-7.66%	-34.43%	-13.12%	-31.15%	-4.38%	3.27%
10 x 10	-6.26%	-33.42%	-11.71%	-29.23%	-4.38%	4.19%
12 x 12	-4.83%	-32.34%	-10.64%	-28.43%	-4.65%	3.91%
% of multiple-customer nodes						
10%	17.63%	-15.50%	-2.56%	-8.37%	-15.81%	7.13%
30%	-3.50%	-31.49%	-8.85%	-25.60%	-4.67%	5.88%
50%	-13.04%	-38.53%	-14.45%	-36.02%	-1.30%	2.51%
70%	-18.64%	-42.56%	-18.88%	-41.93%	-0.24%	0.63%
90%	-21.92%	-44.89%	-21.96%	-44.68%	-0.05%	0.21%
Driver pay rate ($/hour)						
24	-2.26%	-34.54%	-9.51%	-29.63%	-5.74%	6.81%
30	-8.64%	-34.65%	-13.71%	-31.75%	-4.13%	3.89%
36	-12.78%	-34.59%	-16.80%	-32.58%	-3.37%	2.63%

* Time calculations are based on the total work time of driver.

In Table 6, the average savings in cost and driver time for each combination of experimental factor levels is reported. First, the cost savings percentage increases as the number of customer nodes increases in both the current-practice DDH solutions and the proposed DDH solutions. With large customer nodes values, the improvement of switching from the current-practice DDH solution to proposed DDH solution incrementally converges to a stable level around 3.6%. The total cost structure includes two parts: labor cost and fuel cost. When the number of customer nodes is small, the total service time is also small, and the proportion of fuel cost becomes a large part of the total cost. Moreover, when switching from the no-helper solution to the current-practice DDH solution, the visiting sequence is the same. The only cost saving is from the reduction in labor costs due to the replacement of drivers' work time by helpers' work time. With more customer nodes, the proportion of total costs due to drivers' work time becomes larger, which result in large savings percentages.

When switching from the no-helper solution to that of the proposed model, another major savings is from the reduction of the unnecessary helpers' time wasted on single-customer nodes. However, this saving comes with extra drivers' time and extra travel distance. When the service network has more customer nodes, the proposed model has more routing options to mitigate those extra drivers' time and extra travel distances. In other words, when the solution space becomes larger, the proposed model has a higher chance to find a cost improved solution without significantly increasing driver's time and fuel cost.

Second, in terms of service area size, the helper strategies work better in high customer density areas. This may be explained by the fact that when the distances between each node are shorter, drivers can spend less time on driving and helpers can waste less time on traveling with the vehicle if they are not required to assist in delivery. So helpers' time can be used in a more efficient way to replace drivers' time. The improvement when switching from the current-practice DDH solution to that of the proposed model is very stable around 4% to 5%, irrespective of the service area size. These results imply that the use of driver helpers may be a key strategy to reduce the time and cost spent on urban logistics.

Third, in areas with a large number of multiple-customer nodes, the helper strategy works more efficiently. It is easily understandable that a higher concentration of multiple-customer nodes implies more opportunities to save when using the helper strategy. However, in the scenarios with an extremely low percentage of multiple-customer nodes (i.e., when $p = 10\%$), the current-practice DDH solution is 17.63% worse than no-helper solutions. In other words, companies that stick with the current-practice DDH strategy while still saving drivers' time may spend too much on helpers. In those extreme instances, the proposed model can still find ways to provide savings instead of paying the unnecessary helper costs. That is because the proposed model only assigns helpers to visit nodes with positive savings. Over all, if a service area has a low percentage of multiple-customer nodes or the percentages vary each day, the companies may consider reducing the risk of dispatching unnecessary driver helpers by applying proposed DDH solution.

Finally, when the drivers' pay rate is twice that of the helpers', the current-practice DDH solution and proposed DDH solution can save only 2.26% and 9.51%, respectively. However, the saving increases rapidly as the pay rate grows. When the drivers' pay rate is three times that of helpers', the cost savings are 12.78% and 16.8%, respectively. It may imply that both current and proposed helper strategies can help save even more money when companies need to pay extra rates to drivers. Such extra rates can be in the form of overtime during holiday shopping seasons, or when a service network lacks drivers and needs to ask drivers to work overtime on a regular basis. Moreover, the cost saving rate using the current-practice DDH solution is relatively unstable compared to the proposed DDH solution. When the current-practice DDH solution does not work well and leaves large saving residuals, the benefit from switching to the proposed DDH solution becomes larger. For example, in the instances where the drivers' pay rate equals to $24, switching to the proposed model can provide more than three times the savings compared to that in the proposed DDH solution.

Conclusion

In this study, we proposed a brand new DDH model to advance the current-practice DDH solutions. Our approach is based on total cost minimization objective function rather than the vehicle distance minimization objective functions used in current DHDP practices. In addition, the entire route was separated into a with-helper route and a no-helper route. A series of full-factorial simulations were conducted and provided managerial insights based on the experiment results.

The results from the computational experiment prove that the proposed DDH solution can consistently help companies to make more cost-efficient helper schedules than current practices (i.e., either the no-helper solution or the current-practice DDH solution) under all factorial combinations. On average, our proposed model can save 13.34% in total costs with the use of a helper in one service route. That is a 69% improvement on the current wildly used DDH solutions (which is 7.89%). Unlike the current-practice DDH solution has a nearly a fourth of chance to get a worse solution than not using helper, the proposed solution assigns helpers only at nodes that can provide cost savings.

The current-practice DDH solution was found not to work well in some situations. When the number of total customer nodes is small, too many single-customer nodes or the pay rate gaps between drivers and helpers is not large enough, the benefit of using helpers is limited, and sometimes even cost more than not using helpers. On the other hand, the proposed DDH solution can eliminate those negative cost saving solutions and provides a more stable savings range in all circumstances.

The results also show that both the current-practice DDH solution and the proposed DDH solution work better in certain situations. These situations are, 1) when there is a sufficient number of customer nodes, 2) in small-sized service areas, 3) when there is a high percentage of multiple-customer nodes, and 4) when there is a large gap between the drivers pay rate and that of the helpers. Therefore, it can be concluded that the driver helper strategies are suitable for urban areas (e.g., New York City, Los Angeles, Miami, Singapore, Hong Kong) and have the potential to solve some logistics challenges. For example, parking lots are very rare in some urban areas, and drivers need to service as many customers as possible after each parking opportunity. Moreover, limited parking time or service time windows presents additional challenges at some customer nodes. In both cases, helpers can play key roles to reduce service time thus satisfying those time constraints. Therefore, companies need a more time-oriented decision tool for making plans when helpers go along with drivers.

In summary, this study has three major contributions. First, the driver helper literature was extended and the model for a new transportation problem, DHDPs, was introduced which had never been studied before. Second, the results of the experiment show that the proposed DDH model provides a higher cost savings percentage than the current-practice DDH solutions. Finally, a series of experiments were conducted to investigate the conditions under which the proposed DDH model would work most, or least, effectively.

As previously mentioned in the literature review section, the driver helper related issues in dispatching problems has received scant research attention. While it has been shown that simply separating a single with-helper route into two sub-routes can significantly reduce total costs, there should be better ways to coordinate drivers and helpers to boost the utilization rate of the helpers to higher levels. Therefore, in Chapter 3, the study is extended via the consideration of the second type of helper mode (i.e., IDH) to increase the saving potential of helpers. This research suggest that future research design more advanced DHDP models to expand the saving potential.

It is worth noting that when solving larger-sized problems with multiple vehicles, the proposed model may be able to amplify the cost savings by combining several of the same type routes (either no-helper routes or with-helper routes) into a longer one. Each vehicle can be dedicated to either a no-helper route or a with-helper route and thereby further reducing unnecessary vehicle movement. Moreover, the company may hire fewer DDHs or turn those unused DDHs into other usage, for example IDHs, and further reduce the number of dispatched vehicles and drivers. Thus, in Chapter 4, multiple vehicles extensions to the proposed model is developed and evaluated.

CHAPTER 3. HYBRID DRIVER HELPER DISPATCHING MODEL

Abstract

A new hybrid driver helper (HDH) solution to solve DHDP problems is proposed in this study. The concept of the proposed HDH model provides the flexibility to relax the constraints that a helper can only work at one predetermined location in current-practice independent driver helper (IDH) model and that a helper always travels with the vehicle in the current-practice dependent driver helper (DDH) model. Thus, the proposed HDH model combines both the saving opportunities from current-practice DDH solution and from current-practice IDH solution. We conducted a series of full-factorial experiments to prove that the proposed HDH model performs better than both two current solutions in terms of savings in both cost and time. When in small sized service areas with a limited number of customer nodes and a low percentage of multiple-customer nodes, applying the proposed HDH strategy has a higher chance to save more cost than applying the current-practice DDH strategy.

Introduction

In this chapter, the proposed ideas are expanded by taking the second type of helpers, independent driver helpers (IDHs), into consideration. An IDH doesn't travel with a delivery truck but independently deals with all delivery works at a predetermined node. Each day, a delivery truck will unload the packages to a local distribution point at the node, and the independent helper will deliver all of the packages to customers by a light vehicle such as a bike or walk with tools such a hand truck. The independent helper strategy is designed for areas where a lot of packages need to be delivered or picked up. For example, neighborhoods with a lot of apartment complexes, shopping malls, and urban area with high-rise buildings. The major reason for hiring an IDH instead of a DDH is that an IDH does not need to spend time on moving with the vehicle. Therefore, all the IDH's work time can dedicate to delivery service and fully used to replace drivers' work time.

The feature of no wasted time on traveling in IDH model provides an opportunity to fulfill larger savings than DDH model. However, the current IDH model has significant drawbacks. Each IDH serves only at one location because IDH does not move with the vehicle. In addition, IDH locations are predetermined, because the company needs to prepare a local place as the IDH's warehouse in advance. Therefore, an IDH's work time is uncontrollably decided by the daily demand in the IDH location. When the customers' demand at the IDH location is too low to provide enough workload for an IDH regular shift, the investment at the IDH location will become a waste to the company. It makes the IDH dispatching problem a risky decision.

To tackle the problem by assigning an appropriate workload to a driver helper every day to sufficiently reduce the driver's work time, a new Hybrid Driver Helper (HDH) concept that eliminates the boundary between DDH and IDH is proposed. An HDH typically works in DDH mode in most of the visited nodes. However, at high customer density nodes with the opportunity to save more drivers' work time, the HDH can switch to IDH mode. While the helper works independently in a node that needs long service time, the driver can move and provide service to other nodes where the helper cannot provide sufficient help. After the helper finishes the work in the drop off node, the driver goes back to pick up the helper.

Literature Review

Driver helpers are considered as a secondary delivery resource to assist the main delivery resource, a driver with a truck. From this perspective, the literature is reviewed based on logistics operations with multiple delivery resources.

Logistics operations with multiple delivery resources

One of the most popular research streams of logistics operations with multiple delivery resources is the truck and trailer routing problem (Chao, 2002). In this problem, customers are served by either a truck or a complete vehicle (truck plus trailer) and the packages are sent out with a complete vehicle. However, in some places, the trailer needs be parked first, such that the truck can visit customer locations that are less easily accessible by a complete vehicle. Semet (1995) formulated this problem as an integer programming model and solved heuristically by a two-phase procedure. The first phase assigns trailers to trucks and determines customers to be served by each truck or complete vehicle, followed by the second phase of routes generation. Other heuristics for similar problems included construction and improvement heuristics (Gerdessen, 1996), construction heuristics with tabu search (Chao, 2002; Scheuerer, 2006) and simulated annealing (Lin et al., 2009).

Kamoun & Hall (1996) introduced a network system for express mail services in which two types of vehicles operate as a feeder-backbone delivery system. In this system, each feeder vehicles (small van) are assigned to provide pickup and delivery services in a district/route and the backbone vehicle is in charge of the transportation between a sorting facility and drop-boxes. A drop-box works as a transshipment point, where the feeder vehicles put in the collected inbound items (which will be sent back to the sorting facility later by a backbone vehicle) and take the outbound items (which were put in the box earlier by a backbone vehicle) to deliver in the next round. Both feeder vehicles and backbone vehicles would periodically visit drop-boxes. Compared to traditional courier industry practice, such transshipment points design would reduce transportation cost considerably, while keeping the same delivery speed. This feeder-backbone system was later adopted in Mitrović-Minić and Laporte (2006) to solve pickup and delivery problems with time windows (PDPTW) by applying a construction and improvement heuristic.

In terms of using humans as delivery vehicles, a series of studies were made by Lin (2008a), Lin (2008b), and Lin (2011). In these studies, the author proposed an operational mode to solve PDPTW that used two types of delivery resources. A van (heavy resource) may carry both delivery items and one or more foot couriers (lighter resources) on its route assignment. Foot couriers can travel with a van on its outbound and/or return leg, and pick up and deliver items independently. In the latest work, the problem is first formulated as a mixed integer program and then solved by a two-stage heuristic based on the critical chain concept (Lin, 2011). The schedule of the heavy resource units is planned first since it dominates in the coordination system, and then the light resource is scheduled to synchronize with the heavy resource.

Flying sidekick traveling salesman problem

Another research stream with multiple delivery resources is the flying sidekick traveling salesman problem (FSTSP) which was first introduced by Murray and Chu (2015). FSTSP is defined as the optimization routing and scheduling problem where a truck works in collaboration with a drone. The objective of the FSTSP is to minimize the total time required to service all customers and return both vehicles to the depot.

The major differences between driver helpers and drones are the launch and rendezvous procedures. A drone flight path may begin either at the depot or from the truck at any customer location. Prior to launch, a setup time is required for the driver to change the drone's battery and to load the parcel. Once launched, the drone visits a customer and returns to either the location of a customer service by the truck or the depot within the drone's flight endurance limit. If a flight path ends at the truck, another setup time may be required for the driver to recover the drone. If the drone is on its last flight path and going to be out of service, the depot can also be considered as the end node.

Similar to helper dispatching problems, practical-sized FSTSP is hard to be solved by exact algorithms. Murray and Chu (2015) provided a mixed integer linear programming model for the FSTSP and a heuristic solution approach to solve problems of practical size. Ponza (2016) slightly changed the time variables for more consistent and realistic time accounting and used Simulated Annealing metaheuristic to solve the problem.

Another formulation for a similar problem is the traveling salesman problem with drone (TSP-D) by Agatz et al., (2015). The authors formulate this problem as a mixed integer programming (MIP) model and develop route-first-cluster-second heuristics on local search and dynamic programming for the TSP-D. The main difference between FSTSP and TSP-D is the latter assumes the truck and the drone travel on the same road network. This assumption makes the problem solving easier and provides the maximum achievable gains over a tradition truck-only system. However, these assumptions sacrifice the advantages of drones' high speed and ability to take shortcuts via Euclidean distances. Ha et al., (2015) proposes a drone-first-truck-second and a truck-first-drone-second heuristic methods to solve the TSP-D. They also compare their heuristics with both optimal TSP-D tours and the FSTSP on their instances.

Model Formulation

In this section, the mathematical model is constructed which represents the proposed HDH strategy.

Problem definition and illustration

The problem of our interest may be viewed as a variant of the traveling salesman problem, which allows for considering the use of a helper as a DDH to reduce the drivers' work time at some nodes with more than one customer and as an IDH to replace all the drivers' work time at any other nodes. While a helper is working as an IDH at one node, the driver can visit and provide service at other nodes, and then pick up the helper at the IDH location later. Assume that all the customer nodes must be visited by the vehicle once and only once, and the delivery service can be handled by either one person (a driver or a helper in IDH mode) or shared by the driver and the helper in DDH mode.

An example problem is provided with 5 customer nodes to demonstrate how the proposed HDH solution works. The assumed travel time from the depot to any node is 4 minutes and the travel time between any customer nodes is 5 minutes. The service time in each node either done by one worker (the driver or the helper) alone or by two workers (the driver with the helper's assistant) are also shown in Table 7.

Table 7: Expected service time of each node in the example problem

	A	B	C	D	E
Expected Service time for 1 worker (minute)	60	40	5	5	5
Expected Service time for 2 workers (minute)	30	20	5	5	5

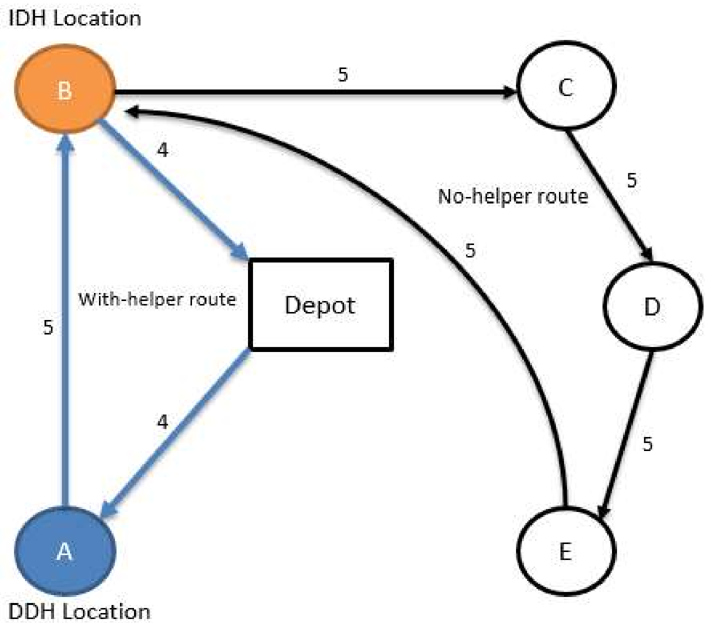

Figure 3: Example problem solved by proposed HDH model
*All figures are in minutes

In Figure 3, the proposed HDH model suggests that, first, the driver and helper go to node A and work together there. Second, the driver drives the helper to node B and let the helper works independently there. In the meantime, the driver begins a no-helper route and visits node C, D, and E by themselves then goes back to pick up the helper at node B. When the driver returns to node B, the driver needs to wait 5 minutes there, because the no-helper route takes 35 minutes of driver's time that is 5 minutes less than the time the helper needs to finish all the work in node B. Finally, the driver and the helper return to the depot together. In this solution, the total time for both the driver and the helper are 83 minutes. The results to those from the two current practices (no-helper solution and current-practice DDH solution) are compared in Table 8.

Table 8: Comparison of the no-helper, current-practice DDH, and proposed HDH solutions

	No-helper Model	Current-practice DDH Model	Proposed HDH Model
Driver's Time	143	93	83
Helper's Time	0	93	83

Since we assume the drivers pay rate is higher than the helpers pay rate, the HDH solution improves cost savings than both the current solutions.

Proposed model

Our proposed HDH model uses three types of decision variables. The first is the 0/1 binary variable X_{ij} that indicates the route decisions in arc (i, j), such that $X_{ij} = 1$ if the route includes travel through arc (i, j); $X_{ij} = 0$ otherwise. The second are the 0/1 binary variables α_i and β_i. These variables jointly indicate whether a node on the route should be served by the helper as a DDH or an IDH. $\alpha_i = 1$, $\beta_i = 0$ if the helper works as a DDH at node i; $\alpha_i = 0$, $\beta_i = 1$ if the helper works as a IDH at node i; $\alpha_i = 0$, $\beta_i = 0$ if the helper doesn't visit node i, where customers are serviced by the driver only while the helper working at another node. The last is the integer variable a_i that indicates the arive time at each node, which does not include the service time at node i. Variable a_i also plays an important role in the subtour-elimination constraint. If $X_{ij} = 1$, then the arrive time at node j must equal to the summary of arrive time at node i, the work time and node i, and the travel time from i to j. Since each node has only one value for a_i variable, the subtour becomes infesible in the model. The depot also has its arive time a_0 that represents the total spent time of the whole route.

If a customer node i has an independent helper working there, the driver will need to go back to node i to pick up the helper after the helper finishes the work at node i. The going back action, however, confuses the time measurement a_i. A a_i can only has one value, which is not able to store the second visiting time when the driver comes back for picking up the helper at the IDH location. To fix the problem, a set of dummy customer nodes were used (node C) to duplicate all customer nodes. In our model, if a customer node i has a independent helper works there, the driver will be forced to visit the dummy node $c + i$ (instaed of node i) to pick up the helper. Therefore, the second visiting time can be stored in $a_{(c+i)}$.

This is the notation used to describe the mathematical model.

- C= {1, 2, …, c}: set of all customer nodes;
- C'= {c + 1, c + 2, …, c + c}: set of all dummy customer nodes where the location of $\text{node}_{(c+i)}$ is the same as the $\text{node}_{(i)}$;
- V= {0, 1, 2, …, c, 2c+1}: set of all real nodes;
- V'= {0, 1, 2, …, c, c + 1, c + 2, …, c + c ,2c+1}: set of all real and dummy nodes;
- d_{ij} : travel distance from node i to node j;
- x_{ij} : binary decision variable that equals 1 if the route includes a travel from node i to node j;
- a_i : auxiliary integer variable that specifies the arrive time at node i on the route;
- M : an arbitrarily large number;

- s_i^1 : work time at node i if all the workload is done by either the driver or the helper; for all dummy nodes s_i^1 =0 $\forall i \in c'$;
- s_i^2 :work time at node i if all the workload is shared by the driver and the helper; for all dummy nodes s_i^2 =0 $\forall i \in c'$;
- α_i: binary decision variable that equals 1 if the helper works as a dependent helper at node i;
- β_i: binary decision variable that equals 1 if the helper works as an independent helper at node i;
- LC : combined labor cost of a driver and a helper per time unit;
- VS : vehicle travel speed;
- TD : total traveled distance of the vehicle;
- FC : fuel cost per distance unit.

Given these, the proposed argorithem is expressed as a mixed integer linear programming model in the following form:

$$\text{Minimize } a_0 \times LC + \sum_{i \in V'} \sum_{j \in V'} d_{ij} x_{ij} \times FC \qquad (1)$$

Subject to:

$$\sum_{j \in V' \setminus \{i\}} x_{ij} = 1 \qquad \forall i \in C \qquad (2)$$

$$\sum_{j \in V' \setminus \{i\}} x_{ij} \le 1 \qquad \forall i \in C' \qquad (3)$$

$$\sum_{q \in V' \setminus \{i\}} x_{qi} = \sum_{j \in V' \setminus \{i\}} x_{ij} \qquad \forall i \in V' \qquad (4)$$

$$x_{i(i+c)} = 0 \qquad \forall i \in C \tag{5}$$

$$x_{(i+c)i} = 0 \qquad \forall i \in C \tag{6}$$

$$x_{ij} \in \{0,1\} \qquad \forall i, j \in V' \tag{7}$$

$$\alpha_i + \beta_i \leq 1 \qquad \forall i \in V' \setminus \{0\} \tag{8}$$

$$\alpha_i + \beta_i \geq x_{0i} \qquad \forall j \in C \tag{9}$$

$$\alpha_j + \beta_j \leq \alpha_i + M(1 - x_{ij}) \qquad \forall i \in V'; \forall j \in V \tag{10}$$

$$\alpha_j + \beta_j \geq \alpha_i - M(1 - x_{ij}) \qquad \forall i \in V'; \forall j \in V \tag{11}$$

$$\sum_{q \in V/\{0\}} x_{q(c+i)} = \beta_i \qquad \forall i \in V \tag{12}$$

$$\alpha_{(c+i)} = \beta_i \qquad \forall i \in V \tag{13}$$

$$\alpha_i \in \{0,1\} \qquad \forall i \in V' \setminus \{0\} \tag{14}$$

$$\beta_i \in \{0,1\} \qquad \forall i \in V' \setminus \{0\} \tag{15}$$

$$a_i \geq \frac{d_{0i} x_{0i}}{vs} \qquad \forall i \in V \setminus \{0\} \tag{16}$$

$$a_j + M(1 - x_{ij}) \geq a_i + s_i^1 + \alpha_i (s_i^2 - s_i^1) - \beta_i s_i^1 + \frac{d_{ij}}{vs} \qquad \forall i \in V' \setminus \{0\}, j \in V'; i \neq j \tag{17}$$

$$a_{c+i} + M(1 - \beta_i) \geq a_i + s_i^1 \qquad \forall i \in V \tag{18}$$

The objective function (1) aims to minimize the total labor cost and fuel cost. Where a_0 represents the totally time for the whole route, and $\sum_{i\in v}\sum_{j\in v} d_{ij}\times x_{ij}$ represents the total travel distance of the vehicle. Constraint (2) makes sure all the customer nodes must be visited once and only once, while constraint (3) limits all the dummy customer nodes to be visited at most once. Constraint (4) ensures that for each node the inflow equals to the outflow. Constraint (5) and (6) eliminate the possibility of a vehicle continuously visiting a customer node and its dummy node and vice versa. Constraint (7) specifies the domain for decision variable x_{ij}.

Constraints (8) to (15) are designed for scheduling the helper. Constraint (8) ensures that all customer nodes can be assigned as either a DDH location or an IDH location but not both. Constraint (9) assigns the helper at the first visit node on the route. Constraint (10) to (11) make sure that if the helper works as a DDH at the precedent node, the helper needs to be assigned as either a DDH or an IDH in the current location. Constraint (12) ensures that if a customer node i has a independent helper working there, the driver will visit the dummy node $c+i$ to pick up the helper later. Constraint (13) serves to make sure that after picking up an independent helper at a dummy node, the next visit node will also have an assigned role for the helper. Constraint (14) and (15) specify the domains for decision variables α_i and β_i.

Constraints (16) to (18) are designed for time alignment. Constraint (16) is used to accumulate the arrival time at the first visit node of the route. Constraint (17) is used to accumulate the arrival time at each node on the with-helper route. Note that $s_i^1+\alpha_i(s_i^2-s_i^1)-\beta_i s_i^1$ in constraint (17) is used to calculate the driver's service time at node i when assigning the helper as a DDH (α_i=1, β_i=0; driver's service time =s_i^2) or as a IDH (α_i=0, β_i=1; driver's service time =0), or without the helper (α_i=0, β_i=0; driver's service time =s_i^1). Constraint (18) ensures that if the driver arrives at the dummy node too early for picking up the independent helper, the driver needs to wait until the helper finishes the work there. Note that the time alignment constraints also work as the sub-tour elimination constraints.

Computational Experiments

In this section, a series of experiments were conducted to investigate the conditions under which the proposed HDH solution works better.

Experimental factors and their ranges

Aligned with the experiments settings in Chapter 2, the same four experiment factors were used to test the cost-saving potential of the HDH solution in different scenarios: (i) the total number of customer nodes, (ii) the size of the service area, (iii) the percentage of multiple-customer nodes, and (iv) driver pay rates. The selected parameters are provided in Table 9.

Table 9: Selected parameters

Parameter	Symbol	Value or Range
Total number of customer nodes	*n*	{6, 8, 10}
Service area size (miles * miles)	*L*(.)	{4x4, 6x6, 8x8, 10x10, 12x12}
Percentage of multiple-customer nodes	*p*	{10%, 30%, 50%, 70%, 90%}
Driver pay rate (dollars per hour)	*DC*	{24, 30, 36}
Helper pay rate (dollars per hour)	*HC*	12
Fuel cost (dollars per mile)	*TC*	0.17
Vehicle speed (miles per hour)	*VS*	30

The only difference in the setting of the current study to those in study 1 is the range of total numbers of customer nodes. First, pilot experiments were conducted and it was found that the computation time is too long when solving large-sized problems because of the duplicated dummy node of each customer location and the new added decision variables and constraints. As a result, the parameter of total customer nodes was limited in a three-level range 6, 8, and 10 in the main experiment. Although the numbers of customer nodes in our experiment were less than those in practical problems, it does not affect the research purpose of testing the impact of each experimental factor. However, it is suggested that future research enhance the proposed algorithm with cut plans or to simplify the model to reduce the computation time.

Design of experiments

The computational experiments randomly generate and solve many DHDP instances under a variety of factorial combinations, and compare the costs of current-practice DDH solutions, current IDH solutions, and proposed HDH solutions to those of no-helper solutions. Visual Basic .NET (2012) was used to generate instances and CPLEX (12.5) to solve instances. A full factorial design of four factors, which are varied in three, five, five, and three levels was used respectively. Each simulation trial was repeated ten times by executing the following steps.

First, a depot was randomly generated and $n \in \{6, 8, 10\}$customer nodes in a service area L(.), where the size of L(.) is assigned as one of the five levels 16, 36, 64, 100, and 144 in mile^2. The distance unit was set as 0.1 mile; for example, a 16 mile^2 service area converts to a 40 (0.1 mile) x 40 (0.1 mile) network with 1600 possible locations for each randomly decided location. After randomly assigning the locations, each customer node was assigned a set of service times either without a helper (s_i^1) or with a helper (s_i^2). The service time at each node is decided by the distribution of customers in nodes. There are $p * n$ of single-customer nodes and $(1 - p) * n$ of multiple customer nodes, where $p \in$ {10%, 30%, 50%, 70%, 90%}. If a node has only one customer, both the service time by a driver alone (s_i^1) and that by a driver and a helper together (s_i^2) are 5 minutes. For each multiple-customer node, the s_i^1 follows a uniform distribution between 10 minutes to 120 minutes, and the s_i^2 is half of s_i^1.

Second, each of the problems was solved with the no-helper solution, current-practice DDH solution, current IDH solution, and proposed HDH solution to obtain four different results. The above simulation trial was repeated (i.e., generation of 225 problem versions, and 900 solutions), 10 times. In total, the experiment generated 3 x 5 x 5 x 3 x 10 =2,250 instances, and 2,250 × 4 = 10,000 solutions. Finally, after all the trials are completed, for each instance, the percentage cost saving over the no-helper solutions attained by the current-practice DDH solutions, current IDH solutions, and proposed HDH solutions were calculated. No-helper solutions are used as benchmarks to evaluate the performance of the three different helper solutions.

Results

Computational results are summarized in Tables 10-12. Table 10 presents the average savings of current-practice DDH solutions, current IDH solutions, and proposed HDH solutions compared to no-helper solutions. Table 11 presents the saving figures of proposed HDH solutions compared to current-practice DDH solutions. In both Tables 10 and 11, the comparison results were categorized into better and worse groups and then the total cost and driver time-saving on average percentage was presented. The combination of the two in the overall column were also presented. Table 12 reports the sensitivity of the effectiveness of the changes in experimental factors.

Table 10: Improvement over no-helper model

	Current-practice DDH Model			Current-practice IDH Model			Proposed HDH Model		
	Better	Worse	Overall	Better	Worse	Overall	Better	Worse	Overall
Probability	72.27%	27.73%	-	100.00%	0.00%	-	76.81%	23.19%	-
Cost	-15.81%	21.37%	-5.63%	-5.42%	-	-5.42%	-16.00%	17.84%	-8.24%
Driver time	-40.27%	-13.36%	-32.90%	-13.06%	-	-13.06%	-40.43%	-16.28%	-34.89%
Helper time	59.73%	86.64%	67.10%	29.87%	-	29.87%	59.57%	83.72%	65.11%
Distance	-	-	-	-	-	-	0.78%	0.00%	0.60%

In Table 10, the analysis focuses on cost improving rate and average changes in cost, driver time and distance. First, the percentage of the frequency counts were calculated finding better or worst results (based on total cost) of the three solutions over no-helper solution in all instances. Second, the cost, driver time, and distance percentage changes of the three solutions over no-helper solution were calculated in each instance and the average figures were presented.

The results show that these three helper solutions all can help parcel service companies achieve cost savings by using helpers' time to replace higher cost drivers' time. On average, the proposed HDH solution performs best and can save 8.24%, while the current-practice DDH solution and current IDH solution can save 5.63% and 5.72%, respectively. Specifically, with current-practice DDH solution, companies are 72.27% more likely to find a more cost-efficient solution with 15.81% cost reduction through replacing 40.27% of the drivers' time by helpers' time. However, in 27.73% of the instances, using the current-practice DDH solutions may lead to higher cost results. In those worse results, although the drivers' time still reduces 13.36%, the total cost increase 21.37%.

With current IDH solution, companies can get 100% better saving results. However, the savings in cost and driver time are lower than those from DDH and HDH solutions. Especially the saving in drivers' time which is limited to only 13.06%. The concept of IDH solution is hiring a helper to provide service at only one location to replace the service time that driver would spend there. The benefit is stable but limited at only one location. As the number of customer nodes increases to a high level or most nodes have multiple customers, companies should use either a DDH or an HDH instead of use IDHs in even more nodes for better improve the effectiveness they can get from helpers.

Applying proposed HDH solutions leads to the best outcome among the three in both cost and time saving; companies have 76.81% chance to find a cost saving opportunity to reduce 16% total cost through replacing 40.43% of the drivers' time with helpers' time. This strategy has very little impact on increasing travel distance (0.60%). It was also found that the results from proposed HDH solutions are consistently slightly better than those from the current-practice DDH solutions. Therefore, a paired comparison of the proposed HDH solution to the current-practice DDH solution is provided in Table 11 to further address the differences between them.

Table 11: Improvement over the current-practice DDH model

	Proposed HDH Solution		
	Better	Same	Overall
Probability	20.90%	79.10%	-
Cost	-10.85%	-	-2.24%
Driver time	-11.48%	-	-2.37%
Helper time	-11.48%		-2.37%
Distance	2.91%	-	0.60%

It is worth noting that the proposed HDH solution is an enhanced version of the current-practice DDH solution. If the solution can find an appropriate IDH location, the solution will take the chance to reschedule for a better solution. Otherwise the solution will be the same as the current-practice DDH solution. From Table 11, in only 20.9% of all instances, the proposed HDH solution finds better schedules than those from the current-practice DDH solution. On average, those better proposed HDH solutions can improve 10.85% in cost savings and reduce 11.48% in driver time. In other words, the proposed HDH solution has the chance to find IDH locations and allow the driver to visit single-customer nodes by themselves while the helper is independently working at IDH locations.

To sum up, in this section, the overall solution qualities from the proposed HDH solution are close to the current-practice DDH solutions but slightly better. In situations when the current-practice DDH can provide positive saving, the proposed HDH provide more; when DDH solution provides negative savings, HDH also provides negative savings but slightly better.

Table 12: Impact of individual factor

Parameter	Current-practice DDH Model over No-helper Model		Proposed HDH Model over No-helper Model		Proposed HDH Model over Current-practice DDH Model	
	Cost	Time	Cost	Time	Cost	Time
Customer nodes						
6	-3.09%	-30.97%	-6.89%	-33.87%	-3.29%	-3.49%
8	-6.19%	-33.35%	-8.59%	-35.18%	-2.05%	-2.16%
10	-7.60%	-34.38%	-9.24%	-35.63%	-1.37%	-1.45%
Service area (miles^2)						
4 x 4	-10.29%	-36.35%	-13.38%	-38.66%	-2.68%	-2.80%
6 x 6	-6.78%	-33.76%	-9.78%	-36.03%	-2.60%	-2.74%
8 x 8	-6.03%	-33.20%	-8.41%	-35.03%	-2.05%	-2.18%
10 x 10	-3.21%	-31.12%	-5.50%	-32.89%	-1.94%	-2.07%
12 x 12	-1.81%	-30.06%	-4.12%	-31.85%	-1.91%	-2.05%
% of multiple-customer nodes						
10%	21.27%	-12.56%	14.45%	-17.80%	-5.42%	-5.76%
30%	-0.67%	-29.40%	-4.84%	-32.56%	-3.71%	-3.93%
50%	-10.88%	-36.98%	-12.46%	-38.17%	-1.55%	-1.63%
70%	-17.03%	-41.42%	-17.46%	-41.74%	-0.41%	-0.44%
90%	-20.82%	-44.14%	-20.89%	-44.19%	-0.09%	-0.09%
Driver pay rate ($/hour)						
24	0.11%	-32.83%	-2.46%	-34.70%	-2.03%	-2.17%
30	-6.13%	-32.76%	-8.99%	-34.95%	-2.51%	-2.65%
36	-10.86%	-33.11%	-13.27%	-35.03%	-2.17%	-2.28%

Table 12 presents the impact of individual parameters to cost savings. The findings are provided as follows. First, both the cost savings percentage of DDH Solution and HDH solution over no-helper solution increase as the number of customer node increases. With a larger number of customer nodes, the percentage of helpers' time spent on service would become larger and provide more help to drivers. However, the savings percentage of switching from HDH solution to DDH solution gradually becomes smaller. The interpretation here is that the DDH solution works well when there are sufficient numbers of customer nodes, and leaves a limited saving residual for HDH solution. However, even the number of customer nodes be added to a large number, the HDH still can prove a stable amount of savings, but the saving improvement will gradually become smaller. In terms of time-saving, adding more customer nodes still helps but doesn't have a large impact.

Second, in terms of service area size, both DDH and HDH strategies work better in high customer density areas, because both DDH and HDH strategies are designed for reducing the service time by travel time. In terms of comparing these two strategies, when in small service networks, the savings percentage of switching from DDH to HDH is slightly higher than those in large areas. If we assume all other factors are the same, the total time in a large service area should be higher than that in a small service area because of the difference in travel time. So even the HDH strategy saves a similar amount of service time in both areas, the percentage saving result is more beneficial to the small sized area. Although the service area size does not affect the amount of time-saving, it does affect the savings percentage.

Third, in areas with more multiple-customer nodes, both DDH and HDH strategies work more efficiently to reduce a large amount of drivers' time. However, when companies overused the helpers in low percentage multiple-customer node areas, for example, when $p = 30\%$, the savings percentage of DDH solution is close to zero, and when $p = 10\%$ the saving even becomes a negative numbers. The results of HDH strategy are similar but stably higher than DDH in all levels. Comparing these two strategies, we found when DDH strategy performs badly in low percentage of multiple-customer nodes areas, the benefit of switching from DDH to HDH are the higher. It aligns with our earlier findings that with more savings residuals, the HDH strategy are easier to find improvement opportunities.

Finally, the gap between drivers' pay rate and helpers' largely affects the saving of driver helper strategies. Generally speaking, the higher the gap, the more saving companies can get from both DDH and HDH strategies. When considering switching from DDH to HDH, the improved percentage are ranged between 2% and 3% in all levels. In terms of time-saving, no obvious effect from pay rate factors was found.

Conclusion

In this study, a new HDH solution to solve DHDP problems was proposed. This is the first study to consider using both DDHs and IDHs in one route. The proposed concept of HDH provides the flexibility to relax the constraint that a helper can only work at one predetermined location in current practice, and the constraint that a helper always travels with the vehicle in the current-practice DDH model. It combines both the saving opportunities from DDH solution and from IDH solution.

We conducted a series of full-factorial experiments to compare pure DDH, pure IDH, and proposed HDH strategies, and proved that the proposed HDH model performs better than both two current solutions in terms of savings in either cost or time. Additional insights were also gleaned from the experimental results. First, the benefit of IDH is stable but limited. In most cases, both DDH and HDH can find better solutions than IDH. Second, the results from HDH model are very similar to those from DDH solutions. Only in 20.9% of all instances, HDH solutions find better results than DDH solutions, which improve 10.85% of cost savings and 11.48% of drivers' time on average. Because the high similarity between DDH and HDH solutions, in situations DDH can perform well, HDH also performs well. On the other hand, in situations where DDH cannot produce a good result, nor can HDH. Finally, improved opportunities via switching from DDH to HDH may happen in all factorial combinations. In particular, when in small sized service areas with a limited number of customer nodes and a low percentage of multiple-customer nodes, applying HDH strategy has a higher chance to save more cost than DDH strategy.

Two suggestions for future research are recommended. First, this study has proved that the proposed HDH strategy performs better than the current-practice DDH and IDH strategies. However, the experiments are limited in small numbers of customer nodes, due to the model complexity. Future research may consider to solve DHDPs with large sized networks by either sticking with exact methods but apply cut plans or applying heuristic methods. Second, there is curiosity about how the proposed HDH model works in multiple vehicle environments. Therefore, it is believed that conducting the HDH strategy in more practical situations such as capacity VRPs (CVRPs) or VRP with time windows (VRPTWs) may also be interesting and promising future research topics.

CHAPTER 4: INTEGRATE DRIVER HELPERS DISPATCHING PROBLEM AND VEHICLE ROUTING PROBLEM WITH TIME WINDOWS

Abstract

This study proposes a mathematical model to solve the vehicle routing problem with time windows (VRPTW) version of DHDPs. First, it proposes a metaheuristic model with a main idea that dedicating each vehicle to either a no-helper route or a with-helper route and finding the most cost-efficient coordinate schedules of drivers and helpers based on time windows and service times at customer nodes. Second, it conducts a series of full factorial computational experiments and proves that the proposed model can achieve more cost savings while reducing a similar level of dispatched vehicles as the current-practice DDH solution. Finally, it investigates the conditions under which the proposed DDH model would work most, or least, effectively. In terms of the effects on both total cost and numbers of need vehicles, the most important factor is the percentage of multiple-customer nodes. Other than that, the network size, customer density, vehicle capacity, and the gap between drivers and helpers pay rates also have significant effects on the success of driver helper strategies in VRPTWs.

Introduction

In this study, we proposed heuristic methods for solving vehicle routing problem with time windows (VRPTW) version of DHDPs. The VRPTW version of helper dispatching problems involve more than one vehicle and much larger numbers of customers. We conduct a metaheuristic method to solve the large sized VRPTWs with the no-helper solution, the current-practice DDH solution, and the proposed solutions. Although metaheuristic methods can not generate the optimal solution to large sized problems in most of cases, the goal of this study is to provide a method that is able to find good enough solutions in a practically acceptable timely manner for practical large-sized VRPTWs.

Literature Review

In this section, is a brief review of possible approaches to solve VRP with driver helper dispatching problems. Note that the introduced VRP version of helper dispatching problems are non-deterministic polynomial-time hard (NP-hard). To date, no one has found a polynomial-time exact algorithm for NP-hard problems. We need alternative solutions with heuristics or metaheuristics approach to solve the problems. Therefore, our literature review is focused on the classical heuristic methods and the metaheuristic methods used to solve VRPs.

Classical heuristics

Following the classification proposed by Laporte and Semet (2001), classical VRP heuristics were classified into three groups: (1) route construction methods, (2) two-phase methods, and (3) route improvement methods.

Route construction methods were the first heuristics for the CVRP and still form the core of many routing applications. These algorithms start with an empty solution and iteratively build routes by inserting customers until all customers are routed. The Clarke and Wright (1964) saving heuristic is the first and most famous route construction heuristic for the VRP. It is based on the concept of saving and is an estimate of the cost reduction obtained by feasibly merging two customers sequentially in the same route. Although many studies have found that the Clarke and Wright saving heuristic is unable to compete with other more complicated methods in solution quality, the fact that the saving heuristic can be easily adapted in other algorithms makes it remain the most popular method in practice (Laporte and Semet, 2001). For example, it is often used to generate an initial solution in more sophisticated algorithms. Since the publication of the saving heuristic for VRP, a wide variety of enhancements have been proposed and adapted to other variants of the VRP (Golden et al., 1977; Nelson et al., 1985; Paessens, 1988; Desrochers and Verhoog, 1989; Altinkemer and Gavish, 1991; Wark and Holt, 1994; Cordeau et al., 2002).

Two-phase methods were based on the decomposition of the VRP solution process into two separate steps: (1) clustering; group customers into subsets, each corresponding to a route, and (2) routing; determine the visiting sequence of each route. Advanced techniques have been proposed for the clustering phase, for example, the sweep algorithm begins with initializing a vehicle route with a random initial customer and then assigns the remaining customers to the current vehicle by considering the polar angle with respect to the initial customer location. Once the current customer cannot be feasibly assigned to the current vehicle, another new route is created with it. After all customers are assigned to vehicles, each route is solved by TSP algorithms separately (Wren and Holliday, 1972; Gillett and Miller, 1974). Other well-known two-phase heuristics includes Foster and Ryan (1976), Christofides et al. (1979), Fisher and Jaikumar (1981), and Bramel and Simchi-Levi (1995).

Route improvement heuristics are often used to improve initial solutions generated by other methods. With a given suboptimal solution, a route improvement heuristics applies simple modifications, such as arc exchanges or customer movements, to obtain better neighbor solutions. Once a better solution is found, it then replaces the current solution, and a new improvement search based on the new current solution starts. The cyclical procedure repeats until no better solution can be identified. Lin (1965) introduced the λ-opt heuristic, where λ edges are removed from the current solution and replaced by λ others as the neighbor solution. More complex route improvement heuristics can be found in Thompson and Psaraftis (1993), Van Breedam (1994), Renaud et al. (1996), and Kindervater and Savelsbergh (1997).

Metaheuristics

In terms of efficiency, metaheuristic approach is another popular way to solve large sized VRPs quickly. Although metaheuristics tend to be more time consuming than classical heuristics, the former typically identify better solution than later. A metaheuristic is a general kind of method that combines local improvement procedures and higher level strategies to escape from local optimal and performs a robust search of a feasible region. Using the metaphor of hill climbing, the approaches used in metaheuristics focus on searching for the tallest hill (global optimum). Since the tallest hill can be anywhere in the feasible region, helping the search process to escape from a local optimum is important in metaheuristics. Three main types of metaheuristics were considered that have been widely used in VRP, namely Simulated Annealing, Tabu Search, and Genetic Algorithms.

Simulated annealing (SA) is a widely used metaheuristic that starts from an initial solution and moves at each iteration to a solution in the neighborhood until a stopping condition is satisfied. The early emphasis of SA is on taking random steps in random directions in order to explore as much of the feasible region as possible, except for rejecting some, but not all, steps that go downward rather than upward. The search process gradually increases the probability of rejecting steps that go downward. Since most of the accepted steps are upward, the search will gradually converge to the feasible region containing the tallest hill. A limited number of SA algorithms were proposed in the early 1990s. Osman (1993) is the most successful work among them. It explored neighborhoods by means of a 2-interchange scheme and designed a special temperature update rule. This algorithm can consistently produce good solutions.

Tabu search (TS) is another widely used metaheuristic where sequences of solutions are examined as in simulated annealing. TS uses a local search strategy that the next move is made to the best neighbor of the current solution, but may require it to be better than the current one. To avoid cycling back away from a local optimum, TS temporarily forbids moves that would return to a solution recently visited for a number of iterations, called tabu. TS begins by using local improvement procedure to find a local optimum, then continues the search by allowing non-improving moves to the neighborhood of the current search region. Once a better solution in the neighborhood is reached, a new round of local improvement procedures is applied to find the new local optimum. A large number of TS algorithms have been produced over the past two decades. A detailed survey is available in Cordeau and Laporte (2004).

Genetic algorithms (GA) is a metaheuristic based on the analogy of the process of biological evolution and has a quite different approach from that used in the first two. GA examines at each step a group of solutions (called a generation in GA) instead of one solution. In GA, feasible solutions for a particular problem are metaphoric as members of a particular species. The fitness of each member is measured by the value of the objective function. GA tends to be particularly effective at exploring various parts of the feasible region and gradually evolving toward the best feasible solution. The basic concepts behind GA is like a child who inherits the better genes of the parents is more likely to survive into adulthood and then become a parent who passes these genes to the next generation. The second key feature of GA is a random, low-level mutation mechanism. A mutation occasionally occurs to changes the features a child inherits from its parents. Children with desirable mutations are slightly more likely to survive and contribute to the future gene pool of the species. In other words, each population is derived from the preceding one by combining its best elements and discarding the worst. Following these mechanisms of GA, the population will become better and better by slowly evolving over time.

With respect to the classical heuristics, metaheuristics are rather time-consuming but provide much better solutions. Based on the survey work of Cordeau et al. (2002), classical methods yield solution values between 2% and 10% above the optimum (or the best-known solution values), while the corresponding figure for the best metaheuristic is often less than 0.5%. Several powerful metaheuristics for the VRPs have emerged, and most of them are derived from the hybridization of concepts from different methods (Toth and Vigo, 2014).

Model Formulation

In this section, we first construct the proposed problems in a mixed integer linear programming model, then introduce a metaheuristic method to solve the problem with the no-helper, current-practice DDH, and proposed models. Note that current-practice IDH model is not considered in this study because the results from the last chapter already show the current-practice IDH solution as having a limited saving potential compared to the current-practice DDH solution. So if the proposed model can perform better than the current-practice DDH model, it should also perform better than the current-practice IDH model.

VRPTW with helper dispatching model

A mixed integer linear programming model was provided for the VRP version of helper dispatching problems with time window constraints in this section. This model is extended from the proposed model in Chapter 2, except the number of vehicles is more than one as $k = \lfloor c/5 \rfloor$, where c is the number of customer nodes. Each driver drives a vehicle and services one route, which is either a no-helper route or a with-helper route. Each customer i is assigned with a time interval $[a_i, b_i]$, called time window. Parameter a_i is the earliest start time, and parameter b_i is the latest start time. On one hand, it violates the time window constraint if a vehicle arrives at node i after its latest start time. On the other hand, if a vehicle arrives at node i before its earliest start time, the employee(s) cannot provide delivery service until the earliest start time. We assume there are only 4 different time windows [0, 120], [120, 240], [240, 360], and [360, 480]. Additionally, we apply an eight-hour total work time constraint as a regular shift of each vehicle and assign a vehicle capacity in each instance as an experimental factor.

The model uses two types of decision variables. The first is the 0/1 binary variables $X_{ijk,}$ and Y_{ijk}. These variables indicate the no-helper route and with-helper route decisions in arc (i, j), such that $X_{ijk} = 1$ if the no-helper routing includes vehicle k travels through arc (i, j); $X_{ijk} = 0$ otherwise; $Y_{ijk} = 1$ if the with-helper route includes vehicle k travels through arc (i, j); $Y_{ijk} = 0$ otherwise. The second is the variables w_{ik} represents the start work time of driver and/or helper with the k_{th} vehicle at node i. Variables w_{ik} also work as the subtour-elimination constraints in this model.

This is the notation used to describe the mathematical model.

- N= {1, 2, …, n}: set of all customer nodes;
- V= {0, 1, 2, …, n, n+1}: set of all nodes, where 0 is the depot as the original node, and n+1 is also the depot but as the vehicle destination;

- K= {1, 2, …, k}: set of all vehicles, $k = \lfloor c/5 \rfloor$
- t_{ij} : travel time from node *i* to node *j*
- d_{ij} : distance between node *i* and node *j*
- *L*: the shift length in minutes (the duration of a driver's regular shift)
- x_{ijk} : binary decision variable that equals 1 if the no-helper routes include vehicle *k* travels from node *i* to node *j*
- y_{ijk} : binary decision variable that equals 1 if the with-helper routes include vehicke *k* travels from node *i* to node *j*
- w_{ik} : decision variable that decides the start work time for the driver and/or the helper with vehicle *k* at node *i*
- a_i : the earliest start work time at node *i* as the time window constant
- b_i : the latest start work time at node *i* as the time window constant
- *M* : is an arbitrarily large number
- s_i^1 : the estimated work time at node i if all the workload is done by one person either the driver or the helper
- s_i^2 : the estimated work time at node i if all the workload is shared by the driver and the helper
- *CV* : the fixed cost of dispatching a vehicle
- *Cx* : the cost of dispatching a vehicle without a helper includes the pay rate for a driver works for a regular shift and the fixed cost of dispatching a vehicle, so $C_x = DC \times SL + CV$

- Cy : the cost of dispatching a vehicle with a helper includes the pay rate for a driver and a helper work for a regular shift and the fixed cost of dispatching a vehicle, so $C_y = (DC + HC) \times SL + CV$
- Cf : the vehicle's average fuel cost per mile
- C : the vehicle capacity

Given the notation, we express the proposed solution as follows.

$$\text{Minimize} \sum_{k \in K} \sum_{i \in N \setminus n+1} x_{0jk} \times c_x + \sum_{k \in K} \sum_{i \in N \setminus n+1} y_{0jk} \times c_y + \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} d_{ij}(x_{ijk} + y_{ijk}) \times c_f \quad (1)$$

Subject to:

$$\sum_{k \in K} \sum_{j \in V \setminus \{0\}} (x_{0jk} + y_{0jk}) = K \quad (2)$$

$$\sum_{k \in K} \sum_{i \in N} (x_{i,n+1,k} + y_{i,n+1,k}) = K \quad (3)$$

$$\sum_{k \in K} \sum_{j \in N \setminus \{i\}} (x_{ijk} + y_{ijk}) = 1 \qquad \forall i \in N \quad (4)$$

$$\sum_{j \in N \setminus \{i\}} x_{ijk} - \sum_{j \in N \setminus \{i\}} x_{jik} = 0 \qquad \forall k \in K, \forall i \in N \quad (5)$$

$$\sum_{j \in N \setminus \{i\}} y_{ijk} - \sum_{j \in N \setminus \{i\}} y_{jik} = 0 \qquad \forall k \in K, \forall i \in N \quad (6)$$

$$w_{ik} + s_i^1 + t_{ij} - w_{jk} \le M(1 - x_{ijk}) \qquad \forall k \in K, \forall i, j \in N \quad (7)$$

$$w_{ik} + s_i^2 + t_{ij} - w_{jk} \le M(1 - y_{ijk}) \qquad \forall k \in K, \forall i, j \in N \quad (8)$$

$$a_{ik} \sum_{j \in N \setminus \{i\}} (x_{ijk} + y_{ijk}) \le w_{ik} \le b_{ik} \sum_{j \in N \setminus \{i\}} (x_{ijk} + y_{ijk}) \qquad \forall k \in K, \forall i \in N \quad (9)$$

$$0 \le w_{ik} \le L \qquad \forall k \in K, \forall i \in \{0, n+1\} \quad (10)$$

$$\sum_{i \in N} s_i^1 \sum_{j \in N} x_{ijk} \le C \quad \forall k \in K \tag{11}$$

$$\sum_{i \in N} s_i^1 \sum_{j \in N} y_{ijk} \le C \quad \forall k \in K \tag{12}$$

$$x_{ijk} \in \{0,1\} \qquad \forall i, j \in V \tag{13}$$

$$y_{ijk} \in \{0,1\} \qquad \forall i, j \in V \tag{14}$$

The objective function (1) aims to minimize the total vehicle dispatching cost and fuel cost. Where the first term of objective function represents the total cost of vehicles dispatched without a helper, and the second term of objective function is the total cost of vehicles dispatched with a helper. The third term of objective function is the total travel cost of all vehicles calculated by the total travel distance multiples the fuel cost.

Constraint (2) and (3) make sure each vehicle can be dispatched at most once either without or with a helper and all vehicle must return to the depot after finishing work. Constraint (4) serves to make sure each customer node is visited once and only once. Constraint (5) and (6) ensure that for each node the inflow equals the outflow. Constraints (7) to (10) are designed for time alignment. Constraint (7) and (8) are used to align the start work time at each node on no-helper routes and with-helper routes, respectively. Constraint (9) ensures the start work time at each node follows the time window. Constraint (10) limits the total work time for each vehicle must be shorter than a regular shift. Constraint (11) and (12) make sure each vehicle has a weight under the vehicle capacity. Constraint (13) and (14) specify the domains for decision variables x_{ijk} and y_{ijk}.

Simulated annealing

VRPTW belongs to the class of "difficult" problems for which optimal solutions for large-scale instances are unattainable within a reasonable amount of computation time using exact optimization approaches (Ohlmann et al., 2004). The computational effort required to obtain an optimal solution in VRPTWs increases exponentially with the problem size. Because it is desirable to solve large sized VRPTWs the model is difficult when solved by standard linear programming software; therefore, a metaheuristic approach is used.

In metaheuristic methods, each VRP solution becomes a series of numbers that represent the visiting sequence of all vehicles. For homogeneous service methods, such as the no-helper solutions or the current-practice DDH solutions, all the vehicles in one solution have the same service time in each customer node. Therefore, the solution only needs one symbol (typically the "0") to separate each route, which may look like the sample in Figure 4. Each non-zero number represents a customer node, while 0 represents the depot. The numbers between two 0s are the visit sequence for one route. The sample solution in Figure 4 represents that the solution needs dispatching two vehicles, the first one visits customer nodes 1, 2 and 3, and the second visits nodes 4, 5, and 6.

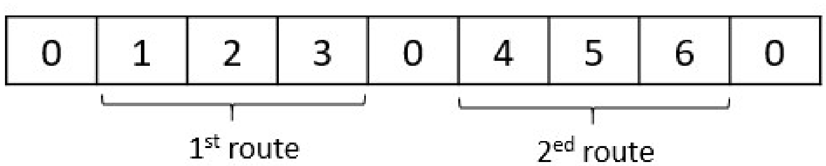

Figure 4. Sample solution for homogeneous service methods

However, the proposed solutions have two types of vehicles with different service time. Another number "-1", was added in the solution sequence to distinguish the two types of routes.

A sample solution is presented in Figure 5. Both -1 and 0 represent the depot. While a with-helper route starts with 0, a no-helper route starts with -1. The total number of -1 is equal to the total available vehicles. Each -1 needs connect to at least one 0 to make sure each dispatched vehicle is either a with-helper route or a no-helper route, and the total dispatch number is equal to the total available vehicles. The sample solution in Figure 5 shows that the solution needs dispatching two vehicles, the first one is a with-helper vehicle that visits customer nodes 1, 2 and 3, and the second is a no-helper vehicle that visits nodes 4, 5, and 6.

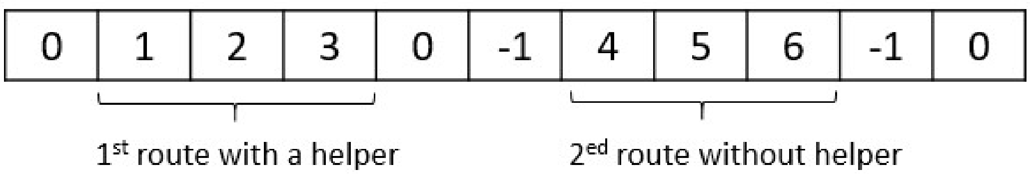

Figure 5. Sample solution for heterogeneous service methods

SA was applied as the problem-solving technique because it is a robust and flexible technique with lower entrance barrier. Moreover, Johnson and Jacobson (2002) have proven SA is capable of finding the global optimum with a careful control of the cooling rate. The main drawback of using SA is the necessary tradeoff between solution quality and computational time. First some pilot tests were conducted, then the results were used to fine tune the parameters, which gave the best solution quality in pilot tests while kept an acceptable running time even for the largest sized problem, in the actual algorithm.

The standard simulated annealing algorithm introduced by Albrigh (2007) was followed to solve problems as follows.

- Let T_0 denotes the initial temperature, and T denotes the temperature ($T > 0$). The higher the temperature, the higher the propability that an neighbor solution will be accepted. As the calculation progresses, the tempertature keeps decreasing.
- Let E denote the "epoch length," which is the number of iterations that each value of the temperature will be used.
- Let r denote the cooling rate ($0 < r < 1$), which is the ration at which the temperature decreases between epochs.

Here is the pseudocode for the SA algorithm:

Generate state *i* (initial solution)
$T = T_0$
Repeat
  Repeat
    K= 0
    Generate state *j* (a neighbor solution)
    $d = f(j) - f(i)$
    If $d < 0$ **then** $i = j$
    Else if *rand*( ) < $\exp(\frac{-d}{T})$ **then** $i = j$
    $k = k + 1$
  Until $k = E$
  $T = T \times r$
Until all terminate criterion satisfied

Most metaheuristic methods invoke the successive application of two modules; a construction method that produces an initial feasible solution and an improvement technique that maintains feasibility whilst reducing the tour cost iteratively. The Clarke and Wright (1964) saving heuristic was adapted to identify the initial feasible solution and the 1-opt procedure was used to generate the neighbor solutions (Lin, 1965). For initial temperature setting, the suggestions from Ohlmann and Thomas (2007) were adapted to generate 5000 pairs of neighbor solution samples to specify an appropriate initial value of temperature as

$$T_0 = \frac{|\overline{\Delta V}|}{\ln(\frac{1}{x_0})}.$$

Where x_0 is the percentage of proposed uphill transitions that we require to be accepted at T_0. $|\overline{\Delta V}|$ is the average absolute difference in objective function over the paired sample transitions. At this value of initial temperature, the actual acceptance ratio over a trial loop of iterations of simulated annealing is monitored. If the actual acceptance ratio is less than x_0, then x_0 is reset at 1.5 times its current value and re-evaluated over a loop of iterations. This procedure is continued until the observed acceptance ratio for a loop of iterations equals or exceeds x_0.

There are numerous terminate conditions for SA in the literature. A hybrid was implemented to terminate conditions that require a minimal 100 times of temperature changes (Bonomi and Lutton, 1984) and the best solution found must not have been updated for 75 of iterations (Johnson et al., 1989). The selected parameters for the conducted SA methods is provided in Table 13. We conducted SA to solve each instance three times separately with the no-helper solution, the current-practice DDH solution, and the proposed solution.

Table 13. Selected parameters for SA

Parameter	Value or Range
Initial acceptance ratio (x_0)	94%
Epoch length (E)	10000
Cooling coefficient (r)	0.95
Minimal times of temperature changes	100
Minimal iterations of no better solution	75

Penalty function

The proposed model includes three sections in the penalty function. We use constant numbers λ_0, λ_1, λ_2 to adjust the multipliers for these three penalty sections. The first penalty section is generated if any driver works longer than a reguler shift length (L). The penalty cost is generated as multiplier λ_0 times the overtime munutes. The second is time window violation penalty, if a vehicle k provides service at node i but its service start time w_{ik} is later than the latest time window b_i, each late munites needs times the penality multipler $(\lambda_0 * \lambda_1)$ as the penalty cost. The last is capacity violation penalty. Service time at each customer node was used as the proxy of total package volume and set the maximum capacity of each vehicle equals to the volume can be delivered within a predicided number of labor service time (C). If any vehicle route has a total service time at all visited nodes (measured in s_i^1) larger than C, the penalty cost each increseased by over one minute times the penality multipler $(\lambda_0 * \lambda_2)$. So the overall penalty function equals to:

$\lambda_0(total\ overtime + \lambda_1 total\ time\ window\ violation + \lambda_2 total\ capacity\ viloation)$.

Where the total overtime is measured as $\sum_{k\in K} \max(w_{(n+1)k} - L, 0)$

the total time window violation is measured as $\sum_{k\in K}\sum_{i\in N} \max(w_{ik} - b_i, 0)$

the total capacity violation is measured as $\sum_{k\in K}\sum_{i\in V}\sum_{j\in V} \max(x_{ijk} + y_{ijk} - C, 0)$.

Because these three penalty functions are all measured in minutes. The λ_1 and λ_2 were kept as constant corelations among penalty sections and adjusted λ_0 as the only penalty coefficient in the SA process. The work overtime was considered the most minor penalty and it was used as the base to set up λ_1 and λ_2 for time window violation and capacity violation, respectively.

If work overtime happens, from a company's perspective, the result is asking the driver to work overtime and pay the extra rate. The extra pay rate is usually between 3/2 to 5/3 times of the regular rate based on our interview results. Therefore, 5/3 times of the highest level of a driver's pay rate was used to estimate the penalty unit cost, which is $1 per minute.

If a time window violation happens, the customer may request a refund and could have a chance to stop using the service from the package delivery company. Literature to justified an appropriate unit cost for time window violations were not found in this research. Therefore, an arbitrary large enough cost of $5 for each minute of time window violation was used.

If a capacity violation happens, it means the company is breaking the transportation laws and will receive an overweight ticket. The overweight fine is based on the total weight over the allowable weight. A rough estimate of $10 for each minute of service time over the total capacity was used.

Thus, $\lambda_1 = 5$ and $\lambda_2 = 10$ were set and adjusted only λ_0 in the main experiment. Small-scale pilot studys were conducted with 100 samples with multiple λ_0 values and it was found that when λ_0=10, the SA could keep the average infesible rate lower than 3%. Therefore, these three penalty parameters were chosen for the main experiment. Moreover, since the infesible solution was not allowed in the main experiment result, a result checking mechanism was added in the SA algorithm that if any solution had a penalty cost larger than 0, the algorithm would disgard the solution and redo the experiment of the same instance up to three times or until a fessible solution was found. The infesible rate was expected to be lower than 3% with the check and redo process. However, infeasible results were still mannually checked. Although eliminating infeasible solutions may effect the reported results, the number of eliminated instances is very small, the effect should also be very limited.

Computational Experiments

In this section, a series of experiments were conducted to investigate the conditions under which the proposed solution works most, or least, effectively.

Experimental factors and their ranges

Five experiment factors were used to test how the cost-saving potential of the proposed solution in different scenarios; (i) the total number of customer nodes, (ii) the size of the service area, (iii) the percentage of multiple-customer nodes, (iv) driver pay rates, and (v) vehicle capacity. The selected parameters are provided in Table 14.

Table 14: Selected parameters

Parameter	Symbol	Value or Range
Total number of customer nodes	n	{50, 100, 150, 200}
Service area size (miles x miles)	$L(.)$	{5x5, 10x10, 15x15, 20x20}
Percentage of multiple-customer nodes	p	{10%, 30%, 50%, 70%, 90%}
Driver pay rate (dollars per shift)	DC	{192, 240, 288}
Vehicle capacity	C	{720, 840, 960}
Helper pay rate (dollars per shift)	HC	96
Fixed cost of dispatching a vehicle (dollars)	CV	150
Fuel cost (dollars per mile)	Cf	0.17
Shift length (minutes)	SL	480
Vehicle speed (miles per hour)	VS	30

The range of total numbers of customer nodes was set in four levels; 50, 100, 150, and 200. For the size of the service network, expert opinions were consulted and four levels were set in this factor 25 mile^2, 100 mile^2, 225 mile^2, and 400 mile^2. For service time in each node, the distribution percentage of the multi-customer nodes was set as p with five levels; 10%, 30%, 50%, 70%, and 90%. If a node has only one customer, both the service time by a driver alone (s_i^1) and that by a driver and a helper together (s_i^2) are 5 minutes. For each multiple-customer node, s_i^1 follows a uniform distribution between 10 minutes to 120 minutes, and s_i^2 is half of s_i^1.

We adopt a fixed cost of dispatching a vehicle as 150 dollars, which is the price of rent a truck for business purpose (Enterprise Holdings. Inc., 2017). For drivers' pay rate, the inputs obtained from industry experts and the public available driver wages database were adopted and a three-level range 192, 240, and 288 dollars per day was set, which were also 2, 2.5, and 3 times of the helpers pay rate (96 dollars) in our experiments. Note that, the daily pay structure was applied that the total labor cost was calculated by the number of dispatched employees multiplied by their daily pay rate. No matter an employee worked 8 hours or a shorter period, the payment was the same. This pay structure assumption leads the algorithm to minimize the total dispatched number of employees and vehicles. This study does not consider overwork time situations because comparing the benefit from different solutions in general situations was the goal.

In terms of vehicle capacity, a precise total service time for a full-loaded delivery vehicle was not found. However, based on the interviews, drivers can work 12 hours or longer in one day in peak seasons and drivers very rarely go back to depot due to the capacity limitations. Thus, it is reasonable to assume the vehicle capacity should be larger or equal to the amount that can be delivered in 12 hours. Thus, 720 minutes (12 hours) was set as the lowest level of the vehicle capacity, and 840 minutes, and 960 minutes was set as the other two levels to test if increased capacity may have an effect on benefit of driver helper strategies.

Design of experiments

The computational experiments randomly generate and solve many VRPTW with driver helper instances under a variety of factorial combinations. The over-used solutions where all vehicles must be dispatching with a helper and proposed solutions where each vehicle can be assigned either without a helper or with a helper was compared to those of no-helper solutions. Visual Basic .NET (2012) was used to generate and solve instances. A full factorial design of four factors was employed, which are varied in four, four, five, and three levels, respectively. Each simulation trial was repeated ten times by executing the following steps.

First, a depot and n ∈{50, 100, 150, 200}customer nodes in a service area L(.) were randomly generated, where the size of L(.) is assigned as one of the five levels 25, 100, 225, and 400 in mile^2. We set the distance unit as 0.1 miles; for example, a 25 mile^2 service area converts to a 50 (distance unit) x 50 (distance unit) network with 2500 possible locations for each randomly decided location. After randomly assigned the locations, each customer node was assigned a set of service time either without a helper (s_i^1) or with a helper (s_i^2). The service time at each node was decided by the distribution of customers in nodes. There are $p * n$ of single-customer nodes and $(1 - p) * n$ of multiple customer nodes, where p ∈{10%, 30%, 50%, 70%, 90%}. If a node had only one customer, both the service time by a driver alone (s_i^1) and that by a driver and a helper together (s_i^2) are 5 minutes. For each multiple-customer node, the s_i^1 follows a uniform distribution between 10 minutes to 120 minutes, and the s_i^2 is half of s_i^1.

Second, each of the VRPTW was solved with a given vehicle capacity C ∈{720, 840, 960} in no-helper solution, current-practice DDH solution, and the proposed solution to obtain three different results. Each of the above simulation trial (i.e., generation of 720 problem versions) was repeated 10 times. In total, our experiment generated 4 x 4 x 5 x 3 x 3 x 10 =7,200 instances, and 2,400 × 3 = 21,600 solutions. Finally, after all the trials are completed, for each instance, the percentage cost saving over the no-helper solutions attained by the current-practice DDH solution and the proposed solution were computed.

Results

Results showed 1.46% of the instances had infeasible solutions, most of them happened in no-helper solutions. Those infeasible solutions were eliminated. We summarize the computational results in Tables 15 and Tables 16. Table 15 reports the average percentage changes between paired solution comparisons. Table 16 reports the sensitivity of the model's effectiveness to the changes in experimental factors.

Table 15: Paired solution comparisons

	Current-practice DDH Model over No-helper Model	Proposed DDH Model over No-helper Model	Proposed DDH Model over Current-practice DDH Model
Cost	-11.25%	-15.33%	-3.71%
# of drivers	-27.97%	-26.98%	1.63%
# of helpers	72.03%	52.35%	-23.65%
Distance	-19.52%	-17.62%	2.87%

From the results of Table 15 when compared to the current-practice DDH solution over the no-helper solution, on average, the current-practice DDH solution can reduce 11.25% of total cost. That cost saving is majorly from reducing 27.97% of the total numbers of dispatched drivers and reducing 19.52% of the distance by hiring extra 72.03% helpers (of the total employees need in no-helper solutions). When comparing proposed solutions over the no-helper solution, on average the proposed solution can reduce 15.33% of total cost. These cost savings are primarily from reducing 26.98% of the total need drivers and reducing 17.62% of the distance by hiring extra 52.35% helpers (of the total employees need in no-helper solutions). While the proposed solution reduces the need of drivers and distance slightly less than the current-practice DDH solution does, the proposed solutions need fewer helpers. Consequently, the proposed solution can save more than the current-practice DDH solution. When looking into the detailed experiment results, overall the current-practice DDH solution was found to have around a 27.14% chance to get worse results than not using a helper.

If a company switches from the current-practice DDH solution to the proposed solution. On average, the company can improve 3.71% of total cost by using 23.65% fewer helpers to finish the same works, while increasing 1.63% of the needed number of drivers and 2.87% of the distance. It also worth noting that the proposed model can always find better, if not the same solution, quality solutions than either the current-practice DDH solutions or the no-helper solutions. In other words, the proposed solution is reliable to provide the best solution among the three solutions. Therefore, we believe the proposed model has the potential to replace the currently widely used DDH dispatching methods.

Table 16: Impact of individual factor

Parameter	Current-practice DDH Model over No-helper Model		Proposed DDH Model over No-helper Model		Proposed DDH Model over Current-practice DDH Model	
	Cost	Vehicles	Cost	Vehicles	Cost	Vehicles
Customer nodes						
50	-9.86%	-26.71%	-15.92%	-24.55%	-5.86%	3.18%
100	-11.83%	-28.38%	-16.14%	-26.85%	-3.96%	2.34%
150	-11.63%	-28.42%	-14.99%	-28.29%	-2.86%	0.56%
200	-11.72%	-28.44%	-14.31%	-28.22%	-2.18%	0.55%
Service area (miles^2)						
5 x 5	-14.57%	-30.97%	-18.02%	-29.69%	-3.43%	2.05%
10 x 10	-11.58%	-28.24%	-15.31%	-27.34%	-3.36%	1.48%
15 x 15	-9.92%	-26.56%	-14.16%	-25.82%	-3.76%	1.25%
20 x 20	-8.81%	-26.01%	-13.72%	-24.98%	-4.29%	1.74%
% of multiple-customer nodes						
10%	16.19%	-4.43%	-1.86%	-4.28%	-11.64%	0.08%
30%	-3.61%	-23.27%	-8.86%	-21.79%	-4.54%	2.02%
50%	-15.19%	-31.22%	-16.85%	-29.60%	-1.76%	2.21%
70%	-20.09%	-34.87%	-21.70%	-33.46%	-1.85%	2.02%
90%	-22.86%	-36.97%	-24.32%	-35.76%	-1.78%	1.80%
Driver pay rate ($/shift)						
192	-7.51%	-25.81%	-13.29%	-24.99%	-5.08%	1.66%
240	-12.34%	-28.95%	-15.67%	-27.74%	-3.11%	1.80%
288	-14.23%	-29.42%	-17.19%	-28.39%	-2.81%	1.50%
Capacity (minutes)						
720	-8.82%	-25.50%	-12.80%	-24.27%	-3.55%	1.88%
840	-11.36%	-28.05%	-15.48%	-27.20%	-3.85%	1.75%
960	-13.76%	-31.44%	-17.69%	-30.46%	-3.72%	1.35%

In general , the current-practice DDH solution and proposed solution perform better than the no-helper solution in most situations. Therefore, the following section will focus on finding and explaining situations in which the driver helper strategies doesn't work well.

In Table 16, the numbers of total customer nodes is an important factor in the savings of the current-practice DDH solution. As the number of customer nodes increases, the cost saving of the current-practice DDH solution keeps in a stable range. It maybe can be explained by the economic of scale in the no-helper solutions, if the numbers of customer nodes are too small, the companies may face problems arranging each vehicle route to satisfy all customers' time-windows while avoiding too much waiting time. Moreover, the no-helper solution tends to have a higher proportion of inefficiency routes where the companies may not have sufficient work to assign to each route with a full regular work schedule. Therefore, the no-helper solutions leave large saving opportunities in networks with fewer customer nodes. On average, the savings from the proposed DDH solutions ranged from 16.14% to 14.31%. The proposed solution gets benefits from small service network with larger savings residuals from no-helper solutions. The current-practice DDH solution also has a stable saving range from 9.86% to 11.83% in the experiments. As the numbers of customer nodes increases, the saving percentages of both helper strategies converge to stable levels.

This is surprising because in earlier studies with TSP version of DHDPs, the results showed an opposite trend, where all helper strategies perform better with large customer sized networks. The interpretation is that adding more customers nodes in VRPTW version of DHDPs is a double-edged sword for driver helper strategies, because all nodes come with time window constraints. On the one hand, it increases the opportunities to create better solutions and on the other hand, it makes the already tight schedule even harder to satisfy all time window constraints and have to add vehicles or change schedules in a less efficient way.

In terms of dispatching vehicles numbers, both the current-practice DDH solution and proposed solution seem to have a stable reducing rate and have an insignificant increasing patterns when the number of customer nodes increases, and gradually converges to stable levels. In terms of comparing the proposed DDH model and the current-practice DDH model, as customer nodes increases, the differences in cost and the number of dispatching vehicles between two strategies are becoming smaller.

Service area is another key factor in helper dispatching decisions. In general, a small area means the average distance between nodes is short. Employees can spend less time and the vehicle uses less fuel on moving among depot and customer nodes. Both helper strategies benefit in small service areas where helpers' time can be efficiently used to provide service, so they have a higher chance to reduce more vehicles and have higher cost savings. As the size of service area increases, the savings from both strategies gradually converge to stable levels.

The factor that has the largest effect on savings is the percentage of the multiple-customer nodes. If most of the nodes have only one customer (i.e., 10% of nodes have multiple customers) the costs of the current-practice DDH solutions might become worse than those of the no-helper solutions, while the proposed DDH model still can prove a small amount of cost savings. There exists a threshold of percentage of multiple-customer nodes when companies want to get savings from using the current-practice DDH solution. In the experiments, when multiple-customer nodes were lower than 30%, using the current-practice DDH solution actually costs more than not using helpers.

As the percentage goes up, both current-practice DDH model and proposed DDH model can provide good cost savings and the gap between the savings from both methods becomes smaller. In areas where 90% of nodes have multiple customers, both strategies can save over 22% in cost and 35% in the number of vehicles. It aligns with the findings in early studies, both helper strategies rely on replacing drivers time by helpers time. As more of the customer nodes provide the saving opportunities, both helper strategies perform better.

The gap between drivers and helpers pay rates does affect the reduction of cost. If the gap is not large enough, the current-practice DDH may not be able to provide significant cost savings. Similarly, the savings from the proposed solution increases as the pay rate gap becomes larger. In terms of the dispatching vehicle numbers, there is also a positive relationship between pay rate and the reducing of dispatching numbers, but the relationship is not as significant as that in cost. Perhaps the major challenge in this model is to satisfy all time constants. From the observations in this study, the total dispatch number is primarily decided by the vehicle needs in the time window segment with the largest number of customer nodes. Replacing no-helper vehicles by with-helper vehicles may reduce service time in some customer nodes. As a consequence, the total dispatch number is reduced in both the current-practice DDH solution and proposed solution. However, no matter the drivers' pay rate, the model always has to dispatch sufficient numbers of vehicles to satisfy time window constraints. As a result, the drivers' pay rate has only a weak effect on the total dispatching numbers.

The capacity factor is also important to helper dispatching decisions. Both the current-practice DDH solution and the proposed solution cannot work well without large-capacity vehicles. Having a low level of vehicle capacity, for example 720 minutes in the experiments, means both the driver and helper can only provide up to 360 minutes service in the route, which is only 75% of the total work time. This limitation may look minor in a large service area with long travel time. However, in small service areas which supposedly provide the largest saving opportunities, the capacity constraints limit the potential of dispatching even fewer vehicles to reduce more cost. The low vehicle capacity also downsizes the benefit of using the current-practice DDH solution. In instances with capacity equal to 720 minutes, the savings of the current-practice DDH solution and proposed solution are 8.82% and 12.80%, respectively. When the capacity becomes 960 minutes, the savings increases to 13.76% and 17.69%.

Sensitivity Analysis

One assumption employed in the experiment is that companies want to maximize the cost savings, which can be from reduction of dispatched vehicles, using less employees, or cutting the total travel distances without any preference. However, based on the information collected from interviews with practitioners, we understand that some practitioners do have a preference that they give models that can reduce the number of dispatched vehicles more credits than that majorly focuses on reducing the total costs but increase the dispatched vehicles.

The results from the main experiment show that the proposed DDH model tends to achieve savings from reducing the dispatched driver helpers but using more vehicles, which may not align with some practitioners' preference. However, the saved resources are actually exchangeable (i.e., companies could turn the saved number of DDHs to IDHs). It could further reduce the dispatched number of vehicles.

To show this exchangeability, a sensitivity analysis is provided in this section to show how it works if companies follow the suggestions in this study that turning the saved DDHs (of switching from the current-practice DDH model to the proposed DDH model) to IDHs and resolve the problem again with the proposed DDH model. Since the purpose here is to test how the preference of reducing vehicles may affect the results, a simpler version of the experiment is conducted with all factors keep constants and repeated the simulation trial 100 times. The selected factor values are provided in Table 17, and the results are reported in Table 18.

Table 17: Selected parameters for sensitivity analysis

Parameter	Symbol	Value
Total number of customer nodes	*n*	200
Service area size (miles x miles)	*L*(.)	10 x10
Percentage of multiple-customer nodes	*p*	50%
Driver pay rate (dollars per shift)	*DC*	240
Vehicle capacity	*C*	840
Helper pay rate (dollars per shift)	*HC*	96
Fixed cost of dispatching a vehicle (dollars)	*CV*	150
Fuel cost (dollars per mile)	*Cf*	0.17
Shift length (minutes)	*SL*	480
Vehicle speed (miles per hour)	*VS*	30

Table 18: Results of sensitivity analysis

	Current-practice DDH Model	Proposed DDH Model	Proposed DDH Model + IDH
Cost	8398.43	8120.24	8426.81
# of Vehicles	16.81	18.35	16.12
# of DDH	16.81	7.66	7.88
# of IDH	0.00	0.00	9.16

The results show that the saved resources from the proposed idea are exchangeable and can be concentrated in prior resources. If a company has a preference not increasing the number of vehicles and follow the suggestion to turn the saved DDHs to IDHs. Although the company may not save as much as the proposed DDH model, it could further reduce more dispatched vehicles than that in the current-practice DDH model. In other words, although our main experiment is focused on minimize the total cost. Companies may adapt and modify the proposed model based on their saving priority to get preferred solutions.

Conclusion

This study has four major contributions. First, a mathematical model of the VRPTW version of helper dispatching problems was introduced. The main idea of the proposed model is to dedicate each vehicle route to either without a helper or with a helper and finding the most cost-efficient schedules based on the time windows and the service time of two types of work teams.

Second, a metaheuristic algorithm was designed and a full factorial computational experiment was conducted to solve the proposed model. The results prove the proposed model works very well in VRPTWs. On average it can save 15.33% of total cost and reduce 26.98% of vehicle need. Moreover, the proposed models can always find better or at least keep the same quality solutions than the current-practice DDH solutions and the no-helper solutions in all instances. That implies that the proposed model eliminates the major drawback of the full-helper strategy that it may get worse results than not using helpers in some instances, the percentage is 27.14 in this study. From practitioners' perspectives, it provides a large motivation to switch from the no-helper solution or the current-practice DDH solution to the proposed model.

Third, the conditions under which the utilization of proposed model works most, or least, effectively was investigated. In terms of the effects on both total cost and numbers of needed vehicles, the most important factor is the percentage of multiple-customer nodes. The benefit from proposed model has a positive relationship with the percentage of multiple-customer nodes. Other than that, the node density is also very important. When there are a large number of multiple-customer nodes in smaller service areas (e.g., New York City, Los Angeles, Miami, Singapore, Hong Kong), the proposed model can save more money and vehicles. Furthermore, the gap between drivers and helpers pay rates is another key factor that enlarges the savings from reducing drivers' time. Finally, vehicle capacity is also a critical requirement for driver helper strategies' success.

Fourth, we conducted a sensitivity analysis to show that the saving resources are exchangeable, and companies can adapt and proposed model and focused on minimized their preferred resources. This exchangeability further enlarges the practical usage of the proposed model.

This study has two major limitations. The first limitation is the solution quality. We applied SA for solving DHDPs, the method does not always generate the optimal solutions, especially in large-sized problems. As it is an unavoidable issue for all metaheuristic method, and this issue supposedly has a similar level of effects on all types of solutions, the comparison among these results is still academically rigorous. However, it is suggested that future research apply more advanced methods such as compressed annealing to improve the quality of solutions.

Another limitation is the assumption that any unused resources, include vehicles, drivers, and helpers, can be turned to cost savings. In practice, this assumption might not be true that a company supposedly need to decide the numbers of vehicles, drivers, and helpers and prepare them in advance. The company may not have the flexibility to save the costs when the solution show that it can reduce the number of resources. Although the proposed model can provide more cost savings by reducing the needed resources, the practitioners still need to design reasonable mechanisms to turn the resource savings to cost savings.

CHAPTER 5: GENERAL CONCLUSION

In this three essay format dissertation, the proposed idea was using helpers time in a more cost efficient way to achieve better cost savings than the current helper dispatch methods. The major ideas include; 1) minimizing of the total cost as the new objective function to replace minimizing the total distance cost that is mostly used in past TSP or VRP algorithms and 2) dispatching vehicle either with a helper or not as part of the routing decision. In TSPs that has only one vehicle, the entire route splits into two subroutes, one with helper another without.

In the first study, the one vehicle version of helper dispatching problem was first introduced and the solving algorithm with exact mix integer linear programming method was proposed. Which helps to estimate the savings potential of our proposed model via using dependent driver helpers (DDH). The results show the proposed model can save more costs by eliminating those inefficient part of using helpers' time.

In the second study, independent driver helper (IDH) was included and the proposed model was evolved to a hybrid driver helper (HDH) model. The proposed model allows a helper either work together with the driver or work independently at a node while the driver provides service to other nodes. The result shows that IDH has the most limited saving potential and HDH perform the best among the three. However in instances with very rare multiple-customer nodes the HDH still can't avoid wasting time in single-customer nodes, just like the DDH solution does. It is suggested that future research combines the splitting route concept (as in first study) in HDH model to improve the solution. Another limitation of this study was that it was necessary to limit the experiments with small numbers of customer nodes because the model has too many decision variables and constraints. This limitation might restrict the understanding of the proposed HDH idea in more general situations. Therefore, it is suggested that future research extend the HDH idea with cutting plans or build up metaheuristic of heuristic approach to check the results of using HDH solution in networks with more customer nodes.

In the third study, the proposed ideas of 1) minimizing the total cost and 2) dispatching vehicles either with or without a helper were used in VRPTWs. We proposed a metaheuristic algorithms and found the proposed model can provide much higher cost savings than the current-practice DDH model while using much fewer numbers of helpers. Moreover, using helpers to reduce the service time is very helpful when servicing customers with time windows. This argument can be improved by the fact that the average improved savings percentage from the proposed model in VRPTWs is higher than that in TSPs in the first study.

In summary, there exist a large saving potential in current DHDP practices. The proposed DDH models (in study 1 and 3) are better than current practices from time, cost, and resources perspectives. While the HDH idea (in study 2) may need to be further reduced the model complexity and redesign for practical VRPs, it shows its potential to further improve our proposed DDH models.

One limitation in this series of study is we could not find real data from practitioners (i.e., parameters of service networks, customer locations, customer orders, etc.) to adopt in our experiments. Future research might consider cooperating with practitioners and conducting simulation experiments with real data to provide more practical results. For example, comparing the savings of the proposed model in different cities (e.g., New York City vs. Ames) to investigate how the different environment factors may affect the savings.

As online shopping and shipping are becoming more and more popular, hiring and dispatching driver helpers becomes a must-do practice in every peak season for package delivery companies. Those companies need more specific tools to help them make good decisions to reduce transportation cost and service time instead of just focusing on minimizing travel distances. Moreover, since the proposed models can consistently reduce total cost, companies may consider regularly hiring driver helpers not just in peak seasons. Hopefully, this series of studies are beginning of the DHDP research stream. New technologies such as drones, autopilot vehicles, and delivery robots may be integrated to enhance current package delivery method soon. With those new technologies, the delivery processes will dramatically change and need new decision tools for routing and scheduling with new practical issues. It is expected to see more and more creative ideas applied into DHDPs, although the new drivers or helpers may no longer be humans.

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