Wisconsin Library Delivery Services & the Vehicle Routing Problem:

A Case Study of Proposals from the Public Library System Redesign Project

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DS 785: Capstone

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August 11, 2021

Abstract

In 2015, the Wisconsin Department of Public Instruction launched the Public Library System Redesign project to create a plan for reconfiguring Wisconsin's public library systems and redesigning the provision of system services, including the statewide interlibrary loan delivery service. As part of that project, a Delivery Workgroup developed two proposals for shifting to a service model based on regional delivery service territories where local libraries would receive delivery stops on routes originating from a regional hub. For this project, I investigated the feasibility of these proposals by modeling regional library delivery services using a variant of the Vehicle Routing Problem and the Google OR-Tools package available for the Python programming language. Given a set of constraints and input data representing real-world distances and travel times retrieved from Google Maps, the OR-Tools routing solver determined whether a feasible route structure existed in the region and suggested a route configuration to minimize total route time. By varying the input parameters for the regional VRPs, I explored how different constraint values and solution search strategies affected routing solver outcomes. The results indicate that the number of routes necessary to serve every library and the volume capacity of the vehicles in the regional fleet will significantly influence the ability of route planners to design a workable route structure.

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Chapter 1: Introduction

Background

Every public library in Wisconsin belongs to one of 16 public library systems. As Wisconsin statutes require, each system provides a range of services, support functions, and resources for member libraries, including a delivery service that facilitates interlibrary lending of materials (Public Library System Redesign Chapter 43 Workgroup, 2018, pp. 4-5). In combination with shared library catalogs, delivery services create a single, system-wide collection of items available to every library patron within the system service area. In addition, Wisconsin has a statewide delivery service that exchanges interlibrary loan materials between systems, allowing patrons to access items owned by any public library in the state. The South Central Library System (SCLS) Delivery Service in Madison manages the intersystem service using a mix of direct service routes and hand-offs to third-party couriers. Along with the public library systems, SCLS also provides delivery service to other types of libraries in Wisconsin, including academic libraries, K-12 school libraries, and libraries at government agencies and correctional institutions. Thus, the SCLS Delivery Service hub acts as a central node in the Wisconsin Libraries' Delivery Network, directly or indirectly connecting over 600 libraries.

The current statewide delivery network configuration with one highly centralized node has several practical disadvantages (Public Library System Redesign Delivery Workgroup, 2018, p. 10). First, this service model leads to longer transit times for interlibrary loan items that must pass through the SCLS hub. In terms of network properties, this inefficiency results from a higher average shortest path length when compared to a model in which library systems exchange materials directly between system delivery hubs. A second shortcoming is low network robustness. For example, SCLS occasionally has to cancel intersystem routes due to weather or vehicle issues. Because there are no alternate paths between systems, these cancellations can add a day or more to item transit times. Finally, the current statewide delivery model produces service redundancies. SCLS intersystem routes make direct delivery stops at academic and other libraries located within the service territories of the other library systems; in some cases, a local delivery route stops at the same libraries.

In recognition of these and other deficiencies, the Wisconsin Department of Public Instruction formed a Delivery Workgroup to participate in the Public Library System Redesign (PLSR) project alongside the other service area workgroups (Public Library System Redesign Project Manager, 2018, p. 5). The Delivery Workgroup developed a proposal for a statewide delivery model that de-emphasized the boundaries of the 16 public library systems as determinants of delivery service territories. Instead, the Workgroup constructed a model with seven regions. The Workgroup sought to keep the regions small enough to offer daily delivery service to all libraries while completing every route within an 8-to-9-hour timeframe. Local delivery routes in each proposed service area would originate from a hub located near a transportation corridor, which, according to the Workgroup, would help establish direct connections between regional hubs (Public Library System Redesign Delivery Workgroup, 2018, p. 12). Increasing these connections would, in turn, reduce average transit times and make the overall network more robust. In addition, regional delivery routes would also stop at libraries of all types (public, academic, etc.) within their territories, eliminating the service redundancies identified in the current system. The Delivery Workgroup created two versions of the regional hub model for their final report. The first was an "ideal" model consisting of seven regions, as shown in Figure 1. In response to feedback from workgroups in other service areas, the Delivery Workgroup devised a second model that reflected concerns related to current inter-system delivery arrangements and shared library catalogs. The result was a "starting point" map with eight regions (see Figure 2), which would allow a gradual transition toward the ideal model.

Figure 1

PLSR Delivery Workgroup Ideal Proposal Service Region Map

Note. From *Wisconsin Public Library System Redesign: Delivery Workgroup Report*, by the Public Library System Redesign Delivery Workgroup, 2018, Wisconsin Department of Public Instruction (https://dpi.wi.gov/sites/default/files/imce/coland/pdf/PLSR_-_Delivery_Workgroup_Report.pdf). In the public domain.

Figure 2

PLSR Delivery Workgroup Starting Point Proposal Service Region Map

Note. Green lines represent library system boundaries and blue stars represent the locations of library system headquarters (current as of June 2021). From *Wisconsin Public Library System Redesign: Delivery Workgroup Report*, by the Public Library System Redesign Delivery Workgroup, 2018, Wisconsin Department of Public Instruction (https://dpi.wi.gov/sites/default/files/imce/coland/pdf/PLSR_-_Delivery_Workgroup_Report.pdf). In the public domain.

Problem Statement

In their report, the PLSR Delivery Workgroup focused on the general framework of the proposed statewide delivery models without delving into the details of regional route structures. Not only would detailed route planning have gone beyond the scope of the Workgroup's charge, but it can also be a complicated and time-consuming task. One factor adding complexity to the route planning process is that the number of possible route configurations increases exponentially with the number of stops. This property makes exhaustive route analysis impractical for regions with 50-100 libraries, especially when done manually. In addition, the Delivery Workgroup understood that their proposals would likely need revisions depending on the findings of the other PLSR workgroups. Parameters such as regional borders, the number of available vehicles, and budget estimates were (and are) subject to change as the PLSR project moves forward. In sum, it would not have been worthwhile for the Workgroup to spend a significant amount of time on detailed route planning at such an early stage of the system redesign process.

Though the PLSR Delivery Workgroup did not draft plans for regional routes, the Workgroup's proposals nonetheless depend on whether delivery service managers can develop feasible route structures within each region that meet specific parameters. The Workgroup outlined the regional constraints in the description of the ideal model proposal (Public Library System Redesign Delivery Workgroup, 2018, p. 12). The restrictions include the already mentioned requirement for route completion times between 8-9 hours and keeping the maximum hub-to-library distance at about 100 miles. Both limitations are necessary to enable material sorting and overnight deliveries between regional hubs. However, the Workgroup did not explain the methodology they used to ensure the design of each region met these constraints, leaving open the question of whether and how thoroughly the Workgroup tested their proposed statewide delivery models for feasibility.

Based on these considerations, one could describe the functionality required of a route modeling tool to enhance the regional design process. Such a tool would need to determine whether a feasible route structure exists for a proposed region. If more than one workable structure exists, the modeling tool should select an optimal or near-optimal configuration. Furthermore, the modeling tool would need the flexibility necessary to model the regions multiple times using different values for regional modeling parameters since these parameters are likely to change as the PLSR project progresses.

Conceptual Framework

The route modeling tool built for this research project relies on a well-studied class of problems in the operations research field known as Vehicle Routing Problems (VRPs). VRPs identify the most efficient route configuration for multiple vehicles making service stops at a set of customer locations (Toth & Vigo, 2002, p. xvii). Since Dantzig and Ramser (1959) first developed the VRP, researchers and logistics managers have adapted the basic VRP framework to various applications. Today, numerous versions of VRPs exist, involving complex constraints and sophisticated metaheuristics to search for solutions. This study, however, utilized a simple version of VRP in which all vehicles leave and return to a single depot while every customer receives one delivery stop on one route. In each VRP, I formulated the objective function to minimize global routing costs measured by total route time for all vehicles. With the addition of constraints on route time and vehicle capacity, this relatively uncomplicated VRP served as a model of each region in the PLSR Delivery Workgroup statewide delivery reconfiguration proposals.

Research Motivation

The purpose of this research was to investigate the practicality of implementing either of the PLSR Delivery Workgroup proposals based on an analysis of regional route structure feasibility. Also, constraint values that produce VRPs with feasible solutions give a preliminary indication of the resources, such as the number of vehicles and driver shift time, which will be required to set up regional delivery services. Finally, the routes identified as optimal by the algorithmic VRP solver provide regional managers with an initial regional route model for further refinement and development.

Research Questions

- Is there a feasible route structure for each region where every library receives one stop, and each route takes less than the maximum suggested route time (8-9 hours)?
- For instances in which a feasible model exists, what is a route configuration that minimizes the cumulative route time of all vehicles?
- What are the parameter values of an optimal regional route structure, particularly the number of vehicles required and the maximum allowed route time? Is it possible to find other optimal or near-optimal route configurations by changing the value of those parameters?

Significance of the Study

The research conducted for this study fills in some of the details of the statewide library delivery proposals created by the PLSR Delivery Workgroup. As noted previously, the overall implementation of either model relies in some measure on the feasibility of regional route structures. This study provides a preliminary analysis that planners can use to determine whether a proposed region is acceptable or needs further revisions. Moreover, the VRP modeling tool built for this project can contribute to this ongoing model development process by supplying a means of quickly checking ideas for reworked regions.

Limitations

The VRPs in this study were simplified models that ignored several complicating factors related to the larger PLSR project. For instance, the regional route structures do not include the connecting routes between hubs. These connectors will require additional staff time, along with staff time needed to sort incoming materials before local delivery routes leave and after they return. Delivery service managers will need to account for these items when budgeting for staffing costs, which, in turn, may reduce their flexibility in configuring regional routes. This study also did not address the potential for realizing efficiencies by having vehicles cross region borders. There might be cases in which it makes sense to service a library (or libraries) in one region using a local delivery route originating from the hub of an adjacent delivery region. In their report (2018), the PLSR Delivery Workgroup discusses Price County as an example of this type of efficiency: in the starting point proposal, Price County libraries would receive delivery from a route originating from the region 3 route despite belonging to a shared catalog with libraries in region 2 (pp. 17-18). The functionality required to identify and automatically adjust to similar exceptions was beyond the scope of the VRPs in this study. Instead, route planners must recognize these opportunities and modify an existing VRP solution or adjust the problem parameters before solving it again.

Chapter 2: Literature Review

The Vehicle Routing Problem (VRP) is a mathematical model that attempts to identify the most efficient way to route a fleet of vehicles from a depot to a set of customer locations so that every customer receives a stop while minimizing global route cost or distance traveled. This class of problems has practical implications for route planners and managers in wholesale distribution, last-mile package delivery, and global supply chain logistics. However, finding an exact solution to a VRP is impractical for problems with more than a few locations. This difficulty arises because the number of possible route combinations grows exponentially with the number of stops, making it impossible to test every option manually (Jumbe, 2019). The VRP and its variants use algorithms and heuristics to conduct an extensive (though often not exhaustive) search through the solution space and identify an optimal or near-optimal route configuration.

The first mathematical formulation of the VRP was proposed in a paper by Dantzig and Ramser in 1959, accompanied by an algorithm for solving it exactly (Toth & Vigo, 2002, p. xvii). Clarke and Wright (1964) expanded on their work by developing a heuristic that could find an acceptable solution to the VRP in a reasonable amount of time. Building on these foundations, academic researchers inspired by real-world delivery problems have created a broad range of VRP variants with different parameters and constraints. At the same time, software vendors have leveraged advancements in mobile technology and computing power to develop route planning software capable of optimizing delivery routes in near-real-time. These two frequently overlapping threads run throughout the VRP literature.

Academic Research

Academic research related to VRPs focuses on two principal areas. The first is the formulation of novel VRP variants, while the second involves proposals for new or improved methods (algorithms, heuristics, and metaheuristics) to solve them. Though the discussion that follows considers these ideas separately, they are closely related. Indeed, new variations of VRPs often require innovative approaches to solve.

VRP Variants

Laporte (2007) notes that the proliferation of variant VRPs reflects academic researchers' attempt to model the "diversity of constraints encountered in practice" (p. 811). My research did not uncover a definitive list of VRP variants, making it difficult to determine how many different versions of the VRP researchers have proposed. Furthermore, while researchers appear to use some naming conventions when labeling VRP variants, it isn't necessarily clear how rigorously the standards are applied. Variants with the same name may describe different problems, or variants with distinct labels may refer to models with similar formulations. Therefore, any accounting of the types and numbers of variants depends on the source consulted. For example, the open-data repository known as "VRP-REP" lists 51 variants shared online by VRP researchers (as of July 8, 2021; Mendoza et al., 2021). In contrast, Toth and Vigo (2002) identify five primary VRP variants: the Capacitated VRP (CVRP), the Distance-Constrained VRP (DCVRP), the VRP with Time Windows (VRPTW), the VRP with Backhauls (VRPB), and the VRP with Pickup and Delivery (VRPPD).

Toth and Vigo's list focuses on the VRP variants, which, at the time of writing in 2002, had been most extensively studied and documented in the literature. In subsequent years researchers have developed and investigated VRPs incorporating many of the additional constraints encountered in real-world situations. Erdoğan and Miller-Hooks (2012), for example, introduced the Green VRP (G-VRP), which models the driving range limitations of alternative fuel vehicles and requires en route refueling stops. Lin et al. (2016) adapted the G-VRP to create the Electric Vehicle Routing Problem (EVRP). The EVRP formulation accounts for the cost of electricity and the effect of load weight on the energy required to power the vehicle. The low-carbon routing problem proposed by Zhang et al. (2015) shares some similarities with the EVRP of Lin et al. (cost of fuel, variable fuel consumption rate) but adds a term representing the cost of carbon emissions. Each of these examples reflects a growing concern with the environmental impact of fleets of delivery vehicles powered by fossil fuels.

A different consideration inspired a VRP variant known as the Consistent Vehicle Routing Problem (ConVRP), which concentrates on customer service as a creator of business value. As first formulated by Groër et al. (2009), the ConVRP attempts to regularly match the same driver to the same customers, with drivers consistently making each stop at the same time of day. As Kovacs et al. point out (2015), this model has applications for companies such as home health care providers and last-mile package couriers. In their paper, Kovacs et al. extend the ConVRP into the generalized consistent VRP or GenConVRP. The GenConVRP loosens the restrictions of the ConVRP by allowing a limited number of drivers to visit the same customer and expanding the delivery time windows for each stop. The authors report that these changes combined with an innovative solution search heuristic can save up to 6.5 percent of route costs. Goeke et al. (2019) further build on these results with a proposal for an exact method of solving the ConVRP, which, according to benchmark testing, can outperform the technique developed by Kovacs et al.

The profusion of VRP variants and the growth of research in the field have motivated researchers to construct schemes for classifying the VRP literature. Eksioglu et al. (2009) devised a taxonomy that separates VRP research along five axes describing the type of study, characteristics of the problem scenario, the physical parameters of the problem, descriptions of the information flow, and properties of the data used. The authors then use this structure to classify almost 1,500 VRP-related articles published between 1954 and 2006. Braekers et al. (2016) apply the same overall framework to 277 papers published between 2009 and 2015 while proposing updates and changes to several taxonomy subcategories. The authors follow this with a statistical analysis of the characteristics of the VRPs and the methods researchers used to solve them. In a 2020 paper, Vidal et al. discuss VRP models in terms of three attributes: the model objectives, their integration with business decisions, and how specifically the models incorporate the properties of real-world problems. The authors define their classification scheme with less rigor than the taxonomy of Eksioglu et al. Instead, Vidal et al. explore how researchers have used VRPs to model business objectives beyond minimizing costs, such as maximizing performance ratios, balancing employee workloads, and simplifying route structures. The resulting survey provides a unique perspective on the VRP literature.

VRP Solution Methods

As previously noted, finding an optimal solution to a VRP by conducting an exhaustive search over all possible solutions is often infeasible for complex problems. While algorithms to find exact optimal solutions exist for some classes of VRP variants, researchers frequently rely on heuristics or metaheuristics to solve VRPs (El-Ghazali, 2009, p. 1). Researchers tend to develop heuristics for solving specific problem instances or problem types. In contrast, metaheuristics are usually general frameworks that researchers can apply to a broader range of VRP variants or other optimization problems (p. 21). Both techniques represent researchers' attempt to balance the trade-off between the time required to find an exact solution and the optimality of the results. Heuristics and metaheuristics identify near-optimal (or, in some cases, "good enough") solutions for large and complicated VRPs, and they do so over reasonable timescales.

Vidal et al. (2013) observe that "thousands of heuristics, meta-heuristics, and solution concepts . . . have been proposed in the [VRP] literature" (p. 1). The authors proceed to describe two types of heuristics: constructive heuristics that iteratively build up solutions and local improvement heuristics that find an initial solution and then search for better options in the surrounding solution space. Vidal et al. also review the metaheuristics commonly used to solve VRPs and group them into four categories: neighborhood-centered search, population-based methods, hybrid metaheuristics, and parallel and cooperative metaheuristics. Within these groups, the authors list some of the specific metaheuristics that, over time, have become well-established approaches to solving VRPs. These metaheuristics include simulated annealing, tabu search, guided local search, variable neighborhood search, genetic algorithms, path relinking, and ant colony optimization.

Research Versus Application

As mentioned previously, researchers have in many cases developed or refined VRP variants to more accurately model real-world routing scenarios. Despite the growing number of variants and the overall increase in VRP-related research, significant gaps remain between the study of VRPs and how logistics managers and route planners apply VRPs in practice. Perhaps ironically, this disparity has also become a topic of academic research. For instance, Drexl (2012) explains that while researchers can customize their programs to explore specific aspects of VRPs, commercial route planning software must be general and adaptable enough for use in a wide range of situations. Furthermore, whereas VRP researchers often work with cleaned, static data sets, real-world data is messy and dynamic. As the author notes, route planners and fleet managers typically don't gain any practical advantage from a sophisticated algorithm that produces marginal increases in the optimality of VRP solutions while increasing solving time. Based on survey results, Rincon-Garcia et al. (2018) report that transport managers are more concerned with other problems, such as route planning software that produces infeasible routing suggestions (for example, routing large trucks on roads with vehicle height limits). Another area of concern is delays and late deliveries caused by road congestion unaccounted for by the planning software. Alvarez et al. (2018) explore this problem in a case study using traffic data collected from Google Maps. The authors found that accounting for congestion and the resulting increases in vehicle travel time enhanced VRP optimization results. In addition, using time-dependent traffic data improved the VRP solutions even further, reducing route times by up to 11 percent.

While Alvarez et al. (2018) used data that measured changes in traffic volume throughout the day, they did not collect the data in real time. The practical need for route planners and dispatchers to respond to events as they happen led researchers to create a VRP variant known as dynamic VRPs (DVRP). As Pillac et al. (2013) explain, DVRPs incorporate incoming information and periodically or continuously reoptimize routes. According to the authors, this incoming data could represent updated traffic conditions, new or revised customer requests, or shifting service times. Mobile communication technology then enables dispatchers to convey necessary route adjustments to drivers, in some instances by automatically updating an in-vehicle navigation system. Eglese and Zambirinis (2018) add to the list of potential incoming data sources in their discussion of disruption management. The data in this context would concern sudden changes to planned delivery routes caused by vehicle breakdowns, emergencies, staffing shortages, or other unforeseen events. Managing these situations requires not only reoptimizing route plans but re-evaluating objectives and re-calculating costs in light of new information.

Dynamic information flows and changing conditions are two potential characteristics of another VRP variant researchers have labeled Rich Vehicle Routing Problems or RVRPs. Compared to standard VRPs, RVRPs typically include constraints and objectives that are more numerous and more complicated, making the resulting model more realistic. However, researchers have not settled on a formal definition of RVRPs, as observed by Lahyani et al. (2015). The first branch describes the attributes of the RVRP scenario associated with strategic and tactical business decisions, such as the number of depots and whether vehicles can run multiple routes. The second branch classifies the physical characteristics of the problem that influence operational decisions, including delivery time windows, vehicle types, and capacity constraints. Lahyani et al. then conduct a clustering analysis on 41 RVRP-related research papers, leading to their proposed definition for RVRPs that specifies the numbers and types of problem attributes required for classification as "rich." Caceres-Cruz et al. (2015) define RVRPs more broadly as VRPs that involve complex constraints and more closely model aspects of real-world route planning scenarios. The authors foresee further developments in RVRP complexity and solution methods that will help close the gap between academic research and real-world applications.

Route Optimization

The preceding discussion gives some sense of both the depth and breadth of academic research into VRPs. Yet, no matter how complex or abstract are the models researchers build, VRPs are ultimately rooted in practical considerations. Indeed, Dantzig & Ramser (1959) formulated their "Truck Dispatching Problem" (p. 80) to optimize delivery routes for tanker trucks servicing gas stations. By the 1980s, software vendors began integrating the VRP modeling techniques developed by researchers into commercially available route-planning software (Scientific Logistics, 2008). Businesses used the new software to revamp or replace existing, highly inefficient, manual route planning processes. As computing power grew, vendors continued to improve their product's performance, in some cases by adapting the algorithms and heuristics developed by academic researchers. Over time, automatic route optimization became an increasingly necessary tool for firms in the transportation and logistics industries, evolving into a critical component of an overall business strategy focused on efficiency and cutting costs.

A Sample of Route Optimization Applications and Benefits

One can find examples of businesses benefiting from route optimization in trade publications across a range of industries. Kelley (2014), for example, reports on a beverage distribution company that lowered their overall fleet mileage by 16% using route planning software. The company restructured routes and reduced its fleet while adapting to a concurrent increase in delivery volume. Marsh (2018) describes the savings realized by a catering company when using routing software developed by Paragon. The caterers lowered overall fuel consumption by seven to nine percent while cutting delivery-related labor costs by $15,000 per month. Hall (2011) briefly notes that global logistics firm Martin-Brower Co., also using a Paragon optimization system, significantly reduced operating costs by trimming 5,000 miles from its weekly fleet mileage. Beaudry (2009) states that the optimization software offered by his company helped one HVAC business cut miles driven by six percent while simultaneously increasing the utilization of its fleet by 20%. Green-Kerr (2020) includes improved customer service among the benefits of route optimization for plumbing and HVAC businesses. Combined with real-time location tracking, routing software can help dispatchers determine which vehicle they should send to reach a customer fastest or within a specific time window. Optimization can also improve efficiency in the waste hauling industry, as detailed by Fickes (2010). The Baltimore Department of Public Works, for example, saved an estimated $6 million by creating a more efficient waste collection route structure and reducing the size of its fleet.

While many companies pursue route optimization purely for cost savings, the resulting reduction in the overall fleet miles driven also provides environmental benefits by decreasing vehicle emissions. Increasing awareness of the environmental impact of delivery and logistics operations has prompted software vendors to account for vehicle emissions when optimizing route plans. For instance, Terreri (2011) reviews a system designed by Transplace that allows shippers to gauge the effects of different routing scenarios on the shipper's carbon footprint. Another product from Roadnet uses dynamic route optimization to increase route density, thereby decreasing emissions. Reeve (2019) reports on the updates that vendors such as Paragon and Trakm8 made to their route planning software to model electric vehicles (EVs). Trakm8's optimization algorithm, for example, factors in the effects of "payload, average speed, route topography, weather, and driver style" on EVs (p. 46), which resonates with the electric vehicle routing problem formulated by Lin et al. (2016). Parker (2020) explores an electric delivery vehicle from the Workhorse Group, Inc., noting the fuel and maintenance savings it provides compared to traditional fossil fuel vehicles. In addition, the Workhorse's EVs include integrated location tracking technology to enable dynamic route optimization and communication of route adjustments.

The collection of vehicle location data in real-time represents a growing trend in the transportation and logistics industries. In addition to route planning, companies can use this data in conjunction with fleet management software to increase vehicle utilization and proactively plan maintenance (Albright, 2016). Many software vendors have integrated route optimization and fleet management functionalities with other components such as cargo tracking tools to produce feature-rich transportation management systems (Hoffman, 2012). Vendors can customize these systems to the needs of individual companies, whether the company uses third-party freight carriers or owns its fleet (McCrea, 2014, "Filling the gaps with TMS"). Larger logistics firms might require even more sophisticated supply chain management software. This enterprise solution connects route planning to optimization processes throughout the supply chain, including warehouse management, vehicle load planning, shipment scheduling, and sequencing ("The Evolution of Optimization Technologies," 2010).

Human Component

Despite the advances in mobile technology, the ever-improving algorithmic solving methods, and full-featured software, route planning remains a hands-on activity. As Huff (2006) notes in an article about courier company DHL, "Often, what a computer calculates as mathematically possible is different from what experienced fleet operators say is reality" (p. 24). At least two factors contribute to this problem. The first is the quality of the road network data used by the route optimization software. Klie

(2006), for example, notes that U.S. highway traffic restriction data was at times incomplete or missing from some early routing software. Drexl (2012) remarks on a similar lack of reliable data for Western European highways. Fortunately, vendors can fix this issue by updating their software to incorporate the latest available information, gradually improving the quality of recommended route plans.

The second factor is more complex, involving the objective functions of the VRPs that underly optimization software. As discussed in the VRP Variants section, researchers often develop versions of the VRP that incorporate multiple aspects of real-life situations. In many cases, this process involves adjusting the mathematical model to add additional cost factors or penalties that decrease the optimality of specific routing options. However, the inverse relationship between model fidelity and model tractability limits the detail researchers can include in any VRP. In addition, no researcher or software vendor can anticipate every local circumstance a driver might encounter on the road. As a result, solutions that optimize the objective function of a VRP may not match solutions that optimally meet the objectives of route planners and drivers. Often, the resolution of this difficulty involves human review. DHL, for example, tasked operations managers with checking suggested route plans and modifying them as needed before the routes were reoptimized (Huff, 2006). Fickes (2011) describes a similar approach among companies in the solid waste industry. Dispatchers can review vehicle location tracking data to learn where drivers deviated from the route suggested by optimization software. Managers then follow up with the drivers to determine why they made changes and decide whether future route plans require similar manual adjustments. In this way, businesses profit from the institutional knowledge held by experienced drivers while taking advantage of the efficiencies produced by route optimization.

Summary and Conclusion

In this literature review, I presented a broad survey of academic research into a wide range of VRP variants, from the basic model Dantzig and Ramser (1959) developed to RVRPs that incorporate multiple, complex restraints and dynamic information flow. I briefly discussed some methods for finding optimal or near-optimal solutions for VRPs, such as heuristics and metaheuristics. I described the apparent gap recognized by Drexl (2012) and others between VRP research and route optimization in practice. I then examined some business applications of VRPs, noting the benefits in terms of cost savings and environmental impacts. I also found that vehicle tracking technology and integration into business optimization processes can enhance the value of route planning software. Finally, I considered the continuing and vital role of experienced route planners and logistics managers in reviewing and revising algorithmically generated route plans.

VRPs, like all models, represent a simplification of the real world. By design, VRPs shift the process of route optimization from reliance on human experience and intuition toward a solid mathematical foundation. In doing so, VRPs necessarily omit many nuances that characterize the route planning collectively done by dispatchers, logistics managers, and drivers. Still, the flexibility of the VRP model and the ability to build complex variants using the same basic framework allow researchers to continue developing versions of the VRP that are more accurate and useful for practical applications. It remains to be seen whether this progress will eventually plateau or whether it will continue indefinitely.

Chapter 3: Research Methodology

This chapter will describe the research methodology used to construct and solve the Vehicle Routing Problems (VRPs) modeling each of the library delivery regions proposed by the Wisconsin Public Library System Redesign (PLSR) Delivery Workgroup (Public Library System Redesign Delivery Workgroup, 2018). This research supplements the work done by the Delivery Workgroup with an analysis of the feasibility of route structures within practical constraints, the calculation of an optimal regional route configuration, and the determination of the parameter values that allow a feasible model. What follows is an explanation of the research approach, the tools used, the collection and preparation of data, and the analytic procedure used to explore the different regional models.

Research Methods

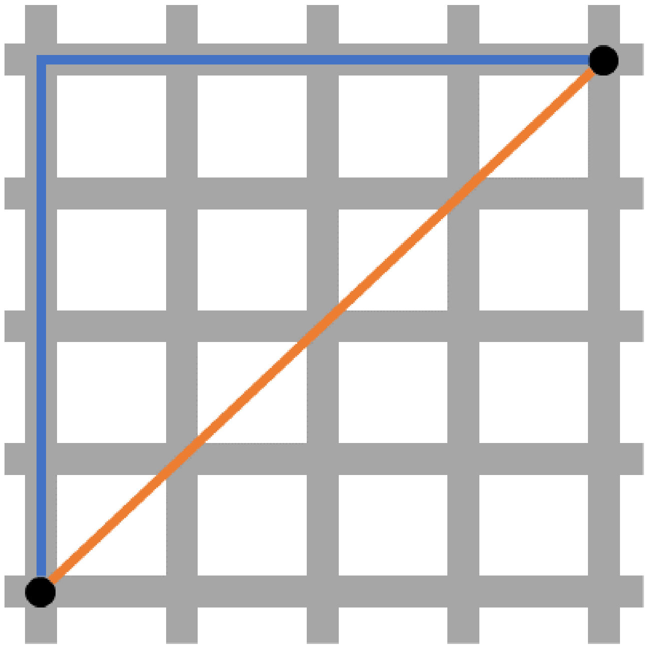
The modeling approach used for this project relies on the similarity between the PLSR Delivery Workgroup's regional library delivery service model and the formulation of the VRP. For example, while recognizing that not every library needs daily delivery, the Workgroup designed each region such that all public libraries in the state would, at least, have delivery services available Monday through Friday (Public Library System Redesign Delivery Workgroup, 2018, p. 34, p. 15). Therefore, the regional route planning process should account for the scenario in which every regional library receives a delivery stop, even if this situation is unlikely to occur. This scenario echoes the standard version of the VRP, where each customer gets one service stop from one vehicle, with no option to skip customers. Thus, the regional VRP solutions could serve as a model for regional routes at their maximal extent that route planners could subsequently adjust to meet actual daily stop schedules. Likewise, the Delivery Workgroup envisioned the local delivery routes in each region originating from and returning to a regional hub, corresponding to the single depot of the basic VRP. The Workgroup also set a goal for the maximum duration of regional routes at eight to nine hours to allow time to sort materials and ship them via inter-system delivery connections (p. 12). Incorporating this constraint extends the standard VRP, making it a Time-Constrained VRP. Furthermore, based on professional experience, I added a vehicle capacity constraint to represent the maximum number of containers that will fit in a typical cargo van. With this final modification, the model for each region became a Time-Constrained Capacitated VRP or TCCVRP.

To construct and solve the regional TCCVRPs, I selected the Google OR-Tools module available for the Python programming language ("OR-Tools," n.d.). This module is free to download and contains an algorithmic solver specifically designed to solve routing problems, such as the Traveling Salesperson Problem and common VRP variants. For these relatively simple problems, the OR-Tools module offers a level of programmatic customization options for problem constraints and parameters that is practical without being overwhelming. In addition, Google provides code samples in the online documentation for the routing library ("Vehicle Routing | OR-Tools," n.d.), which I adapted for use in this project. Appendix A contains a link to the project code hosted on Github and descriptions of the Python script files.

Among the sample programs in the OR-Tools routing library documentation is code demonstrating the use of the Google Distance Matrix Application Programming Interface (API) to build distance and duration matrices ("Vehicle Routing Problem | OR-Tools," n.d., "Using the Google Distance Matrix API"). The distance matrix stores the distance from each stop in the VRP to the depot and every other location, while the duration matrix represents the same information measured in terms of travel time. One or both matrices can serve as VRP input data for use by the OR-Tools routing solver. An advantage of Google's Distance Matrix API is that it returns distance and duration measurements as

Figure 3

Example of Euclidean Distance Versus Along-the-Road Distance



Note. The blue line represents along-the-road distance between the two points, which in this example is 8 units. The orange line shows the Euclidean path and has a length of $\sqrt{32} \approx 5.66$ units. Adapted from *Taxicab geometry*, by Psychonaut, 2006, Wikipedia (https://en.wikipedia.org/wiki/Taxicab_geometry). In the public domain.

traveled on the real-world road network between two locations rather than a Euclidean distance measured along a straight line from one point to the other. As demonstrated in Figure 3, Euclidean paths are shorter than along-the-road paths in terms of length and, assuming a constant speed, time. In a 2018 paper, De Miranda Sá and Maghrebi investigated the difference between actual travel times and Euclidean (or spatial) travel times in the context of a specialized VRP variant known as the Ready Mixed Concrete Dispatching Problem. According to data collected from the Google Maps API, the authors found that Euclidean duration measurements underestimated actual point-to-point travel time by 21.3% (p. 7).

While Google's Distance Matrix API provides accurate distance and travel time measurements, the service has a fee schedule that rendered it impractical to use for this project. Instead, I collected the VRP input matrix data from a free platform maintained by the Heidelberg Institute for Geoinformation Technology called OpenrouteService ("Openrouteservice," 2020). Like the Google Maps Platform, Openrouteservice provides a Python module and an API to its Matrix Service, from which users can request both distance and duration matrix data. To limit the number of API calls needed to complete my research, I used the Python 'pickle' module to save the matrices for each PLSR region to external files. Storing the data allowed me to avoid API request quotas and eliminated the need for real-time matrix data collection from an Internet source, reducing the time required to solve VRPs. Copies of the pickled matrix data are available in the project code GitHub repository; see Appendix A for the link to the project page.

Data Collection

The regional library delivery TCCVRP requires two pieces of information for each library stop. The first is the library's location. On their website, the Wisconsin Department of Public Instruction maintains a directory listing the address of every public library, library branch, and outreach service (such as bookmobiles) in the state ("Wisconsin Public Library Directory," n.d.). The data in the online directory is also available as an Excel file. I downloaded the Excel workbook and modified it to serve as a pseudo-database consolidating data on all Wisconsin library delivery stops, public and non-public (academic, school, and state government libraries). For non-public libraries, I collected addresses from library websites or location searches on Google Maps and manually entered the data into the spreadsheet. The complete data set consisted of 626 libraries and, after accounting for redundant addresses, 591 separate delivery stops.

The second input data necessary for the TCCVRP is the demand at each stop, i.e., the volume of outgoing material. In 2017, the PLSR Delivery Workgroup conducted a weeklong volume sample to estimate how many delivery containers public library system delivery services throughout the state typically transferred. Through correspondence with Delivery Workgroup member Corey Baumann (C. Baumann, personal communication, June 14, 2021), I obtained a copy of the PLSR sample data, which I added to the library data Excel file. I retrieved additional volume data for non-public library stops that receive direct service from the South Central Library System from records I maintain. Though the PLSR Delivery Workgroup did not record the exact dates of the public library data sample in their report, I attempted to match the non-public library demand data to roughly the same time in spring 2017.

Data Preparation

I began preparing the data by manually splitting each library address into elements stored in separate spreadsheet columns. The list of address components included:

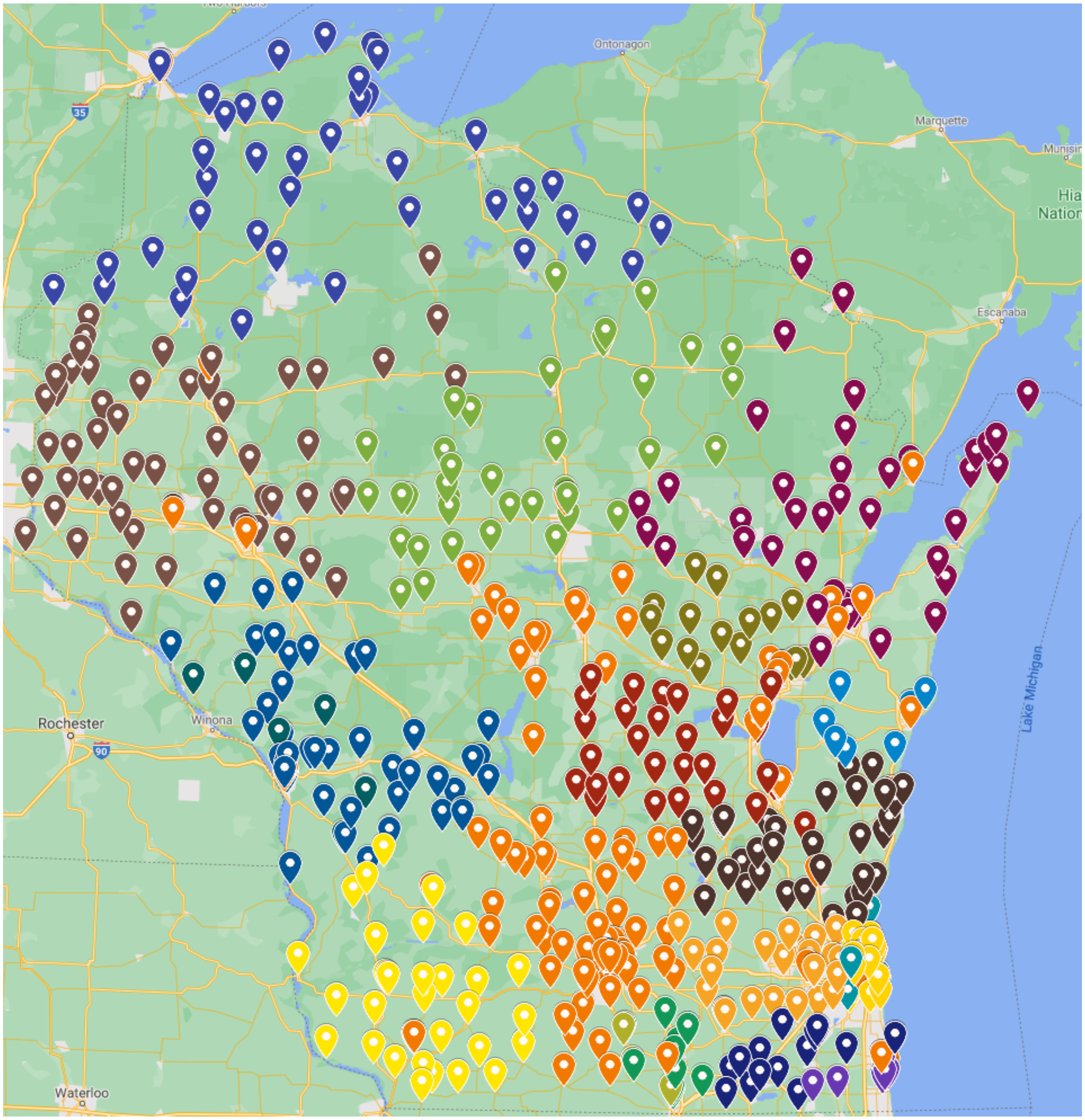
- building number
- street direction prefix
- street name
- street type suffix
- street direction suffix
- building unit number (e.g., "Suite L," "#100")
- city
- state
- zip code

Next, I used Excel functions to reassemble the address fields into a single string. I omitted the building unit numbers because they appeared to cause parsing problems and plotting errors in the step that immediately followed: importing the data set into a Google Map with a marker for each library's location, as shown in Figure 4. This map enabled a process of manual verification to check that the addresses recognized by Google Maps corresponded to real-world library sites. Fifty-two stops had plotting errors with various causes; for these stops, I retrieved a Google Maps Plus Code ("Plus Codes," n.d.) and copied it to the library data file. Next, I wrote a utility script designed to send a data request to the Google Maps Geocoding service and translate each stop's address or Plus Code into a set of geographical coordinates ("Overview | Geocoding API," n.d.). Finally, I created a new Google Map that re-plotted the library sites using their geolocations, then I manually verified that the Google Maps service had accurately marked each stop. Converting the location data for each library to geographical coordinates not only ensured formatting consistency, but it made the data easier to process in subsequent steps such as constructing Openrouteservice's Matrix Service API requests.

The delivery volume data required fewer preparatory steps. For the PLSR Delivery Workgroup sample, library systems recorded the number of containers dropped off and picked up at each stop for every day of the sample week. I summarized this data by calculating the average daily pick-up at each library to represent typical demand. I rounded this figure up to the nearest integer using the rationale that partially filled containers take up the same amount of space in a delivery vehicle as full containers. For stops with no data, I assumed a weekly average demand of one container. My reasoning for this imputation was that every library would usually have something to pick up over a week. Furthermore, while the number of items picked up might be minimal, they nonetheless would consume some of the available vehicle capacity and, therefore, the TCCVRP should account for them.

Figure 4

Wisconsin Library Locations Plotted on a Google Map



Note. Markers are color-coded by delivery service provider as of July 2021.

Subsequent steps in the data preparation process involved adding columns to the spreadsheet to serve as additional fields in each library record. Some of the fields were useful for reporting results from the Google OR-Tools routing solver, including the library type (e.g., "public library," "uw madison," etc.), a shortened form of the library name, and the library system from which the stop currently receives delivery service. I also added Boolean fields to track whether the library delivery volume data was missing in the PLSR Delivery Workgroup volume sampling data set and whether the stop was a redundant address (such as a library system headquartered in a library building). The latter field provided a means of filtering the delivery stops in each region to include only those at unique locations, with implications related to the estimated service time required to complete the delivery. Service time represents an additional stop cost accounted for in the TCCVRP models in terms of route duration. As far as I am aware, no data measuring actual service time at individual stops exists, but the estimate commonly used is seven minutes (C. Baumann, personal communication, June 14, 2021). I included this figure in another spreadsheet column. Two more Boolean columns indicated whether a stop was a potential regional hub in either the ideal proposal of the PLSR Delivery Workgroup or the starting point proposal (Table B1 in Appendix B lists the regional hub locations). Finally, I wrote another utility script to map each library to a region number in both proposals. Conveniently, the service area borders proposed by the Workgroup followed county lines; thus, I used the "County" field included in the Wisconsin Department of Public Instruction's Public Library Directory as the lookup value to determine the proposed region number. The project code GitHub repository contains copies of the original data file used for this project and the same file after processing to add geocoded location data and regional designations for each library. Appendix A contains a link to the project code and descriptions of the data files.

Data Analysis

I conducted the bulk of the data analysis for this project using the Google OR-Tools routing solver. Using Python, I developed a program to configure each regional TCCVRP according to parameters submitted by a user through command line arguments. I intended to allow flexibility in setting up the TCCVRP models to enable users to explore various routing scenarios. The input parameters, for example, included:

- the number of delivery vehicles available,
- the maximum number of hours allowed per shift,
- the maximum number of miles driven allowed per route,
- the capacity of each vehicle measured by the number of containers, and
- the driver's break time in minutes.

In addition, users could select the strategy used by the routing solver to construct an initial solution to the TCCVRP and the metaheuristic approach used to search for a more optimal solution within the local solution space of the current best model. The routing solver in the Google OR-Tools module includes 13 alternatives for the first solution strategy and five search metaheuristics. There is also an "automatic" option that allows the solver to choose the methods. Finally, users could decide whether the solver should balance routes in terms of time or distance traveled.

As previously mentioned, the PLSR Delivery Workgroup set a goal for a maximum route duration of 8-9 hours (Public Library System Redesign Delivery Workgroup, 2018, p. 12). However, while the Workgroup did report a desire to keep every regional library within a 100-mile radius of the delivery hub, they did not specify a maximum route distance. Based on this information, I attempted to solve each regional TCCVRP twice, once using a route duration constraint value of 8 hours and once using 10 hours. I simultaneously deprioritized the route distance constraint by setting it at 500 miles, a value longer than most existing library delivery routes. I used three different values for the vehicle capacity constraint, 40 containers, 60 containers, and 200 containers. Like the approach taken with the route distance constraint, I included the last number to negate the volume constraint. However, this technique proved insufficient for some regions, so I created a version of each regional model with the capacity constraint programmatically removed (a Time-Constrained VRP or TCVRP). The final parameter was the length of mandatory driver break time – I used a value of 30 minutes for every TCCVRP and TCVRP I analyzed.

In the interest of completeness, I planned to run each regional TCCVRP model using every combination of first solution construction strategies and local search metaheuristics compatible with the problem configuration. As I will discuss in detail in Chapter 4, preliminary results led me to reduce the number of initial solution strategies from the 13 available to four, including the automatic option. I also allowed the solver to select the search metaheuristic automatically throughout my research. With two possible shift lengths and four possible vehicle capacities (40, 60, 200, and none), I solved each regional model 32 times. Accounting for the seven regions of the Delivery Workgroup's ideal proposal and the eight in the starting point proposal resulted in 480 model runs. I also designed the program with a feature to iteratively solve the TCCVRPs with a variable number of vehicles, starting with one and successively incrementing until the solver returned a solution or reached a maximum of 15. The changeable fleet size increased the maximum number of model parameter combinations to 7,200, though, in practice, I did not test every possible vehicle count.

To track the results of these experiments, I created a numbering system by which I could encode parameter values and identify each version of the TCCVRP (an explanation of the numbering system codes is included in Appendix C). I used these model ID numbers in an Excel spreadsheet to track whether the routing solver found a feasible solution to the regional TCCVRP, addressing my first research question. To answer the second question regarding route configurations, I added two software features for recording the solver's results. The first was exporting the results to a text file. For each route in a region, I saved the stop sequence, the distance, time, pick-up volume, count of stops, and the start and end times of the driver's mandatory break. I also included the sums of time and distance for all vehicles in the regional fleet, as shown in Figure 5. The second output was a plot of the routes on a Google map saved as an HTML file. This visualization showed the library stop sequence and the suggested path of each vehicle on the real-world road network, as demonstrated in Figure 6. Finally, to resolve my third research question about route parameters, I documented the size of the fleet in each model where the solver found an optimal solution. This data, along with the information encoded in the model identification number, allowed me to determine which combinations of parameters produced feasible models.

Figure 5

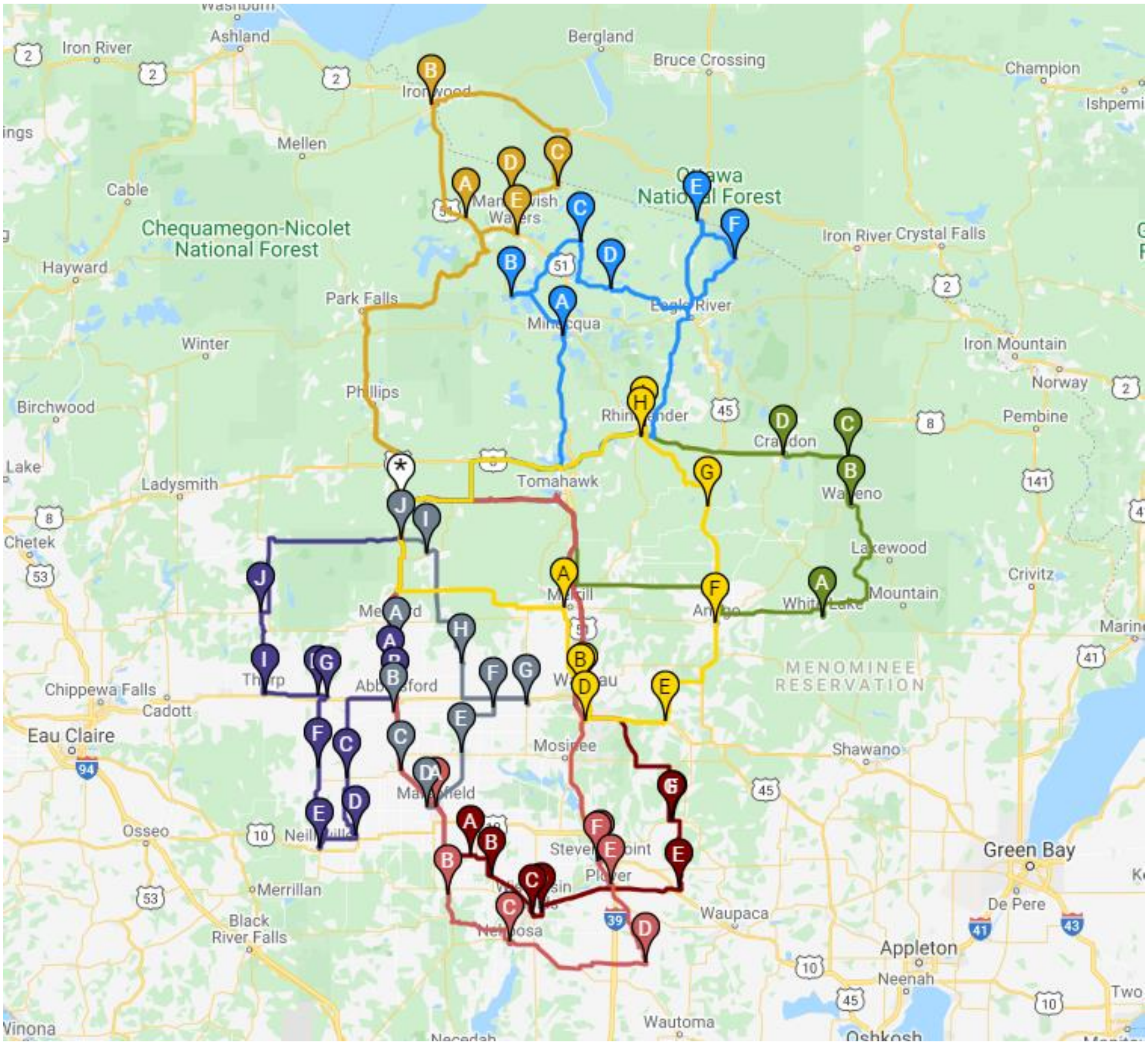
Sample Routing Solver Solution Formatted as Text

```
Model ID: str5_100205
Starter proposal, region 5

Solution strategies:
    First solution strategy: savings
    Local search metaheuristic: automatic

Model parameters:
    Maximum hours per route: 10.0
    Maximum distance per route: 500.0 miles
    Vehicle capacity: 60
    Driver break time: 30.0 minutes
    Number of vehicles/routes: 3

Route for vehicle 1:
    Winding Rivers LS -> LaxCo - Holmen PL -> Trempealeau PL -> Cochrane-Fountain City SD -> Alma PL -> Mondovi PL ->
    Strum PL -> Osseo PL -> Whitehall PL -> Independence PL -> Arcadia PL -> Arcadia HS -> Blair PL -> Taylor PL ->
    Jackson CI -> Black River Falls PL -> Melrose-Mindoro SD ->  Winding Rivers LS

    Route distance: 228.00 miles
    Route time: 8 hours, 28 minutes
    Route load: 39 containers
    Number of stops: 16
    Break: start time = 5 hours, 34 minutes; end time = 6 hours, 4 minutes

Route for vehicle 2:
    Winding Rivers LS -> LaxPL - North Community Branch -> Western TC -> Viterbo University -> LaxPL - South Community
    Branch -> Coon Valley PL -> Westby PL -> Viroqua SD -> Viroqua PL -> La Farge HS -> La Farge PL -> Hillsboro PL ->
    Wonewoc PL -> Wonewoc-Union Center HS -> Elroy PL -> Kendall PL -> Ontario PL -> Cashton HS -> Cashton PL ->
    Norwalk PL -> Wilton PL -> Tomah PL -> Sparta PL -> LaxCo - Bangor Branch -> LaxCo - West Salem PL ->  Winding
    Rivers LS

    Route distance: 196.76 miles
    Route time: 8 hours, 37 minutes
    Route load: 59 containers
    Number of stops: 24
    Break: start time = 5 hours, 41 minutes; end time = 6 hours, 11 minutes

Route for vehicle 3:
    Winding Rivers LS -> Holmen MS/HS -> Galesville PL -> Ettrick PL -> LaxCo - Onalaska PL -> LaxCo - Campbell Branch
    -> LaxPL - La Crosse PL -> UW-La Crosse -> De Soto PL -> Readstown PL -> Mauston PL -> New Lisbon PL -> New Lisbon
    CI -> Necedah PL ->  Winding Rivers LS

    Route distance: 263.96 miles
    Route time: 8 hours, 32 minutes
    Route load: 52 containers
    Number of stops: 13
    Break: start time = 4 hours, 18 minutes; end time = 4 hours, 48 minutes

Total distance, all routes: 688.72 miles
Total time, all routes: 25 hours, 38 minutes
```

Note. The sample output shown is for region 5 of the PLSR Delivery Workgroup starting point proposal.

Figure 6

Sample Routing Solver Solution Visualized as a Google Map



Note. The sample output shown is for region 2 of the PLSR Delivery Workgroup ideal proposal.

Chapter 4: Research Results and Findings

This chapter will summarize the results obtained from solving Time-Constrained, Capacitated Vehicle Routing Problems (TCCVRPs) representing all the library delivery regions proposed by the Wisconsin Public Library System Redesign (PLSR) Delivery Workgroup (Public Library System Redesign Delivery Workgroup, 2018). The first section describes exploratory research into reducing the number of parameter options available from the Google OR-Tools routing solver for the first solution strategy and local search metaheuristic. The second section lists the results found by the solver using different values for the vehicle capacity parameter and discusses data quality issues related to library demand data. Finally, section three examines how the choice of the first solution strategy and the value of the maximum route time constraint affect the regional TCCVRP models.

Preliminary Research: First Solution Strategies and Local Search Metaheuristics

As discussed in the "Data Analysis" section of Chapter 3, the Google OR-Tools package allows users to specify which technique the routing solver should use to construct an initial feasible solution to a VRP ("Routing Options | OR-Tools," n.d.). Of the 13 possible choices, five were incompatible with the VRP formulations used in this research: three require additional inputs related to model settings, and two apply only VRPs with optional stops. Discarding these methods left seven first solution strategies available for further investigation, plus an automatic option in which the solver chooses the strategy. The OR-Tools module also includes five metaheuristic approaches by which the solver attempts to improve upon the initial result with a search of the nearby solution space. Four of these options were compatible with the regional TCCVRPs (greedy descent, guided local search, simulated annealing, and tabu search) along with another automatic option. Having no previous experience with VRP research, I decided to investigate which combinations of solve and search methods produced the best results while solving the same problem.

To begin this exploratory research, I first chose the VRP formulation of region 1 of the PLSR Delivery Workgroup ideal proposal as my standard model. I then selected values for the other VRP setup parameters. I held these values constant while varying the choices of the first solution strategy and local search metaheuristic. The parameter values I selected were:

- "duration" (or route time) as the constraint by which the solver should attempt to balance the solution
- maximum route time of 8 hours
- maximum route distance of 500 miles
- vehicle capacity of 60 containers
- mandatory 30-minute driver break

In addition, I set a 15-second time limit for the solver to search for an improved solution, after which it would return the current best solution.

To measure the performance of the initial solution strategy and metaheuristic combinations, I recorded the number of vehicles needed for the routing solver to find a feasible solution to the ideal proposal region 1 TCCVRP. The reasoning behind my choice of performance metric was that all else being equal, a smaller fleet size likely represented a more efficient solution and, therefore, a better mix of approaches to solving the VRP. To find the required fleet size as efficiently as possible, I enabled the iterative solving feature to automatically add one vehicle to the TCCVRP formulation until the solver found a feasible solution. As shown in Table 1, the first solution strategies that identified solutions using the smallest fleets were the savings algorithm, the Christofides algorithm, and the parallel cheapest insertion method. In subsequent modeling, I varied the first solution strategy among these three methods and the automatic option, which I included for a baseline comparison. The preliminary modeling results also indicated that changing the local search metaheuristic did not affect the number of vehicles the routing solver needed to find an optimal solution. Therefore, rather than run each regional TCCVRP model using every combination of solve and search strategies, I chose to use the automatic setting for metaheuristic selection throughout my subsequent research.

Table 1

Number of Vehicles Needed to Solve PLSR Delivery Workgroup Ideal Proposal Region 1 TCCVRP

First solution strategy	Local search metaheuristic				
	Greedy descent	Guided local search	Simulated annealing	Tabu search	Automatic
Path cheapest arc	13	13	13	13	13
Savings algorithm	11	11	11	11	11
Christofides algorithm	12	12	12	12	12
Parallel cheapest insertion	12	12	12	12	12
Local cheapest insertion	14	14	14	14	14
Global cheapest arc	NA	NA	NA	NA	NA
Local cheapest arc	NA	NA	NA	NA	NA
First unbound minimum value	NA	NA	NA	NA	NA
Automatic	13	13	13	13	13

Note. "NA" indicates the routing solver did not find a feasible solution using a fleet size of 15 vehicles or less.

Routing Solver Results: Analysis of Vehicle Capacity Parameter

The first research question addressed by this project asked whether the Google OR-Tools routing solver could identify a feasible route structure for each regional service area proposed by the PLSR Delivery Workgroup within a time constraint of 8-9 hours, a range which I expanded to 8-10 hours. The results produced by the solver indicate that there is a feasible route structure for every region but not necessarily within a consistent or realistic set of parameter values. Summaries of the solutions found for each regional TCCVRP follow, organized by the value of the vehicle capacity parameter chosen for each group of models.

Vehicle Capacity: 40 Containers

As Table 2 shows, setting the vehicle capacity parameter to a maximum of 40 containers resulted in several models where the routing solver could not find a feasible solution using any combination of first solution strategy, maximum route time, and the number of vehicles. In some cases, aggregate library demand in the region exceeded the 600-container upper limit on cumulative vehicle capacity (allowed maximum 15 vehicles X 40 containers per vehicle = 600 containers). Regions 6 & 7 from the PLSR Delivery Workgroup's ideal proposal and regions 7 & 8 of the starting point proposal (labeled "starter" proposal in the table) violated this constraint. Regions 3 & 5 of the ideal proposal and starting point proposal regions 4 & 6 included individual libraries with demand greater than or equal to 40, making feasible solutions impossible. The explanation for the failure to solve region 1 of the ideal proposal is less clear. However, this region does include one library with a demand value of 35 baskets, which would limit the number of additional stops the route vehicle could make. This region is also geographically widespread (refer to Figure 1, Chapter 1), so reducing the length of one route may have made it impossible to serve the rest of the libraries within the maximum route time constraint.

Table 2

Number of Vehicles Needed to Solve Regional TCCVRPs with Vehicle Capacity 40

Proposed region	First solution strategy & maximum route time							
	Savings		Christofides		Parallel cheapest insertion		Automatic	
	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.
Ideal proposal 1	NA	NA	NA	NA	NA	NA	NA	NA
Ideal proposal 2	8	NA	7	6	9	8	9	7
Ideal proposal 3	NA	NA	NA	NA	NA	NA	NA	NA
Ideal proposal 4	NA	5	5	4	6	6	6	5
Ideal proposal 5	NA	NA	NA	NA	NA	NA	NA	NA
Ideal proposal 6	NA	NA	NA	NA	NA	NA	NA	NA
Ideal proposal 7	NA	NA	NA	NA	NA	NA	NA	NA
Starter proposal 1	6	4	6	5	6	5	6	5
Starter proposal 2	NA	NA	9	9	9	9	9	9
Starter proposal 3	5	4	5	4	5	4	5	5
Starter proposal 4	NA	NA	NA	NA	NA	NA	NA	NA
Starter proposal 5	5	4	5	4	5	5	5	4
Starter proposal 6	NA	NA	NA	NA	NA	NA	NA	NA
Starter proposal 7	NA	NA	NA	NA	NA	NA	NA	NA
Starter proposal 8	NA	NA	NA	NA	NA	NA	NA	NA

Note. "NA" indicates the routing solver did not find a feasible solution using a fleet size of 15 vehicles or less.

Vehicle Capacity: 60 Containers

Table 3 lists the results found after increasing the vehicle capacity to 60 containers. Within this group of models, region 5 of the ideal proposal and region 6 in the starting point proposal include the Oshkosh Public Library. According to PLSR sample data, Oshkosh has an average demand of 79 baskets. Regarding the vehicle capacity constraint, this demand value renders all possible VRP solutions infeasible. Because the PLSR data lacks accompanying documentation, the reason for this anomaly is not entirely evident. Reasonable speculation might be that this number represents the containers delivered to the Winnefox Library System hub located in the same building. If so, the quantity measured is the average sum of containers dropped off daily at Winnefox member public libraries, which is not relevant in this context. This issue also raises questions regarding the reliability of demand figures listed for other public libraries that house library system hubs, such as the Racine Public Library (Lakeshores Library System) and Appleton Public Library (Outagamie-Waupaca Library System).

Vehicle Capacity: 200 Containers

One means of counteracting the effect of inaccurate library demand data is to loosen the demand constraint by setting the vehicle capacity to an improbably high value like 200 containers. The results in Table 4 show that this change makes nearly every model variation solvable, with solutions generally in line with expectations. The largest fleets, for example, were required for region 1 of the ideal proposal (extensive geographic range) and region 7 of the starting point proposal (high volume and a large number of stops). Notably, the savings algorithm failed to solve five regional VRPs. The routing solver documentation does not include any details regarding the algorithm's programmatic implementation ("Routing Options | OR-Tools," n.d.), so it is unclear why this strategy, in particular, could not find an initial solution for some regions.

Table 3

Number of Vehicles Needed to Solve Regional TCCVRPs With Vehicle Capacity 60

Proposed region	First solution strategy & maximum route time							
	Savings		Christofides		Parallel cheapest insertion		Automatic	
	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.
Ideal proposal 1	11	NA	12	9	12	10	13	10
Ideal proposal 2	NA	6	8	6	9	7	8	7
Ideal proposal 3	7	6	8	6	9	7	8	6
Ideal proposal 4	5	4	6	4	6	4	6	4
Ideal proposal 5	NA	NA	NA	NA	NA	NA	NA	NA
Ideal proposal 6	NA	NA	13	12	13	12	13	11
Ideal proposal 7	NA	NA	12	12	12	NA	12	12
Starter proposal 1	6	4	6	5	6	6	6	4
Starter proposal 2	NA	NA	6	6	7	6	7	6
Starter proposal 3	NA	4	5	3	5	4	5	4
Starter proposal 4	7	6	8	6	8	7	8	6
Starter proposal 5	4	3	4	3	5	4	5	4
Starter proposal 6	NA	NA	NA	NA	NA	NA	NA	NA
Starter proposal 7	14	NA	15	13	15	13	15	13
Starter proposal 8	12	12	13	NA	12	NA	12	12

Note. "NA" indicates the routing solver did not find a feasible solution using a fleet size of 15 vehicles or less.

Table 4

Number of Vehicles Needed to Solve Regional TCCVRPs With Vehicle Capacity 200

Proposed region	First solution strategy & maximum route time							
	Savings		Christofides		Parallel cheapest insertion		Automatic	
	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.
Ideal proposal 1	9	NA	10	7	11	7	11	8
Ideal proposal 2	NA	5	8	6	9	6	8	6
Ideal proposal 3	5	4	7	5	7	6	7	5
Ideal proposal 4	5	4	6	4	5	4	5	4
Ideal proposal 5	6	4	6	5	6	5	6	5
Ideal proposal 6	7	6	8	6	8	6	7	6
Ideal proposal 7	NA	4	5	4	5	4	5	4
Starter proposal 1	6	4	6	5	6	6	6	4
Starter proposal 2	5	3	5	4	5	4	5	4
Starter proposal 3	NA	3	5	3	5	4	5	4
Starter proposal 4	5	4	7	5	7	6	7	5
Starter proposal 5	4	3	4	3	4	3	4	3
Starter proposal 6	7	5	8	6	7	5	8	5
Starter proposal 7	NA	7	10	8	11	8	10	8
Starter proposal 8	5	4	5	5	6	5	6	4

Note. "NA" indicates the routing solver did not find a feasible solution using a fleet size of 15 vehicles or less.

Removing Capacity Constraints

The results obtained from this research highlighted some of the data quality issues present in the PLSR volume sample data. One difficulty involved the inconsistency of counting methods across public library systems. The counts recorded for the Oshkosh Public Library, for example, are noticeable outliers, possibly caused by confusion between system container volume and library volume. The sample also contained missing data and counts recorded in non-useful ways (i.e., "handful of bins"). Considering the number of libraries sampled and the relative inexperience many library systems had with volume tracking, these types of problems were relatively rare. A more significant and widespread complication arose from the variety of container sizes used by different delivery services and the lack of an established method to standardize volume counts across the state. For instance, both the Northern Waters Library Service and the Outagamie-Waupaca Library System deliver materials using a mix of bins and bags, each counted separately. The question arises regarding how much volumetric space a presumably flexible bag occupies versus a rigid, plastic container. For libraries sending 10-20 bags daily, the answer is not trivial, and it could potentially transform a solvable capacitated VRP into one with no feasible solution.

While setting the vehicle capacity parameter at 200 containers likely helped mitigate these issues, stops with unusually high demand like Oshkosh Public Library could nonetheless affect the route structures produced by the routing solver. With this idea in mind, I decided to re-run the regional TCCVRPs with the capacity constraint removed, reducing each model to a Time-Constrained VRP. I continued with the same set of problem parameters values I used previously and recorded the number of vehicles the solver needed to find a feasible solution. Table 5 shows the results of this approach.

Table 5

Number of Vehicles Needed to Solve Regional TCVRPs With No Vehicle Capacity Constraint

Proposed region	First solution strategy & maximum route time							
	Savings		Christofides		Parallel cheapest insertion		Automatic	
	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.	8 hrs.	10 hrs.
Ideal proposal 1	9	NA	10	7	11	7	11	8
Ideal proposal 2	NA	5	8	6	9	6	8	6
Ideal proposal 3	5	4	7	5	7	6	7	5
Ideal proposal 4	5	4	6	4	5	4	5	4
Ideal proposal 5	6	4	6	5	6	5	6	5
Ideal proposal 6	7	5	7	6	8	6	7	5
Ideal proposal 7	4	4	5	4	5	4	5	4
Starter proposal 1	6	4	6	5	6	6	6	4
Starter proposal 2	5	3	5	4	5	4	5	4
Starter proposal 3	NA	3	5	3	5	4	5	4
Starter proposal 4	5	4	7	5	7	6	7	5
Starter proposal 5	4	3	4	3	4	3	4	3
Starter proposal 6	7	5	8	6	7	5	8	5
Starter proposal 7	9	7	10	8	11	8	10	7
Starter proposal 8	5	4	5	4	6	4	6	4

Note. "NA" indicates the routing solver did not find a feasible solution using a fleet size of 15 vehicles or less. Highlighted cells represent results that differ from the results obtained using a vehicle capacity of 200 containers (refer to Table 4 for comparison).

Removing the capacity constraint produced different outcomes for eight of the 120 models, roughly 7% of the total. In most cases (6 of 8), the solver identified a feasible route structure utilizing one fewer vehicle than the same model with a 200-container vehicle capacity. The other two models were instances in which the savings algorithm discovered a solution despite previously failing. Again, this difference in results was unique to the savings algorithm, and the cause was not immediately apparent. Finding an explanation, however, went beyond the scope of this project.

Vehicle Capacity Constraint: Summary

The preceding analysis shows that vehicle capacity significantly impacts the results returned by the OR-Tools routing solver. For some regions, limited capacity made it impossible to find a feasible solution to a regional TCCVRP. For almost every model, relatively larger vehicles provided the solver with more flexibility to solve the problem. In the real world, library delivery services in Wisconsin typically maintain a nearly homogenous fleet of cargo vans, each of which can carry 40-60 containers. Adding larger vehicles such as box trucks to the fleet would raise new concerns for these service providers. Chief among these is the vehicle purchase price: trucks and higher-capacity vans are generally more expensive than cargo vans. A varied fleet makeup also reduces the ability to benefit from economies of scale related to vehicle servicing. Trucks, for example, have unique maintenance needs and require different replacement parts than cargo vans. Finally, larger vehicles might be subject to travel restrictions such as vehicle height limits, or they could create navigation challenges in urban settings. Regional managers will have to determine the relative importance of each of these considerations while developing route plans. Ultimately, managers will need to decide whether an increase in vehicle capacity can reduce operational expenses and improve the efficiency of the regional route structure or whether the higher costs associated with trucks and mixed fleets would negate any savings.

Routing Solver Results: Analysis of Additional VRP Parameters

In my research into the influence of vehicle capacity constraint values on TCCVRP solutions, I evaluated the results solely by comparing the number of vehicles the OR-Tools routing solver needed to identify a feasible solution. However, the routing solver also tracked the cumulative route time and route distance for the regional fleet. I saved these metrics, along with individual route stop sequences, to text files for later review (Figure 5 in Chapter 3 shows an example of solver output). In addition to vehicle capacity, the duration and mileage results show the influence of two factors on solver outcomes: the strategy used to find an initial solution to the TCCVRP and the maximum number of hours allowed per route.

Initial Solution Strategy

This project focused on four methods used to find preliminary solutions to each regional TCCVRP: the savings algorithm, the Christofides algorithm, the parallel cheapest insertion method, and the automatic option in which the OR-Tools solver selects an appropriate technique ("Routing Options | OR-Tools," n.d.). For TCCVRPs with identical constraint values, the number of vehicles required for a feasible solution varied depending on the first solution strategy selected. Typically, the difference between strategies was one or two vehicles. This variation is modest in absolute terms, yet any increase in fleet size represents additional costs for vehicle purchases, fleet maintenance expenses, and staffing. As the PLSR project progresses, route planners and regional administrators will, without doubt, have a strong incentive to minimize the number of vehicles needed to deliver to all the libraries in their service territory. Therefore, determining which initial solution strategy or strategies produce results consistent with this goal is an additional question of interest for this project.

An exhaustive analysis of solution strategies and the mathematical processes by which each method builds an initial solution was beyond this project's scope. Still, even without this analysis, one can observe patterns in the results obtained by applying different strategies to the same problem. These observations could guide future research or practical applications of the regional TCCVRP modeling approach. The results in Table 6 describe the solutions found by the Google OR-Tools solver applied to a version of the regional VRPs with the vehicle capacity constraint removed. I used standard values for the other problem parameters: balancing routes by duration, 500 miles maximum route distance, mandatory 30-minute driver break, and a 15-second limit on the solver to find a better solution. In addition to fleet size, the table lists the cumulative route distance and cumulative route time for each feasible solution. Though I modeled all the regions in both PLSR Delivery Workgroup proposals, I selected three regions for inclusion in the table to illustrate the general trends found in the complete results set. For example, in general, the solutions found by the savings algorithm tend to require fewer vehicles when compared to the other initial solution strategies, as seen in the results for region 4 of the starting point proposal. However, in region 5 of the starting point proposal, the number of vehicles used by the savings algorithm matches the results of one or more other strategies. In cases such as these, it appears that the savings algorithm does not necessarily produce the feasible solution with the minimum possible cumulative route distance or cumulative route time. Furthermore, as discussed in the preceding section, and as shown for ideal proposal region 1, the savings algorithm occasionally fails to solve a VRP despite other initial solution strategies demonstrating a feasible solution exists.

The results in Table 6 suggest two considerations related to TCCVRP solution strategies for route planners and delivery managers developing regional route structures for the PLSR project. The first and most evident is that the choice of initial solution strategy influences the results returned by the routing solver. Furthermore, no technique appears to outperform any other universally. Therefore, assuming time and resources allow, it might be best to compare the solutions identified by multiple solving methods available in the Google OR-Tools package. The strategies chosen for comparison need not be

Table 6

Results for Three Regional TCVRPs Compared by Initial Solution Strategy

Initial solution strategy	Comparison measure & maximum route time					
	Fleet size (number of vehicles)		Total distance (miles)		Total time (hours, minutes)	
	8 hours	10 hours	8 hours	10 hours	8 hours	10 hours
Starting point proposal, region 4						
Savings algorithm	5	4	1104.15	985.32	38 h, 47 m	35 h, 35 m
Christofides algorithm	7	5	1329.89	1127.87	42 h, 45 m	38 h, 45 m
Parallel cheapest insertion	7	6	1283.95	1283.95	42 h, 14 m	42 h, 41 m
Automatic	7	5	1120.31	1120.31	45 h, 36 m	38 h, 55 m
Starting point proposal, region 5						
Savings algorithm	4	3	714.67	773.89	25 h, 53 m	26 h, 47 m
Christofides algorithm	4	3	677.02	699.95	24h, 42 m	25 h, 42 m
Parallel cheapest insertion	4	3	787.09	676.83	28 h, 20 m	25 h, 27 m
Automatic	4	3	761.41	678.32	27 h, 38 m	25 h, 12 m
Ideal proposal, region 1						
Savings algorithm	9	NA	2177.80	NA	68 h, 22 m	NA
Christofides algorithm	10	7	2211.38	1765.12	69 h, 46 m	59 h, 12 m
Parallel cheapest insertion	11	7	2197.42	1841.94	69 h, 6 m	61 h, 11 m
Automatic	11	8	2373.54	2033.75	71 h, 36 m	65 h, 35 m

Note. "NA" indicates the routing solver did not find a feasible solution using a fleet size of 15 vehicles or less. Shaded cells highlight minimum distance and duration values for each model.

limited to those I selected for focus in this research: route planners could use any of the OR-Tools strategies compatible with the TCCVRP formulation. The second consideration is the availability of cumulative route time and route distance as additional criteria for comparing TCCVRP solutions and deciding among alternative route structures. Presumably, route planners would seek to minimize the total route length and duration just as they most likely would for fleet size. However, exceptions to this general rule might be necessary to meet other goals, such as preferred stop sequences or route paths.

Route Time Constraint

In addition to the initial solution strategy, the data in Table 6 enables comparison between results found using an 8-hour or 10-hour maximum route time constraint. With all other constraint values held constant and the vehicle capacity constraint removed, models with 10-hour shifts generally require fewer vehicles, less cumulative distance, and less cumulative route time than models with 8-hour shifts. A possible explanation is longer trips with fewer vehicles eliminate a portion of the mileage traveled on each route between the regional hub and the first delivery stop and the return trip mileage from the last delivery stop back to the depot. The trade-off for fewer total vehicles is that every route would include more libraries and would likely need a larger van or truck to accommodate the associated container volume. As noted in the discussion of capacity constraints, this vehicle upscaling might not always be practical, particularly in metropolitan areas or regions in which highway traffic restrictions, such as vehicle height limits, limit the roads available for routing. In addition, delays and vehicle breakdowns on longer routes would impact more libraries than shorter routes, potentially increasing customer service concerns. Service disruptions could also push the return times of longer regional routes beyond the limit required to sort materials before outgoing shipment on intersystem connection routes; 10-hour shifts would have less available slack time to meet sorting deadlines than 8-hour shifts.

In sum, route planners will need to balance fleet and labor expenses against multiple factors when deciding which route time constraints best meet the unique needs of their region.

Chapter 5: Summary, Discussion, Recommendations, and Conclusion

Summary

The results analyzed in Chapter 4 indicate that a feasible route structure exists for every region in the Wisconsin Public Library System Redesign (PLSR) Delivery Workgroup's ideal and starting point proposals (Public Library System Redesign Delivery Workgroup, 2018). For every region, the Google OR-Tools routing solver found a solution to at least one formulation of the Time-Constrained, Capacitated Vehicle Routing Problem (TCCVRP). This outcome signifies a positive answer to the project's first research question related to the overall practicability of the Delivery Workgroup's proposals. However, the analysis comes with an important caveat: it is unknown how the parameter values of the TCCVRPs with feasible solutions will compare to the real-world constraints encountered during the PLSR implementation process. Therefore, the first research question will require ongoing efforts to adjust the regional models and determine whether the routing solver can solve the updated VRPs.

The discussion included in the "Data Analysis" section of Chapter 3 demonstrates the methods by which I answered the second research question regarding optimal route configurations. I recorded the route sequences of each feasible solution in the form of text (see Figure 4) and route maps (see Figure 5). As with the first research question, the results I obtained are preliminary based on the information available as of July 2021. Nonetheless, the flexible system I developed to recommend route structures for a range of constraint values is perhaps more valuable than the results specific to this project. Such a system can help refine route structures as PLSR planners gather additional data that describes the regional service areas with increased accuracy.

The final research question sought to determine the parameter values that produced optimal solutions to the regional TCCVRPs. The findings discussed in Chapter 4 show the influence of at least three factors on the routing solver's output: the capacity of the delivery vehicles, the strategy used to find an initial solution to the TCCVRP, and the maximum hours allowed per route. Of these three, both the vehicle capacity and route time limits had notable impacts on the number of vehicles needed by the solver to find a feasible TCCVRP solution. The choice of initial solution strategy can also alter the minimum required fleet size but, at least for the techniques I explored in my research, apparently to a lesser extent. However, different strategies produced solutions that varied in cumulative route time and route distance while using the same number of vehicles. PLSR route planners might want to consider these additional metrics when analyzing future modeling results and use multiple strategies to find initial TCCVRP solutions for later comparison.

Discussion

Research Implications

As of July 2021, the implementation process for the PLSR Delivery Workgroup's recommendations is still in its early phases. Too much uncertainty remains to draw firm conclusions regarding the practical implications of this project's research findings. For example, while the Delivery Workgroup narrowed the potential hub locations to selected cities, they did not mention specific sites or addresses. Yet, the TCCVRP routing solutions will likely change depending on where the hubs end up and the site's location within the road and highway network. Likewise, regional borders in both the ideal proposal and the starting point proposal are subject to further revision in response to other considerations such as shared library catalog agreements, statutory limitations, or availability of third-party delivery service providers. Still, the results of this project should be of interest to delivery service managers and administrators involved with translating the PLSR Delivery Workgroup's recommendations into practical operations. The research shows that the identification of feasible route structures depends on the parameters of the regional TCCVRP, particularly the number of vehicles, the vehicle capacity, and the maximum allowed route time. This finding could help guide decisions on delivery service resource allocation as the overall PLSR project progresses. Alternatively, as administrators finalize regional budgets and real-world constraint values become clear, delivery managers can modify the models created for this research and solve the TCCVRPs again for feasibility analysis and guidance while making any necessary adjustments to route structures.

Research Context

The modeling carried out in this study relied on extensive academic research into the formulation and solving of Vehicle Routing Problems (VRPs) and their numerous variants. The Time-Constrained, Capacitated Vehicle Routing Problems (TCCVRPs) I created for this project are relatively simple VRP variants, similar in many ways to the earliest VRP models developed by Dantzig and Ramser (1959) and Clarke and Wright (1964). Similarly, the algorithms and metaheuristics I used to solve the TCCVRPs are well-established in the operations research field and do not represent recent innovations. In this context, and consideration of the limitations of my research approach, the results I obtained using the Google OR-Tools routing solver were consistent with expectations for accuracy and fidelity to real-world situations. Based on the literature discussed in the "Human Component" section of Chapter 2, I expect route planners would need to revise the feasible route structures identified by the solver substantially before implementing route plans. As such, the research conducted for this project should be considered preliminary and exploratory rather than prescriptive or definitive.

Research Limitations

In addition to the uncertainties associated with the PLSR implementation process, several limitations influenced the research results and could diminish the utility of the TCCVRP modeling approach. The first, and perhaps most significant, was the quality of the data measuring library demand volume. As detailed in the "Removing Capacity Constraints" section of Chapter 4, the data appeared to contain a modest number of errors that impacted the ability of the routing solver to identify feasible solutions for some regional TCCVRPs. Another shortcoming I noted in this section was the lack of an established conversion factor for standardizing counts of the various-sized containers used by library delivery systems. An additional challenge was the age of the PLSR volume sample: the Delivery Workgroup collected the data in 2017, but local and global circumstances have likely led to considerable changes in typical library delivery volume as of 2021. What is more, the PLSR sample comprises a single week of counts, so any data anomalies or recording errors would disproportionately affect the solver's results.

Beyond data quality issues, the gap between the TCCVRP formulations and the reality encountered by delivery service managers limited the research I conducted for this study. For instance, route planners might need to ensure that particular stops are included on the same route, sometimes in a specific sequence. Two examples of this type of situation occur within the South Central Library System (SCLS). First, several counties in the SCLS service area regularly rotate collections of shared materials between public libraries in the same county, making it advantageous to keep the libraries on the same route. The second example is academic libraries on the UW-Madison campus, which expect en route item forwarding to later route stops. This service reduces item transit times and increases efficiency by decreasing the amount of material that requires sorting at the SCLS Delivery hub. The Google OR-Tools package includes functionality to enforce these types of connections; however, the programming steps needed to add this feature to a VRP are complicated, and time constraints prevented me from completing them.

Future Directions

Foremost among the recommendations for future research is improving the data collection process for library volume samples. Detailed and complete volume data would create a more accurate model of real-world delivery route structures and enhance the results found by the OR-Tools routing solver. To that end, delivery managers and other stakeholders should engage in a development process to establish data collection standards and best practices. The PLSR project manager or other members of the Wisconsin Department of Public Instruction Library Development Team could facilitate this process, which should involve at least one representative from each current Wisconsin Public Library System. Potential discussion topics for this group might include:

- committing to a regular schedule for volume sampling such as annual or quarterly counts to create a fuller picture of the variations in volume over both the short and long terms;
- measuring the volume differences between various container sizes and calculating equivalencies or conversion factors (e.g., the volume of one bin = three bags, etc.); and
- determining vehicle capacity based on the type of vehicle and size of container used.

With sufficient historical volume data available, researchers could extend the TCCVRP formulation I created for this project to incorporate additional features. For example, they might consider modeling library demand stochastically rather than using a static mean value. Researchers could also use this data to account for periodic demand fluctuations related to the period of the year or the day of the week. Furthermore, the Google OR-Tools package allows users to model heterogeneous fleets by setting a unique capacity value for every vehicle. Combined with the additional volume data, this feature would help researchers increase the fidelity of their models to real-world routing problems in which mixed fleets may be necessary.

A final suggestion for future study involves a detailed examination of the first solution strategies and metaheuristics available for the Google OR-Tools routing solver. Such research could help ground the selection of solving methods in established mathematical theory rather than limited experimentation. It could also help determine whether particular techniques are preferred for TCCVRPs and, if so, why. This type of analysis would not only improve the credibility of research results obtained using the OR-Tools package, but it would save needless effort for future researchers by allowing them to omit the exploratory research I conducted.

Conclusion

The Wisconsin Public Library System Redesign (PLSR) project culminates years of data gathering, analysis, and planning. As the project transitions from the preparation phase to implementation, the statewide, inter-system delivery service will be among the first of the core library service areas to carry out the recommendations included in the PLSR Workgroup reports ("Public Library System Redesign (PLSR)," 2020). This research project explored the feasibility of two proposals made by the PLSR Delivery Workgroup for restructuring delivery services using a regional service paradigm. I modeled the Workgroup's proposed regions using an operations research optimization tool known as the Vehicle Routing Problem (VRP), to which I added time and vehicle capacity constraints. The input data for the VRPs consisted of library geolocations, along-the-road distance and duration measurements retrieved from the Google Maps Platform, and estimates of library demand derived from a 2017 volume sample. My research found that feasible solutions exist for every region in the Delivery Workgroup proposals. However, the values of the vehicle capacity, maximum route time, and fleet size parameters required to find these solutions may not be practical in real-world scenarios due to resource limitations and other practical considerations. Therefore, I cannot make any specific, actionable recommendations based on my research. Still, I hope that this project will represent a positive and meaningful contribution to the process of implementing the PLSR Delivery Workgroup's recommendations, whether in terms of the results I found, the research tools I developed, or the data quality and collection issues I identified.

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Appendix A:

Project Code Link and File Descriptions

All code for this project is available on GitHub at the following URL: https://github.com/tdrexler1/wilib_vrp. General descriptions of the code and data files follow – the code comments and docstrings of individual files contain further details.

Python scripts

- "wi_lib_vrp.py" – The main entry point for the project code. This script runs from the command line and parses the arguments describing the Vehicle Routing Problem (VRP) set-up options, problem parameters, solution search strategies, and solution output options. The script also reads the library data from the input file into a Pandas DataFrame, then organizes calls to other modules to process the data, build the VRP input distance and duration matrices, create the VRP model, and solve the VRP. Finally, this script manages the various solution output options to display the solution on the console, write it to a text file, create a Google Map of the optimal routes, and save a screenshot of the map as a PNG file.
- "wi_lib_vrp_VrpModelObj.py" – This script defines a Python class to handle operations related to creating and solving a VRP. Class methods generate a unique model ID for every VRP, format the input data for the Google OR-Tools routing solver, initialize the OR-Tools model and constraints, and solve the model. Additional methods format the solution output in a readable form for display on screen or output to a text file and generate route stop sequences used to create Google Maps visualizations.
- "wi_lib_vrp_finalize_data.py" – Utility script to add regional designations and geolocation data for each library to the input data file. This script runs from the command line and users need to run it

one time to prepare the data before running the main script, "wi_lib_vrp.py." With command-line arguments, users can add regional data, geolocation data, or both and specify the format of the output file as either CSV or XLSX.

- "wi_lib_vrp_gmaps_mod_classes.py" – This file contains class definitions and methods used to patch selected code from the "gmplot" package that creates Google Maps files. I separated this code from other scripts for organizational and readability purposes. The "wi_lib_vrp_route_viz.py" script imports the modified definitions and methods and overwrites the originals contained in the GoogleMapPlotter class of the "gmplot" package.
- "wi_lib_vrp_matrix_build.py" – A script used to create the distance and duration matrices for input to the Google OR-Tools routing solver. A function filters the full input data set to the region of interest and formats the data for use in the Openrouteservice Matrix Service API request ("Openrouteservice," 2020). The code builds the matrices piecewise to accommodate API request quotas, then assembles the pieces into full versions and checks the results to ensure proper formatting. Users can run the script from the command line as a standalone program which creates the matrices and saves them to Python pickle files for later use. If needed, it can also be called from the "wi_lib_vrp.py" script to create the matrices in real-time. Note that the latter approach requires a significant amount of time to retrieve the data and can exceed daily API request quotas if used excessively.
- "wi_lib_vrp_route_viz.py" – The code in this file uses the "gmplot" package to create an HTML file with a Google Map showing the optimal routes found by the OR-Tools routing solver. The script patches the "gmplot" GoogleMapPlotter class methods as needed (see description of "wi_lib_vrp_gmaps_mod_classes.py"), creates a map object, draws color-coded lines showing each route, and adds markers at each route stop. The stop markers are clickable and display an

InfoWindow with more information about the library. This file also contains functions for opening the HTML output file in a web browser and saving a screenshot of the map to a PNG file.

Other files and directories

- "wi_library_directory.csv" and "wi_library_directory_geo_reg.csv" – The first file is a copy of the input data file containing information on all Wisconsin library delivery stops. The second file includes additional columns added listing proposed regional designations and geocoded location data.
- "chromedriver_win32" – A copy of the "selenium" package web driver for the Chrome browser. The screenshot functionality in "wi_lib_route_viz.py" requires the driver to open a headless browser. Note that users must add the path to the directory to the PATH environment variable, but they can store the directory and EXE file in any location.
- "vrp_matrix_data" – This directory contains Python pickle files that store pre-generated distance and duration matrices in a dictionary object. Each file corresponds to a region in either the PLSR Delivery Workgroup's ideal or starting point proposal.
- "vrp_output" – This directory contains subdirectories to store output files generated by the OR-Tools routing solver: "map_files" (HTML files of Google Maps), "solution_files" (TXT files of formatted solutions), and "screenshots" (PNG files of Google Maps screenshots).

Appendix B:

Potential Regional Hub Locations

In their report, the Public Library System Redesign Delivery Workgroup did not provide specific locations for the regional delivery service hubs beyond indicating the potential host cities on two maps, one for the ideal proposal and one for the starting point proposal (Public Library System Redesign Chapter 43 Workgroup, 2018, pp. 17 & 20). Based on these maps and conversation with Delivery Workgroup member Corey Baumann (C. Baumann, personal communication, June 14, 2021), I chose locations from the library input file to use as depots in the regional Time-Constrained, Capacitated Vehicle Routing Problems. The sites I selected correspond to delivery service hubs in existing public library systems in all but two cases. Table B1 lists the cities identified as potential hosts for regional hubs, the name of the location I used as a depot for modeling, and the ID string of the library or library system as listed in the "wi_library_directory.csv" input file.

Table B1

Hub Locations of PLSR Delivery Workgroup Proposed Regions

Proposed Region	Host City	Selected Hub Location	Hub LIBID
Ideal proposal 1	Rice Lake	Rice Lake Public Library	WI0275
Ideal proposal 2	Wausau	Wisconsin Valley Library Service	WI2700
Ideal proposal 3	Green Bay	Nicolet Federated Library System	WI1900
Ideal proposal 4	La Crosse	Winding Rivers Library System	WI2500
Ideal proposal 5	Fond du Lac	Fond du Lac Public Library	WI0103
Ideal proposal 6	Madison	South Central Library System Delivery Service	WI2200
Ideal proposal 7	Waukesha	Bridges Library System	WI2400
Starter proposal 1	Ashland	Northern Waters Library Service	WI2000
Starter proposal 2	Eau Claire	IFLS	WI1300
Starter proposal 3	Wausau	Wisconsin Valley Library Service	WI2700
Starter proposal 4	Green Bay	Nicolet Federated Library System	WI1900
Starter proposal 5	La Crosse	Winding Rivers Library System	WI2500
Starter proposal 6	Oshkosh	Winnefox Library System	WI2600
Starter proposal 7	Madison	South Central Library System Delivery Service	WI2200
Starter proposal 8	Waukesha	Bridges Library System	WI2400

Appendix C:

Model ID Codes

Model IDs comprise five components separated by underscores. Each component describes a characteristic of the model, its parameters, or the solution strategies used by the Google OR-Tools routing solver. A list of the possible component values and their meanings follows.

Component 1 – Public Library System Redesign Delivery Workgroup proposal and region number

- possible values:
    - 'idlX' – 'idl' = Delivery Workgroup ideal proposal, X = region number
    - 'strX' – 'str' = Delivery Workgroup starting point proposal, X = region number

Component 2 – maximum route length parameter

- possible values:
    - '08' = 8 hours
    - '10' = 10 hours

Component 3 – Google OR-Tools routing solver first solution strategy ("Routing Options | OR-Tools," n.d.)

- possible values:
    - '01' = PATH_CHEAPEST_ARC
    - '02' = SAVINGS
    - '03' = SWEEP
    - '04' = CHRISTOFIDES

  - '05' = PARALLEL_CHEAPEST_INSERTION
  - '06' = LOCAL_CHEAPEST_INSERTION
  - '07' = GLOBAL_CHEAPEST_ARC
  - '08' = LOCAL_CHEAPEST_ARC
  - '09' = FIRST_UNBOUND_MIN_VALUE
  - '10' = AUTOMATIC

Component 4 – Google OR-Tools routing solver local search metaheuristic ("Routing Options | OR-Tools," n.d.)

- possible values:
  - '01' = GREEDY_DESCENT
  - '02' = GUIDED_LOCAL_SEARCH
  - '03' = SIMULATED_ANNEALING
  - '04' = TABU_SEARCH
  - '05' = AUTOMATIC

Component 5 – vehicle capacity parameter

- possible values:
  - '040' = 40 containers
  - '060' = 60 containers
  - '200' = 200 containers
  - '000' = capacity constraint removed