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Optimal Transfer Point Locations in Two-Stage Distribution Systems

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ABSTRACT Limited range of emerging delivery vehicles, specifically unmanned aerial systems, creates gaps in last mile retail distribution networks and excludes significant numbers of potential customers. Implementing a two-stage distribution process is one approach that eliminates this deficit. However, dispatchers must load the vehicles hauling orders in the initial stage of the process and assign orders for delivery to transfer points in a way that ensures timely arrival while utilizing only the minimum required resources. This paper investigates the capacitated transfer point covering problem which has, until now, been unstudied. The research proposes a mathematical programming model to provide an optimal solution. The model is then applied to a realistic delivery situation using a distribution case study on the eastern coast of the U.S. and solved using a commercial optimization software. The results are analyzed, insights provided, and areas are identified for future research.

INDEX TERMS Distribution network, mathematical programing, transfer point location problem, unmanned aerial systems, vehicle routing.

I. INTRODUCTION

Given the location of a central facility and a set of demand points, Berman *et al.* [1]–[3] defined the transfer point location problem (TPLP) as the establishment of a new location called a ‘‘transfer point’’ which allows combination of services over a portion of the delivery route. Cost along the combined portion of the route is reduced by a factor of $\alpha < 1$ while unit travel cost along the remainder of the route does not change. TPLP optimization research has focused on finding a location for transfer points such that cost or distance to all the demand points through the transfer points is minimized.

TPLPs have a wide range of applications. The example frequently referred to in most TPLP studies is movement of patients to a hospital using helicopters. In this example, injured patients are transferred to a common helicopter pad – which acts as the transfer point – by ground ambulance. The speed that patients can travel by helicopter is greater than that of the ground ambulance. Because the location of the patients is known and the enduring nature of the hospital make it fixed, the problem becomes determining the optimal place to consolidate patients and land the helicopters for transfer. The general model would also determine the optimal location of the hospital if it was temporary in nature or analysis was being conducted prior to establishing a new facility.

Similarly, TPLPs could consider locating train stations that lead to stadiums, shopping malls, or other events assembling large numbers of people. This location would act as the fixed facility in the model. Passengers would drive by car or walk to a train station – the transfer point – and ride the much faster train to the centralized downtown venue. The model might also be used to investigate the problem of locating collection points for recyclable materials in a city. Residents bring their recyclable material to a collection point where it is transferred to more economical trucks and then periodically moved to a fixed recycling plant for processing. In addition, the TPLP can be used to optimally locate several regional warehouses to stock a set number of stores. Merchandise is transported from a larger central warehouse to the regional warehouses or transfer points at reduced cost, and from there to the stores at normal cost. These are just a few examples of how TPLP might be used. The range of examples remains large with possibilities including portions of many of the distribution and collection networks used today. Delivery of online purchases by drones is once such distribution network that will benefit from TPLP research.

II. PROBLEM AND PRACTICAL CASE STUDY

Expansion of the internet and advances in communications have significantly changed how people currently purchase retail products. Today consumers can research, compare, and purchase a wide variety of items from the convenience of their home or place of business. They enjoy the ability to examine similar products from multiple vendors offering a variety of quality and price using computers and the internet. In addition, the convenience of having their purchased items delivered directly to their front door is a very attractive feature for most customers.

The internet has conditioned e-commerce customers to expect immediate receipt of information, service, and now merchandise. This expectation has made the logistics of expedited business-to-customer delivery one of the most important elements of retail market sales [4], [5]. Corporations that rely on e-commerce transactions have spent significant time and effort developing strategies to enable delivery of physical products to customers in hours or minutes rather than days [6]. Recently, several notable companies have begun investing in the research and development of techniques to deliver products directly to the consumer using unmanned aerial systems (UAS). Amazon, Google, DHL, Domino's, and the Australian Postal Service, to name a few, have announced research efforts, tests, and in some instances, customer trials of the aerial delivery concept [7]. The prospect is for small-unmanned aircraft to carry merchandise directly from fulfillment or retail locations to customers; thus, providing dedicated and immediate service [8]. This initiative has the potential to significantly impact e-commerce transactions mainly from the business-to-customer logistics perspective. Retail and delivery businesses concerned with last mile distribution recognize benefits gained by the more efficient transportation of packages, reduction in delivery costs, and expansion of on-time delivery areas to include remote locations typically not readily accessible by road networks. Consumers will enjoy the rapid arrival of products to their home or business, the option to expedite delivery of time-critical items like medication, and share in the cost savings of delivery. There remain, however, challenges and gaps to be addressed for successful field implementation of unmanned aerial delivery.

One substantial constraint in the UAS delivery strategy is the limited flight range of aerial systems. Currently, airframes are limited to a maximum radius of 20 miles. With this limited range, a significant portion of customers would not be eligible for delivery service and be required to revert to the longer traditional delivery process via trucks. For example, using Amazon's current fulfillment center footprint (i.e., 96 fulfillment centers), analysts estimate that only 30% of potential customers would be eligible for the UAS delivery service due to the 20-mile range limit [9].

Researchers have begun exploring concepts to extend system range and increase the number of customers who would be eligible for UAS deliveries. One technique being considered is a two-stage distribution process. Fig. 1 provides a graphical representation of the general delivery concept. In the first stage of this process, packages are moved by ground transport trucks to designated transfer points. Trucks at transfer points act as mobile launch and recovery vehicles for the UAS. From that location, in the second stage, delivery routes are completed using UAS. Various prototype UAS-transporting trucks have already been developed as companies attempt to utilize them in future delivery concepts. For example, Workhorse Group Incorporated has developed a delivery system where an UAS – called HorseFly – travels atop a modified electric van titled WorkHorse [10]. Mercedes-Benz has begun similar work, developing the Vision Van concept [11], [12]. Mercedes' ground vehicle acts like a commercial distribution hub on wheels carrying two small drones affixed to its roof for remote deliveries. Using these and similar methods, UAS delivery could extend beyond its current range and provide home delivery service to more customers by air. Important to the concept, however, is the location of the transfer hub where deliveries change modes from ground transportation to delivery by UAS.

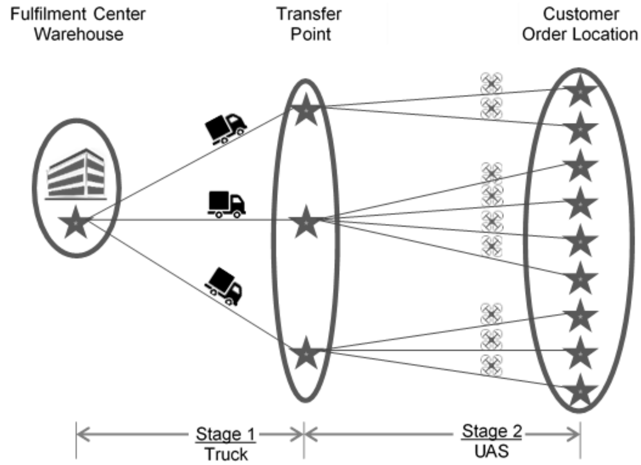

FIGURE 1. Graphic conceptual representation of the two-stage distribution network using transfer points.

As business-to-customer distribution networks explore two-stage systems for the home delivery of retail products, fulfillment center dispatchers must direct the timely deliveries of orders. Retail customer deliveries must utilize no more than the minimum required resources to best manage this system and maximize profits. Distribution decision makers must know how to optimally and simultaneously assign deliveries, determine transfer locations, and identify departure times from fulfillment center warehouses. Therefore, there is a current need to develop an algorithm for the two-stage distribution network with transfer points that utilizes the least amount of resources to deliver packages within associated time windows.

This paper introduces an integer programming model for the two-stage distribution network with transfer points. The developed model has three objectives. First, it must determine the optimal set of transfer points needed to meet customer demands. Second, it must determine the assignment

TABLE 1. Transfer point location problem literature.

Problem	Objective	Facility to Transfer Point Discount	Demand	Topology	Arc or Hub Capacity	Solution
TPLP [1] Transfer Point Location Problem	Minisum Minimax	$\alpha < 1$	Homogeneous	Plane Network	Uncapacitated	Exact
FTPLP [2] Facility and Transfer Point Location Problem	Minisum Minimax	$\alpha < 1$	Homogeneous	Network	Uncapacitated	Heuristic
FTPLP [20] Facility and Transfer Point Location Problem	Minisum	$\alpha < 1$	Homogeneous	Network	Uncapacitated	Exact
MLTP [3] Multiple Location of Transfer Point	Minisum Minimax	$\alpha < 1$	Homogeneous	Plane Network	Uncapacitated	Heuristic

of customer orders to trucks prior to their departure from the fulfillment center. Third, it must determine the optimal departure time required for each truck to meet the expected delivery times for each order. A central Pennsylvania delivery zone was used as a case study to show implementation of the developed model. A commercial optimization software package was used to run the model. The results provided insights about the capacity of vehicles, locations of transfer points, and required time needed for deliveries to arrive. Future research areas associated with the capacitated transfer point covering problem (TPCP) were identified.

III. RELATED RESEARCH

While choices about locations have been made throughout time, it was not until the mid-1630s that the topic was formally seen in literature [13]. It was at that time Pierre de Fermat, a French lawyer and mathematician, offered a location puzzle to his colleagues in his essay ''Method for the Study of Maxima and Minima [14]–[16].'' But it was more recently, in 1986, when the topic was narrowed and the investigation of hub locations and their implications emerged [17]. Since the formal appearance of the hub location problem in 1986, there has been an increasing trend in research about the problem. In the last five years, over 150 peer-reviewed articles have been published. This is nearly a threefold increase from the number of publications seen between the years 2001 and 2005. There also has been a shift in the focus of research. Prior to the year 2000, research focused on the establishment of foundational hub location frameworks and the development of models that could accurately represent them [18]. It was about that time when the modeling of hub problems reached maturity and attention shifted to optimization [18]. Since then, increased effort has been placed on the development of advanced models and solution methods allowing problems of greater size and complexity to be optimally solved [19]. One topic of research emerging in the last 10 years has been the study of transfer points.

In 2007, researchers introduced a model for the TPLP [1]. Here, the authors proposed a model and method to find the optimal location of a single transfer point between a single resource facility and a number of demand nodes. This basic TPLP considers distribution or collection of goods or services between facility and n demand points. The problem attempts to reduce resources during a portion of the route to demand points by creating a transfer point and combining individual routes. The cost to travel along this combined portion of the route, between the facility and the transfer point is multiplied by a reduction factor of $\alpha < 1$, while the cost of traveling from the transfer point to the demand point does not change. The model locates both the facility and a set of transfer points to minimize the total travel time for all customers.

Since its introduction, there has been few published papers on the TPLP or its variants. In [1], the TPLP was formulated using a mini-sum objective and a mini-max objective on both a plane and network solution space. In [2], the authors formulated the problem of location for a single facility and p transfer points to serve a given set of n demands. Similarly to [1], the problem was formulated using mini-sum and mini-max objectives on both planar and network solution spaces. The authors then designed heuristic algorithms for each using a descent approach, simulated annealing, and tabu search. Those results, however, did not allow them to determine if any one heuristic was advantageous to the others. In [3], the authors proposed a heuristic for the problem and provided analysis of input variable; however, they were not able to develop an exact solution because of the size of the problems. The authors in [20] have also worked to find solutions to TPLP. Their paper demonstrated that multiple location transfer point problems with mini-sum and mini-max objectives can be formulated as p-median and p-center problems, respectively. When limiting the number of sourcing facilities to a single location, they were able to find optimal solutions using this technique; however, when multiple facilities were considered, the problem became too large and procedures to determine upper and lower bounds were needed.

Table 1 compares relevant research on TPLP to date using common classifications from accepted location problem taxonomies [18], [19], [21]–[23]. The result highlights the similarities in research, identifies areas currently unexplored, and points to opportunities for future discovery and improvement in the field. Of the six attributes compared, five areas were identified as having unexplored areas potentially containing useful insights. The most common trait used to classify location problems is the model objective. Objectives for all location problems are variants of the formulation of mini-max, mini-sum, and covering models [24]. Problems with a mini-sum objective pursue solutions where the sum of all costs between the facility and customer are minimized, while those with a mini-max objective minimize the largest cost between a customer and its assigned facility [24]. In contrast, covering models do not include the facility-customer movement cost in the objective function; instead, these costs are considered as constraints and only matter if they exceed a preset value [13]. The objective in a covering problem is to minimize the number of facilities needed while providing adequate service to all customers. To date, all TPLP research has focused on problems having mini-sum and/or mini-max objectives leaving a gap in TPLP research that focuses on the minimum use of transfer points. A problem that ensures the requirements of all customers are sufficiently attended is one of the classical objectives in location modeling and referred to as a "coverage" problem. Their goal is to minimize the number of intermediate points while still satisfying some constraint in delivery time or cost. The objective, formally introduced by Church and ReVelle [25], can be applied to a wide variety of settings. The wide applicability of the basic coverage framework has sparked strong interest in the research community. However, none of the many publications produced on various aspects of coverage models over the last 35 years discuss transfer points specifically [26]. This paper will specifically address how to minimize the number of assigned transfer points using a covering problem and develops a general mathematical model for the TPCP.

Research focused on minimizing facility-customer movement costs leads to the second common trait found among TPLP studies. Each study in the table investigates problems where $\alpha < 1$; that is, when the cost associated with movement between the facility and transfer point creates some reduction in cost by combining routes. When using both mini-max and mini-sum objective functions to minimize travel, a value for $\alpha \geq 1$ creates no economic advantage and was therefore not studied. However, when investigating models where the objective is to find the minimal transfer points required to satisfy or cover all demands, it is reasonable to investigate cases where merging routes will incur additional travel costs in order to reduce those points. Studies investigating $\alpha \geq 1$ may be useful as transfer point research matures and investigates problems having objectives that focus on covering demand with minimal transfer points.

The third trait often used to categorize location problems is the nature of the demands found in the model. Inspecting TPLP research found that all models assumed homogeneous demands. None of the studies accounted for dissimilar requirements that might alter how those products are distributed and then impact the location of either the transfer point or the facility. As more robust models are developed, investigating this aspect of the problem may prove useful.

Location problems are commonly studied on several topologies (e.g. tree, network, planar) [19]. Current TPLP literature focuses on models where solutions occur in networked and planar domains. A networked solution domain allows candidate transfer points to occur at discrete locations on an established arrangement of nodes and connections. A planar domain allows solutions to occur continuously in two-dimensional space that generally represents deliveries at any location within the delivery area. While each of these solution domain spaces were looked at individually in previous TPLP studies, they are not explored if they occur simultaneously (e.g., selection of transfer points must be on a road network, while the location of demands may occur at any location on the plane). Exploring models that incorporate more than one topology might uncover insights to how two or more solution spaces interact. This study looks at networked and planar solution spaces simultaneously as trucks navigate a road network during the first phase of delivery and then transition to the less constrained planar domain during the second phase.

Finally, the current research makes no mention regarding the impacts due to limited capacity. In each case, the models assume no issues will arise either at the transfer point along the arcs connecting it to either the demand points or the facility. Limiting movement through transfer points by either of these constraints could significantly change results and should be investigated.

IV. PROBLEM SPECIFICATIONS

Amazon has established a robust distribution network attempting to shorten the time between customer ordering and the ultimate delivery of a product to its final location. Currently, Amazon's network consists of over 96 fulfillment centers in North America. The city of Carlisle, Pennsylvania is the home of three of those fulfillment centers maintaining almost 2.5 million square feet of warehouse space used for both maintaining inventory and processing orders. The fulfillment centers in Carlisle provide a case study from which realistic specifications can be drawn to further study optimal placement of transfer points in a two-stage distribution system.

The problem can be specified using a graph, $G = (V, E)$, where nodes represent locations of the fulfillment center, transfer points, and customers. The arcs of the graph represent links between the fulfillment center and transfer points in the first stage of the delivery; and links between transfer points and customers in the second stage. Each type of node and arc is discussed briefly in the following sections.

A. FULFILLMENT CENTER LOCATIONS

One of the largest fulfillment centers currently owned by Amazon was opened in August 2010 and is located just west of Carlisle. This single center maintains just over 1.2 million

TABLE 2. Location of central pennsylvania fulfillment center.

Description	Latitude/ Longitude	MGRS
Main Warehouse Amazon Fulfillment Center Carlisle, PA	N 40° 10' 30.43" W 77° 13' 52.97"	18TUK 10009 49581

square feet of floor space and sits adjacent to a second Amazon fulfillment center maintaining 700 thousand square feet of floor space. Amazon, along with several other distribution companies, have selected Carlisle as a distribution hub to take advantage of the proximity to several major cities and the road networks on the eastern coast of the United States. Its location also benefits from the intersection of several established road and rail exchanges providing access to high-speed routes linking multiple warehouses across the nation and providing road access to suitable transfer points. This study investigates customer orders requiring delivery occurring east of the Carlisle fulfillment center. The large size of the fulfillment center permits significant inventory and assumes sourcing orders from that inventory will account for no delay. Details on the location of the fulfillment center in Carlisle are listed in Table 2.

B. TRANSFER POINT LOCATIONS

Transfer points are the locations where in-transit orders switch from the first stage of delivery to the second stage. This is also the point where deliveries change their mode of transportation. Initially customer orders move by trucks carrying multiple UAS and their respective packages. In the second stage, individual UAS depart from the trucks and carry their delivery to each customer's final location. Transfer locations are prearranged by Amazon and relatively permanent.

Prior coordination with the land owner and launch site analysis ensure each location sufficiently meets safety and logistic requirements. Using the fulfillment facility as a circle's center, the closest transfer points are located along the edge of a circle having a radius of 10 miles from warehouse. Additional transfer points are located along the edge of circles having radii increasing at 10 mile intervals. To ensure lateral coverage of the delivery area, the number of transfer points increases at a rate proportional to the distance from the fulfillment center. Using the circle as a guide, final placement of transfer points is made accounting for access to improved road networks, any hazards that might imped takeoff and landing of aircraft, and allowing the broadest coverage of the delivery area. Fig. 2 visually shows the location of transfer points east of the Carlisle fulfillment center. Table 3 provides detailed information about each transfer points location selected in this case study. Using as few transfer points as possible benefits the delivery company by reducing expenses and risks incurred during the first phase of delivery.

C. DELIVERY LOCATIONS

Customer orders east of Carlisle fall into three delivery categories. The first are those within a 20-mile radius of the

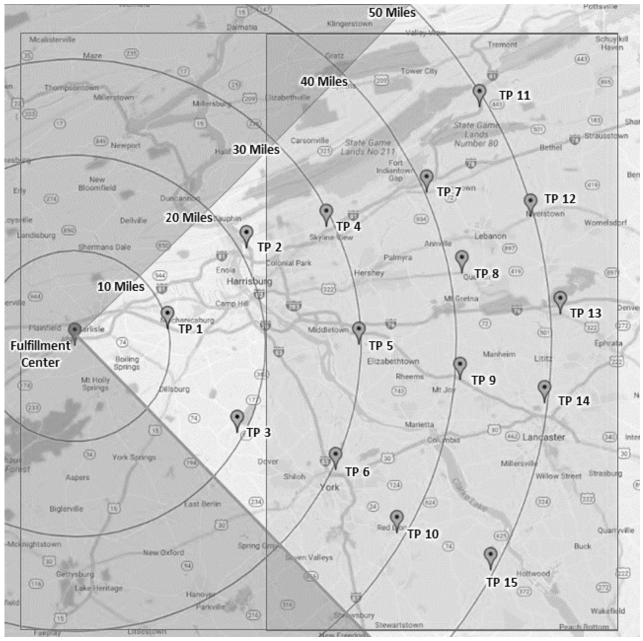

FIGURE 2. Established transfer point locations for consideration relative to fulfillment center in Carlisle, PA.

fulfillment center. These deliveries do not exceed the range limitations of UAS leaving directly from the warehouse and therefore do not require delivery using the two-stage distribution system. The second are orders located so far from the fulfillment center that they cannot be delivered within the established time window even using the two-stage methodology. The physical distance and speed limitations make timely delivery impossible regardless of resourcing. The third and final set of deliveries are those of interest. Those deliveries require the two-stage distribution network. A box east of Carlisle was established to capture orders that meet this third criteria. Within this area, individual orders occur randomly and are uniformly distributed. Customer order locations originate within the geographic area and are identified using the Military Grid Reference System (MGRS), a geo-coordinate derivation of the Universal Transverse Mercator (UTM) grid system. The area from which orders may originate and an example set of one hundred customer orders is shown in the Fig. 3. Each iteration of deliveries investigated a new set of one hundred orders.

D. STAGE ONE ROAD NETWORKS

The first stage of delivery occurs by truck traveling over established road networks. Distance and time from the Carlisle fulfillment center to each transfer point is calculated using the Customizable Route Planning (CRP) tool found in Microsoft's Bing Maps [27]. This tool finds the fastest route along the road network accounting for congestion, maximum allowable speeds and driving conditions. Using j as an index, the cost to move from the fulfillment center to each transfer point is found and represented by τ_j. These costs are shown in Table 4.

TABLE 3. Transfer point location descriptions.

Radius	Description	Latitude/ Longitude	MGRS
10	Transfer Point 1 Keystone Petroleum Mechanicsburg, PA	N 40° 12' 2.95" W 77° 2' 52.08"	18TUK 25707 52057
20	Transfer Point 2 Mack Sales and Services Harrisburg, PA	N 40° 19' 18.70" W 76° 53' 30.74"	18TUK 39266 65199
20	Transfer Point 3 Lebarron's Auto Salvage Dover, PA	N 40° 2' 39.50" W 76° 54' 35.55"	18TUK 37073 34422
30	Transfer Point 4 UPS Supply Solutions Harrisburg, PA	N 40° 21' 13.58" W 76° 44' 8.30"	18TUK 52610 68469
30	Transfer Point 5 Zeager Bros, Inc Middletown, PA	N 40° 10' 38.04" W 76° 40' 9.83"	18TUK 57866 48764
30	Transfer Point 6 Harley Davidson York, PA	N 39° 59' 13.97" W 76° 43' 0.17"	18TUK 53430 27749
40	Transfer Point 7 JP Donmoyer Trucking Annville, PA	N 40° 24' 21.18" W 76° 32' 12.83"	18TUK 69588 73941
40	Transfer Point 8 Terre Hill Concrete Lebanon, PA	N 40° 17' 4.80" W 76° 28' 4.56"	18TUK 75217 60386
40	Transfer Point 9 Associated Builders Manheim, PA	N 40° 7' 25.29" W 76° 28' 18.23"	18TUK 74598 42524
40	Transfer Point 10 Dawn Food Products Red Lion, PA	N 39° 53' 32.94" W 76° 35' 43.21"	18TUK 63605 17042
50	Transfer Point 11 Pilot Travel Center Pine Grove, PA	N 40° 32' 3.55" W 76° 25' 58.04"	18TUK 78654 88050
50	Transfer Point 12 Arthouse's Nursery Myerstown, PA	N 40° 22' 12.79" W 76° 19' 56.42"	18TUK 86886 69701
50	Transfer Point 13 Esbenshade's Garden Ctr Lititz, PA	N 40° 13' 21.76" W 76° 16' 23.63"	18TUK 91670 53254
50	Transfer Point 14 Brook Lawn Farm Market Lancaster, PA	N 40° 5' 18.60" W 76° 18' 17.39"	18TUK 88762 38395
50	Transfer Point 15 Jordan Bros Farm Airville, PA	N 39° 50' 9.92" W 76° 24' 40.64"	18TUK 79243 10517

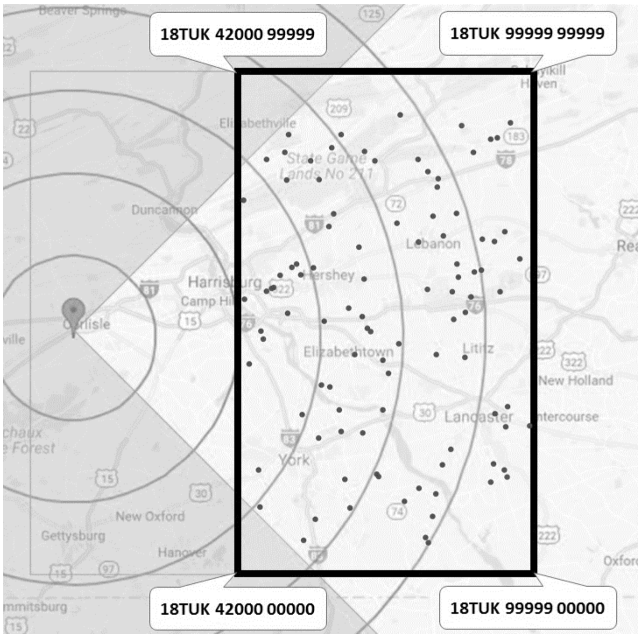

FIGURE 3. Example of 100 customer orders locations requiring delivery using transfer points.

TABLE 4. First-stage delivery costs – facility to transfer points.

Description	Road Distance	Road Travel Time
Transfer Point 1 Keystone Petroleum	11 miles	τ_1 = 18 minutes
Transfer Point 2 Mack Sales and Services	24 miles	τ_2 = 26 minutes
Transfer Point 3 Lebarron's Auto Salvage	24 miles	τ_3 = 40 minutes
Transfer Point 4 UPS Supply Solutions	34 miles	τ_4 = 35 minutes
Transfer Point 5 Zeager Bros, Inc	39 miles	τ_5 = 42 minutes
Transfer Point 6 Harley Davidson	45 miles	τ_6 = 48 minutes
Transfer Point 7 JP Donmoyer Trucking	45 miles	τ_7 = 45 minutes
Transfer Point 8 Terre Hill Concrete	47 miles	τ_8 = 58 minutes
Transfer Point 9 Associated Builders	51 miles	τ_9 = 51 minutes
Transfer Point 10 Dawn Food Products	54 miles	τ_{10} = 67 minutes
Transfer Point 11 Pilot Travel Center	57 miles	τ_{11} = 54 minutes
Transfer Point 12 Arthouse's Nursery	64 miles	τ_{12} = 68 minutes
Transfer Point 13 Esbenshade's Garden Cntr	62 miles	τ_{13} = 67 minutes
Transfer Point 14 Brook Lawn Farm Market	62 miles	τ_{14} = 65 minutes
Transfer Point 15 Jordan Bros Farm	65 miles	τ_{15} = 79 minutes

E. STAGE TWO AIR CORRIDORS

Once orders depart transfer points, delivery occurs to individual customer order locations using a UAS traveling along an air corridors. With few exceptions, flight patterns between the transfer point and order destinations are assumed to be in a straight line. The distance from each transfer point, j, and each customer's location, k, is signified by d_{jk} and determined using the Euclidean metric. A cost matrix, $D = d_{jk}$, then captures all possible distances in the second stage of delivery.

Parameter τ_{jk} represents the travel time from the transfer point to customer order locations. Time along this portion of the route is calculated using the distance cost matrix, D, and multiplying by the average flight speed. A new cost matrix $T = \tau_{jk}$ represents travel time in minutes. In this example, the average UAS speed during flight is assumed to be 50 mph.

This average speed accounts for take-off, landing, and error caused by route deviations.

V. MODEL FORMULATION

This section describes the proscriptive mathematical programming model used load and dispatch delivery vehicles. More specifically, the following subsections describe the decision variables, objective function, and constraints used to find optimal vehicle routing.

A. DECISION VARIABLES

Two interrelated decisions must be made by dispatchers as they identify the best delivery schedule for an existing set of customer orders. The first decision is to determine which transfer points to open. The second decision is to determine which customer orders to route through each of the transfer points. To arrive at an optimal solution, these two decisions must be made in conjunction with each other. Ignoring the impact of one when making the other could lead to an infeasible or less than optimal solution. These decisions are represented by the following two decision variables.

1) TRANSFER POINT UTILIZATION

Y_j denotes if transfer point (j) is opened or closed. The decision is represented as a binary variable for the set of transfer points, signified by T and indexed by the variable j. In the Carlisle example, we have established fifteen transfer points from which to choose and therefore $T = 15$ and $j = (1, 2, \ldots, T)$.

$$Y_j = \begin{cases} 1: & \textit{if transfer point } (f) \textit{ is open} \\ 0: & \textit{if transfer point } (f) \textit{ is closed} \end{cases} \tag{1}$$

2) STAGE TWO DELIVERY UTILIZATION

Similar to transfer point utilization, X_{jk} indicates if an unmanned aerial vehicle travels from transfer point (j) and delivers to customer order location (k). Like the previous decision this choice is binary for the combination of all routes between the transfer points in T and orders locations in N. In our example one hundred orders must be dispatched and therefore $N = 100$ and $k = (1, 2, \ldots, N)$.

$$X_{jk} = \begin{cases} 1: & \textit{if delivery made from } (j) \textit{ to } (k) \\ 0: & \textit{if delivery not made from } (j) \textit{ to } (k) \end{cases} \tag{2}$$

B. OBJECTIVE FUNCTION

Dispatchers responsible for scheduling deliveries are ever mindful of the customer's expectation for delivery within an assured time window. In previous studies on TPLP, objective functions have been focused on minimization of that travel costs. The TPCP, however, minimizes the number of transfer points required to make deliveries. The problem then accounts for the promised delivery time by using constraints. Research on transfer point problems using a covering objective has not been found in published literature.

Minimizing the number of transfer points benefits the delivery company as it manages resources. Reducing the number of transfer points lessens the number of trucks needed during the initial stage of delivery. The requirement for less trucks allows delivery companies to maintain smaller fleets reducing sunk purchasing and maintenance costs. It also places less vehicles on the road network where they run the risk of delays caused by traffic congestion. Additionally, utilizing the minimum number of transfer points loads transport trucks to their highest feasible capacity. This potentially reduces trucks traveling at less-than-truckload (LTL) capacity and helps eliminate wasted opportunities for limited resources.

The dispatcher's objective therefore is to use the least amount of transfer points to deliver all orders in a timely manner. Using the binary decision variable Y_j to indicate if a transfer point is utilized, the objective function is mathematically represented in (3).

$$\min (z) = \min (\text{transfer points}) = \min \sum_{j=1}^{T} Y_j \tag{3}$$

C. CONSTRAINTS

Several conditions must be accounted for to ensure the model and the solution it provides represents realistic behavior, does not exceed the capabilities of the distribution network, and allows dependent variables to act as indicators of only true or false decisions. These conditions are described using the following seven constraints.

1) CONSTRAINT 1

Equation (4) ensures each customer location can only receive delivery from one transfer point by only allowing one route open to each customer location. Each order location must be checked and therefore creates N constraints.

$$\sum_{j=1}^{T} X_{jk} = 1 \quad (k = 1, 2, \ldots, N) \tag{4}$$

2) CONSTRAINT 2

The second constraint checks each transfer point to determine if it is open. If a transfer point is closed, (5) ensures no deliveries from that location will be allowed. Potential air routes used between transfer points and order locations in the second stage of delivery are checked creating a total of TxN constraints.

$$X_{jk} \leq Y_j \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{5}$$

3) CONSTRAINT 3

The third constraint ensures deliveries are only made using routes that allow arrival within the predesignated time window. Amazon initially set the benchmark for unmanned aerial vehicle delivery at thirty minutes when delivering directly from fulfillment centers [8]. An additional 90 minutes allows for truck movement along road networks using the two-phase concept. This two hour on-time delivery promise has become the new industry goal as retailers enable shipments to be delivered in hours rather than days [6]. Parameter β represents the allowable maximum transportation cost in time (minutes) and is the maximum time guaranteed by companies from the initial ordering of a product to delivery. For this case study $\beta = 120$ minutes or the two hours set as the industry goal. Parameter β is often referred to as the covering threshold or covering radius in classical covering models. This threshold is checked against the time required for each route to the customer location in (6). As in the last constraint, every possible route must be checked creating $T\ x\ N$ constraints.

$$X_{jk}(\tau_j + \tau_{jk}) \leq \beta \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{6}$$

4) CONSTRAINT 4

The fourth constraint checks the distance of the customer's order to from each transfer point and ensures it is not beyond the range of the unmanned aerial system. The range of the vehicle is currently 20 miles and signified by γ. All potential routes between transfer points and order locations must be checked and there are $T\ x\ N$ constraints.

$$d_{jk}X_{jk} \leq \gamma \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{7}$$

5) CONSTRAINT 5

This constraint considers the capacity of trucks moving from the fulfillment center to the transfer point. While packages are relatively small each truck can only move a finite number of unmanned aerial systems. Trucks within the model are homogeneous and their capacity is represented by ω. This constraint checks each transfer point and ensures no more than ω systems can fly from that location, thus ensuring only that number are delivered to transfer point j. Each transfer point must be checked and therefore T constraints of this type are included in the model.

$$\sum_{k=1}^{N} X_{jk} \leq \omega \quad (j = 1, 2, \ldots, T) \tag{8}$$

6) CONSTRAINT 6 AND 7

The constraints found in (9) and (10) establish our decision variables, Y_j and X_{jk} as binary variables.

$$Y_j \in \{0, 1\} \quad (j = 1, 2, \ldots, T) \tag{9}$$

$$X_{jk} \in \{0, 1\} \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{10}$$

D. COMPLETED MODEL

Combining the objective function and the constraints results in the following prescriptive or optimization model.

Objective:

$$\min\,(\mathrm{z}) = \min \sum_{j=1}^{T} Y_j \tag{3}$$

Subject to:

$$\sum_{j=1}^{T} X_{jk} = 1 \quad (k = 1, 2, \ldots, N) \tag{4}$$

$$X_{jk} \leq Y_j \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{5}$$

$$X_{jk}(\tau_j + \tau_{jk}) \leq \beta \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{6}$$

$$d_{jk}X_{jk} \leq \gamma \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{7}$$

$$\sum_{k=1}^{N} X_{jk} \leq \omega \quad (j = 1, 2, \ldots, T) \tag{8}$$

$$Y_j \in \{0, 1\} \quad (j = 1, 2, \ldots, T) \tag{9}$$

$$X_{jk} \in \{0, 1\} \quad \begin{pmatrix} j = 1, 2, \ldots, T; \\ k = 1, 2, \ldots, N \end{pmatrix} \tag{10}$$

E. OPTIMIZATION SUITES

Several companies have developed computer software to assist in the modeling and solving of optimization problems. These tools solve all major types of mathematical programing problems and interface with a wide variety of programming languages. Most software companies offer limited versions of their product for trial use, however a rental agreement or license is required for commercial use and access to the unconstrained product. Some companies provide full-featured licenses for the academic community conducting classes or research in math programing or optimization.

One software package that has more recently arrived on the market is Gurobi Optimizer. The Gurobi Company originated in 2008 and derives its name from the first letters of the last name of each of its founders: Zonghau Gu, Ed Rothberg and Bob Bixby [28]. Along with backgrounds in operations research, computer science and industrial engineering they were all key players in the development of CPLEX, another computer optimization package originally created in 1988 and now owned by IBM [29].

Gurobi Optimizer pairs the most recently developed software architectures and the implementations of the latest algorithms to create solvers for the following optimization problems [28]:

- linear programming,
- mixed-integer linear programming,
- mixed-integer quadratic programming,
- quadratic programming,
- quadratically constrained programming, and
- mixed-integer quadratically constrained programming.

Gurobi is not its own modeling language. Instead it is a set of application programming interfaces or subroutines that can be referenced from whatever programming language you are using. The software supports interfaces with Object-oriented interfaces, Matrix-oriented interfaces, and links to standard modeling languages [28]. It also links to Microsoft Excel through their Analytic Solver.

For this case study, Java code was written utilizing Gurobi solvers. The results of the program provided optimal

TABLE 5. Minimum required transfer points.

limit	Truck Capacity	Iteration 1	2	3	4	5	6	7	8	9	10
15	7	15	15	15	15	15	15	15	15	15	15
10	10	10	10	10	10	10	10	10	10	10	10
7	15	7	7	7	7	7	7	7	7	7	7
5	20	5	5	5	5	5	5	5	5	5	5
4	25	4	4	4	4	5	5	4	5	5	4
4	30	4	4	4	4	5	4	4	4	4	4
3	35	4	4	4	4	5	4	4	4	4	4
3	40	4	4	4	4	5	4	4	4	4	4
3	45	4	4	4	4	5	4	4	4	4	4
2	50	4	4	4	4	5	4	4	4	4	4

TABLE 6. Longest delivery times (minutes).

Truck Capacity	Iteration 1	2	3	4	5	6	7	8	9	10
7	97.7	101.0	94.3	101.4	97.0	100.5	100.8	102.3	102.4	99.3
10	101.2	101.4	100.0	101.4	98.4	93.5	103.2	102.2	96.4	101.4
15	90.0	102.9	100.2	89.8	101.5	99.5	103.2	102.4	102.0	102.8
20	90.9	102.0	90.3	91.7	99.8	99.6	102.3	102.3	102.0	89.3
25	92.0	102.9	88.9	89.8	99.0	99.6	102.3	100.1	102.0	90.8
30	90.0	102.9	89.3	90.3	99.0	103.0	102.3	102.4	102.4	90.8
35	90.0	102.9	88.6	90.3	101.5	102.2	102.3	102.4	102.4	89.3
40	90.0	102.9	88.4	89.8	101.5	103.0	102.5	102.4	102.4	90.8
45	90.5	102.9	88.4	90.5	101.5	103.0	102.5	102.4	102.4	90.8
50	90.5	102.9	88.4	90.3	101.5	103.0	102.5	102.4	102.4	90.8

dispatching decisions for each set of customer orders using the transfer point cover problem found in (3)-(10).

VI. CALCULATIONS AND RESULTS

Gurobi provides academic users a full version of their optimization tool without limit on the number of variables or constraints. Access to the full version of the software allowed assessment of one hundred customer orders as they were routed through fifteen potential transfer point. Therefore, $T = 15$ transfer points and $N = 100$ customer orders. These parameters produced $3NT + T + N$ or 4615 constraints. The model was run for ten repetitions, each using a new set of random customer orders. During each iteration, the Java program and Gurobi interface assessed the minimum number of transfer points required. It also provided a output listing of the transfer points to be utilized, what orders would assigned to trucks going to each transfer point, and the time required for each order to arrive at its destination.

Various truck capacities, ω, were also investigated using the ten sets of customer orders. During the first phase of the delivery route, trucks able to carry 7, 10, 15, 20, 25, 30, 35, 40, 45, and 50 aerial systems were used to determine the best delivery strategy. Table 5 shows the least number of transfer points required to make timely deliveries as the truck capacity changed. The left hand "limit' column indicates the minimum number of trucks needed if travel cost constraints are relaxed and only the truck capacity constraint was imposed. The highlighted results in Table 5 show where the number of required transfer points exceeded the unconstrained "limit" number and identify solutions constrained by delivery time or range. In most cases, regardless of truck capacity, dispatchers require four or more transfer points to make deliveries within required time windows. The results also show that developing trucks with capacity of more than 35 orders provides no advantage in decreasing required transfer points. This TPCP, however, did not allow for multiple trucks to utilize the same transfer point. No more than one truck can use each transfer point during any repetition. Therefore, advantages in transfer point assignments might occur at higher truck capacities if multiple trucks are assigned to the same transfer point.

The time required to delivery each order was also collected using the model developed with Java and Gurobi. The longest delivery time in each iteration is shown in Table 6. All solutions fell well below the 2-hour (120 minute) threshold introduced in the initial model. In all cases, customer orders arrived almost 20 minutes prior to the required delivery time. This 20-minute slack might be used to reduce the model delivery time threshold, expand the delivery footprint by expanding the area from orders are taken, or be maintained to mitigate risks of hazards that might occur along transportation routes.

Table 6 shows that the longest delivery times in each iteration does not consistently improve or worsen as truck capacity changes. It also shows that solutions in each iteration often share a common longest delivery time even though truck capacity and routing assignments change. Investigating where times vary reinforces the covering model's primary objective. The model is designed to find the minimal transfer points required using the upper time limit as a constraint and not an objective. It does not consider the cost of travel, unless it exceeds this pre-established constraint. However, in some cases, it is possible to find a faster time to complete deliveries using the minimal number of transfer points. To do this, the model was run iteratively, reducing the allowable maximum transportation time, β, below the previous longest delivery time. This process was continued until additional transfer points were required or there is no longer a feasible covering solution. The last feasible solution then becomes a result satisfying minimum transfer points and minimum time of delivery. Table 7 shows the updated results after using the above approach. The highlighted cells are delivery times that might be improved more, but only at the cost of increasing the required transfer points.

Table 8 compares the original TPCP model with the iterative approach which minimized delivery times while using the least required transfer points. The table shows the potential time savings when the iterative approach is used to reduce the longest delivery time. The iterative process reduces the longest delivery time in over 80% of the samples. Where improvements could be made, the iterative process saved an average of over five minutes in travel time. This savings accounted for a reduction of 5% of the average longest delivery time.

TABLE 7. Multi-objective longest delivery times (minutes).

Truck Capacity	Iteration 1	2	3	4	5	6	7	8	9	10
7	90.3	93.1	88.1	90.0	94.2	93.5	96.5	94.3	95.1	85.0
10	89.5	93.1	87.7	89.2	94.2	93.5	96.7	94.3	95.1	86.1
15	90.0	93.1	87.2	89.8	94.2	94.0	96.5	94.3	94.8	85.4
20	90.9	98.5	87.4	90.3	97.0	94.0	96.2	98.9	98.6	85.3
25	92.0	101.9	87.6	89.8	95.1	94.0	102.3	94.3	95.1	85.9
30	90.0	100.4	87.1	90.3	95.1	99.6	96.7	100.1	100.7	85.9
35	90.0	100.4	87.6	90.3	95.1	99.6	96.7	100.1	100.7	86.2
40	90.0	100.4	87.1	89.8	95.1	99.6	96.7	100.1	100.7	86.2
45	90.5	100.4	87.1	90.5	95.1	99.6	96.7	100.1	100.7	86.2
50	90.5	100.4	87.1	90.3	95.1	99.6	96.7	100.1	100.7	86.2

TABLE 8. Potential savings in delivery times (minutes).

Truck Capacity	Iteration 1	2	3	4	5	6	7	8	9	10
7	7.4	7.9	6.2	11.4	2.8	7.0	4.3	8.0	7.3	14.3
10	11.7	8.3	12.3	12.2	4.2	-	6.5	7.9	1.3	15.3
15	-	9.8	13.0	-	7.3	5.5	6.7	8.1	7.2	17.4
20	-	3.5	2.9	1.4	2.8	5.6	6.1	3.4	3.4	4.0
25	-	1.0	1.3	-	3.9	5.6	-	5.8	6.9	4.9
30	-	2.5	2.2	-	3.9	3.4	5.6	2.3	1.7	4.9
35	-	2.5	1.0	-	6.4	2.6	5.6	2.3	1.7	3.1
40	-	2.5	1.3	-	6.4	3.4	5.8	2.3	1.7	4.6
45	-	2.5	1.3	-	6.4	3.4	5.8	2.3	1.7	4.6
50	-	2.5	1.3	-	6.4	3.4	5.8	2.3	1.7	4.6

VII. FUTURE STUDY

The research described in this article provides a first look at optimizing transfer point location problems using a covering objective. It proposed a general mathematical model for the TPCP and then applied it to a real-world logistics delivery system. Using computer optimization tools, a solution was found to minimize the number of transfer points and trucks needed to make all deliveries required in a predetermined time window. The research also developed a technique to optimize multiple objectives in transfer point problems. The results were analyzed and insights about the model were provided. However, several unexplored topics remain and provide the opportunity for future study in areas relating to optimizing transfer points with the goal of minimizing their number.

This research provided a set of potential prearranged transfer points for the optimization model to select from as it identified optimal routes. These transfer points were uniformly distributed along road networks throughout the delivery area. Future studies are needed on how best to distribute and locate transfer points in the delivery area. Selecting, coordinating, and purchasing the right to use land create additional cost for distributors. These costs are committed regardless if the location is selected for use or not. Tools assisting in site selection prior to establishing transfer points ensure the best utilization of resources and to minimize costs incurred to the company as they set up distribution networks. Exploring models saturated with virtual transfer points might provide decision makers with insight about the best transfer point distribution.

Increasing the number of potential transfer points provides opportunity to investigate capacity limitations at individual transfer points in ways other than increasing truck capacity. Current, the model does not allow multiple trucks to use a single transfer point. Once a capacitated vehicle is sent to a transfer point, all subsequent trucks must be routed to different points even at the expense of additional travel time. Establishing duplicate transfer nodes at a single location would further investigate solutions that optimize delivery resources. This technique might prove useful when orders temporarily surge in a localized area or when additional throughput at a transfer point would significantly decreases delivery times.

This study derives an optimal solution to the TPCP by opening and routing customer orders through select transfer points. Initially, candidate transfer points were distributed uniformly throughout the entire delivery area to ensure coverage of customers. Analysis of transfer point utilization patterns would provide insights into best practices for site identification and selection. Results may show the uniform distribution is not as cost-effective as clustering or banding transfer points throughout the delivery area.

This model investigates dispatching all orders from the fulfillment center simultaneously. It accumulated a large set of customer orders and then determined an optimal solution taking all orders into account. It did not investigate how delivery trucks and their associated orders should independently depart the fulfillment center. It also did not account for order arrival times throughout and during the delivery cycle. Additional work should look at the sequential arrival of orders and how those orders might be processed to determine most advantageous departure times for transport trucks. While the mathematical programming model will inform that research in this area, the more complex model will likely require the use of a computer discrete event simulation where the dynamic arrival of customer orders and the dispatching of delivery trucks can be studied over time. The iterative technique used in simulation also provides an approach to investigate the multi-objective optimization problem discussed earlier in the results.

Finally, there are many parameters not accounted for using the linear programming model. Congestion along ground and air routes should be modeled to replicate more realistic traffic patterns. Impact of order weight, weather, and regulatory restrictions might also impact optimal solutions and should be considered. Adding these additional parameters to a mathematical model increases the number of needed constraints, complicates model interactions, and makes conceptualization more difficult. Simulation offers additional flexibility in model formulation and permits more realism to be achieved. Most simulation models use logical arithmetic operations performed in a prearranged sequence and do not require defining the problem exclusively in analytic terms [30]. When uncertainties are an important characteristic of the decision, the use simulations can prove particularly useful. The development of an acceptable simulation provides an alternate solution method for larger problems that provides users with the ability to deal with complicated models of correspondingly complicated networks [31].

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