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A Quantitative Model for Truck Parking Utilization with Hours of Service Regulations

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Abstract

Continual growth in traffic volume on U.S. Highways and insufficient parking for commercial trucking vehicles has led to significant safety concerns for truck drivers. Hours of Service (HOS) regulations dictate driving and rest periods of truck drivers. When a truck driver must stop as designated by the HOS regulations and the nearest parking location is at capacity, the trucker must either continue driving past the HOS limit or park in an undesignated and possibly illegal or unsafe spot such as an off-ramp. The combination of these two variables play an important role in the safety of truck drivers on a daily basis. Previous research on truck parking shortages has followed a survey-based approach while research on HOS regulations in conjunction with truck routing and driver scheduling has not included the full suite of HOS regulations as well as restrictions on parking availability. Current research techniques do not take into account parking capacity on a driver's route while following HOS regulations. Because there are limitations governing where along a route a driver can rest, including some customer locations and parking locations at capacity, these models do not prove to be an accurate measure of trip planning for truck drivers. This research aims to develop a mathematical model to link truck parking with hours of service regulations in order to determine feasible routes for truck drivers and optimal truck parking locations on the highway network.

Keywords

Transportation; Hours of Service; Parking; Vehicle Routing; Clarke-Wright;

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1. Introduction

Truck parking and hours-of-service (HOS) regulations are consistently reported as two of the top ten concerns in the trucking industry according to an annual survey of industry stakeholders (ATRI, 2014). Nationally, 75% of truck drivers reported problems finding safe parking and 72% of state DOTs reported parking deficiencies (The Federal Highway Administration, 2015). The Arkansas Highway Transportation Department's (AHTD) truck parking study found that in 2015, 23 parking facilities along major freight corridors were operating over capacity with seven operating at over 200% of capacity (AHTD, 2016). With freight tonnage increasing over the planning horizon, problems finding safe and available parking will only compound.

HOS rules set by the Federal Motor Carrier Safety Administration (FMCSA) define driving, working, and rest hours for truck drivers on a daily and weekly basis. Parking shortages are a function of inadequate parking capacity and changes to HOS regulations requiring drivers to stop more frequently and/or for longer periods. Scarce truck parking forces truck drivers to either park in unsafe locations or continue driving beyond HOS limits to find safe parking. This can lead to reportedly dangerous and deadly situations for truck drivers (The Federal Highway Administration, 2015). In addition, as freight movements become increasingly multimodal, delays to the road-based portion of goods' movements due to parking and HOS limitations can have cascading effects on rail and maritime portions of the supply chain.

The public sector relies on surveys and field data collection to determine parking deficiencies. These approaches limit the ability of public stakeholders to make effective investment decisions regarding where to improve parking. This is because field data can only capture parking usage at one point in time and surveys are limited to reported behaviors which may differ from actual behaviors. In addition, traditional data collection approaches do not inform decision makers of how parking locations interact, how to forecast or determine the time of day patterns, and how HOS regulations impact system wide parking utilization. The combination of both HOS regulations and parking availability play an important role in the timeliness of the truck drivers' routes, which affects not only their deliveries but can also have effects on other parts of the supply chain.

The aim of this thesis is to quantify the relationship between truck parking and HOS regulations using quantitative analysis. With the ultimate goal of developing an optimization framework in future studies, this thesis implements a heuristic to relate truck parking availability to HOS regulations. To demonstrate the necessity of such a heuristic, we provide a sensitivity analysis on the effects of varied parking availability and U.S. HOS regulations for two different network configurations. The proposed model determines the routes truck drivers should take to visit a set of customer locations and incorporates decisions on where and when drivers should park for required rest breaks. Thus, the proposed model is formulated as a vehicle routing problem with a single vehicle, HOS regulations, and specific parking locations. We heuristically solve this problem by extending the Clarke-Wright Savings Heuristic. The heuristic is applied to two case studies that vary in the distribution of customer locations. For each of the case studies, parking availability at each customer location is randomly assigned. This captures the real world condition that not all customers allow parking and that parking spots are not always available when needed.

This work can help to analyze parking implications involving how changes in HOS regulations impact truck parking availability, where improvements should be made to existing parking capacity, and how scarce parking and strict HOS regulations impact safety and timeliness. The main contributions of this work are (1) the incorporation of the daily and weekly cumulative HOS regulations and (2) the restrictions on parking availability into the heuristic.

In the next section, we review the U.S. HOS regulations and synthesize the family of truck models that exist to date. In Section 3, we provide the formal problem definition and proposed solution method. In Section 4, we detail two case studies and provide the results from sensitivity analysis. In Section 5, we present avenues for future work and in Section 6 we conclude.

2. Background

The US Department of Transportation conducts Jason's Law Truck Parking Survey as mandated by MAP-21, which governs transportation spending. Truck driver, Jason Rivenburg, was the motivation for Jason's Law. When Mr. Rivenburg could not find parking at designated truck parking facilities, he was forced to park at an abandoned gas station in order to comply with HOS regulations. Unfortunately, while resting in his truck, he was murdered for the little amount of money he had. Jason's Law was a result of this tragedy and aims to "guarantee safe parking for the freight haulers" (Jason's Legacy and Jason's Law, 2017). The 2015 study concluded that most states report problems with parking shortages and illegal parking on interchange ramps and shoulders. In addition, 75% of truck drivers reported problems with finding safe parking locations when rest was needed (The Federal Highway Administration, 2015).

Parking shortage studies including the Federal Highway Administrations' (FHWA) Jason's Law truck study (The Federal Highway Administration, 2015) and the Arkansas State Highway and Transportation Department (AHTD) truck parking study (AHTD, 2016) rely on qualitative, survey-based approaches to determine truck parking deficiencies. Unfortunately, these approaches do not quantify the interaction between HOS and parking capacity, leading to knowledge gaps. Therefore, the proposed study will develop a mathematical framework to link truck parking and HOS regulations to give quantitative assessments of truck parking capacity shortages.

2.1 Hours of Service Regulations

Hours of Service (HOS) regulations are mandated by the Federal Motor Carrier Safety Administration (FMCSA) and limit the driving and duty hours of truck and bus drivers. In this thesis, we consider the current rules which were implemented December 2014. The rules are described as follows and are summarized in Table 1.

1) 11-Hour Driving Rule – This rule states that a truck driver may drive a maximum of 11 hours within the 14-hour driving window after 10 consecutive hours off duty.

2) 14-Hour Rule – This rule states that a driver may not drive beyond the 14th consecutive hour after coming on duty, following 10 consecutive hours off duty. This is also known as a 14-Hour "Driving Window". An example of this 14 hour time window is given with the Sleeper Berth Provision in Rule 4. Lunch breaks or other off-duty time cannot extend the 14-hour limit. In other words, the time you take for lunch breaks or off-duty assignments are counted in the 14 hour driving window. A truck driver can perform on duty work after the 14th hour, but cannot drive.

<u>3) 30 Minute Rest Break Rule</u>- A truck driver may drive up to 8 hours since the last rest break of at least 30 minutes, e.g., a driver must take a 30 minute rest break after driving a maximum of 8 hours. The 30 minute break does count towards the 14 hours in the 14-hour Driving Window.

<u>4) 60/70 Hour Rule</u> - This rule states that a driver may not drive after 60/70 hours on duty in 7/8 consecutive days. It is important to note that this rule uses a rolling count to total the 60/70 hours in 7/8 days. If the company does not operate vehicles every day of the week, the truck driver must follow the 60-hour/7 day limit. If the company operates vehicles every day of the week, the driver can follow either of the two limits. For our research purposes, we have chosen to model that a company that operates vehicles every day of the week will follow the 70-hour/8 day limit, which is consistent with what is followed by local major trucking companies. A driver may perform 'non-driving' work after reaching the 60/70 hour limit. Figure 1 provides an example of a truck driver's week that calculates how long the driver has been on duty in 8 consecutive days to determine how long the driver may drive each day. In the example, we are using the 70 hours in 8 day rule. From Sunday to Sunday the driver has accumulated 67 hours of on duty or driving time. The driver has not violated HOS rules at this point. Now, in order to see how long the driver can drive on Monday we must go back and count the number of hours from the previous Monday. By driving 4 hours on the 2nd Monday the driver is still within the regulation at 69 hours. However, if the driver drove 6 hours on the 2nd Monday, this would be a violation because the driver would have accumulated more than 70 hours in an 8 day period. This example is critical for our research as we will show later.

DAY	ON-DUTY
1. Sunday	2
2. Monday	8
3. Tuesday	8.5
4. Wednesday	12.5
5. Thursday	9
6. Friday	10
7. Saturday	12
8. Sunday	5
1. Monday	4

67 hours

69 hours

Figure 1. Example of 60/70 Hour Limit

5) 34-Hour Restart Rule- A driver may restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty. We will use the example in Figure 1 again to describe this rule. In Figure 1, the driver had accumulated 67 hours in 8 days from Sunday to Sunday. Rather than continuing with this consecutive 8 day rolling count as illustrated in Figure 1, the driver could instead have taken 34-consecutive hours off duty. If this break was started on Sunday at midnight, the driver would then be able to drive at 10 am on Tuesday. In this case, the driver would not have to count back 8 days to calculate how long he could drive on Tuesday. Instead, the 8 day period starts on Tuesday and from this point on the driver must take a cumulative count of the hours acquired. For example, on Wednesday the driver would just need to subtract 70 hours from the hours driven on Tuesday to comply with the rule.

6) Sleeper Berth Rule – Truck drivers may use a sleeper berth in order to rest or take breaks. In this case, the truck driver must take at least 8 consecutive hours in the sleeper berth, plus a separate 2 consecutive hours either in the sleeper berth, off duty, or any combination of the two. The driver may also take 10 consecutive hours in the sleeper berth as stated in Rule 1.

Figure 2 gives an explanation of the sleeper berth provision with the split rest breaks and the 14-Hour Driving Window. In this example, the driver has started with 10 consecutive hours off duty. CP#1 stands for the first calculation point, indicating a start to the 14-Hour Driving Window. Each calculation point indicates where the 14 Hour Driving Window starts. CP#2 begins at 2 am on day two, after the first rest type (the long rest) of the rest set, which will be explained in more detail later in the example. After resting 10 consecutive hours, a worker can drive up to 11 hours in the next 14 hours, but must take a 30 minute break after at least 8 hours. On day 1 the driver drives 8 hours. At this point in time he needs to take a 30 minute rest break. However, with the split sleeper berth rule he has chosen to take his first rest of 8 hours. This is one way that the split sleeper berth allows the driver to drive more in the 14 hour time window because now the 8 hour rest counts as his 30 minute rest break as well. The driver then drives another 2 hours. At this point he can drive up to 1 hour more (11-Hour driving limit) in the 4 hours left in the driving window. The longer rest period of the two (8 hours in this case) does not count as part of the 14 hour window, which is why the driver still has 4 hours left. The driver then takes his second rest type of 2 hours in the sleeper berth. His first 8 hours does not count in the 14 hour driving window, but the 2 hour rest will. However, after completing the second rest break a new calculation point will begin at the end of his first rest period. This is important. After taking the second rest break type of the split sleeper berth provision, a new calculation point for the 14 hour time window starts after the FIRST rest break type. It does not matter if the long or short rest break is taken first. At 6 a.m. on day two after the driver has taken the second rest, a new calculation point, CP#2, is at 2 am on day two. From this new calculation point, at 6 am the driver now has 9 hours of driving available from the 11 hour driving limit. The driver then drives 7 hours and takes the ½ hour break at 1 p.m. He then drives another two hours and completes on duty non driving work for ½ hour. At this point in time (4 pm on day 2) the driver has exhausted the 11 hour driving limit and cannot drive any further. The driver then takes another rest break of 8 hours. This rest break is in conjunction with the last rest break of two hours. In other words, the 2 hour sleeper berth break at 4 am on day 2 counts towards the first set of rest breaks (10 am on day 1) and the second set of rest breaks (4 pm on day 2). Therefore the new calculation point for the 14 hour driving window is now after the first rest break type of the second rest set at 6 am on day 2 (FMCSA, 2015).

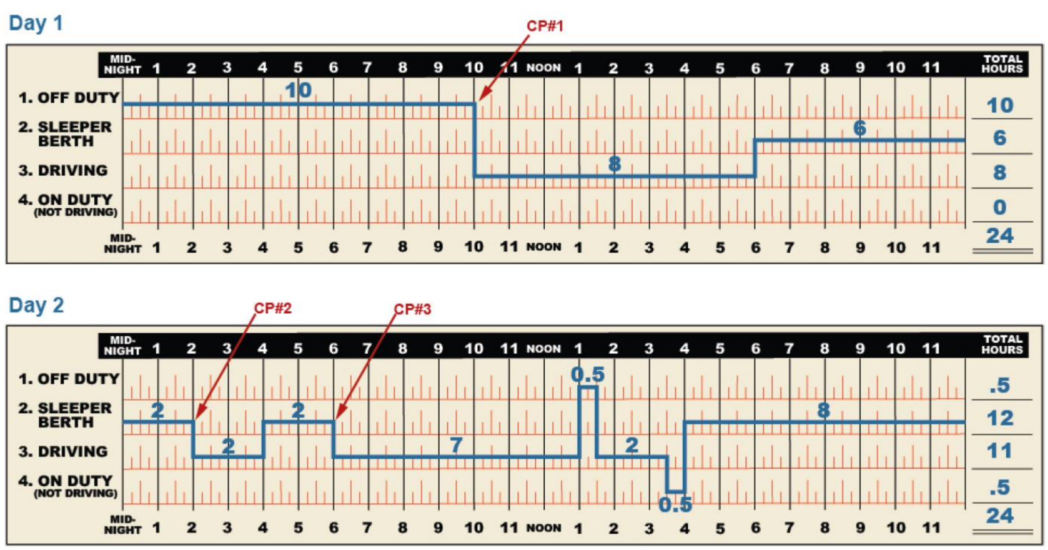


Figure 2. Example of 14 Hour Driving Window and Sleeper Berth Provision (FMCSA, 2015)

Table 1. Hours of Service Regulations (FMCSA, 2017)

#	Rule	Description
1	11-Hour Driving Rule	After accumulating 11 hours of driving, must take rest period of 10 consecutive hours
2	14-Hour Rule	May not drive beyond the 14th consecutive hour after coming on duty, following 10 consecutive hours off duty.
3	30 Minute Rest Break Rule	Driver cannot drive after 8 hours have elapsed since the end of the last off-duty period of at least 30 minutes
4	60/70 Hour Rule	May not drive after 60/70 hours on duty in 7/8 consecutive days
5	34 Hour Restart Rule	A driver may restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty.
6	Sleeper Berth Rule	Drivers using the sleeper berth provision must take at least 8 consecutive hours in the sleeper berth, plus a separate 2 consecutive hours either in the sleeper berth, off duty, or any combination of the two

2.2 Literature Review

There are several approaches that have incorporated Hours of Service (HOS) regulations in conjunction with routing and scheduling truck drivers' trips with very few having included parking policies. Approaches have involved either solving versions of a Vehicle Routing Problem (Dantzig and Ramser, 1959) or a Shortest Path Problem (Ahuja et al., 1993). The Vehicle Routing Problem aims to find the optimal set of routes that minimizes the cost for a fleet of vehicles stationed at a central location who must serve a set of customer requests. The Shortest Path Problem on the other hand finds the shortest way to get from a set origin to a set destination. We have considered literature that looks at U.S. HOS regulations only because they greatly differ from other countries' regulations. The factors evaluated for this research are the type of problem (VRP or Shortest Path), the incorporation of the 11-Hour Daily and 70-Hour Weekly Rule, and incorporation of parking capacity.

Table 2 summarizes how existing models found in the academic literature satisfy each of the defined factors. There are a variety of formulations that solve versions of either a Vehicle Routing Problem or Shortest Path Problem. Many include the 11-Hour Daily Rule, with few considering the 70-Hour Weekly Rule. However, the papers that have stated using the 70-Hour rule do so by limiting the time horizon to less than 8 days, or the authors state to enforce the rule with no specific details or constraints in a formulation. This research aims to tackle a VRP with any length of time horizon, including ones greater than 8 days. In addition, many of these formulations assume you can park anywhere along the route, or at any customer locations at any time. From talking with industry stakeholders we know that this is not always the case. We model real parking locations by restricting parking to select customer locations. In summary, the proposed model enforces the rolling hourly limit defined by the 70 hour rule and realistically models parking availability by restricting parking to allowable locations.

Table 2. Characteristics of Relevant Literature

	Problem		**Regulations**		**Parking Policies**
Article	VRP	Path	70-hour Rule	11-hour Rule	Parking Policies
Savelsbergh and Sol (1998)	X				
Zapfel and Bogl (2008)	X				
Ceselli, Righini, and Salani (2009)	X				
Xu et al. (2003)	X			X	
Goel and Irnich (2014)	X			X	
Goel (2014)	X			X	
Goel and Vidal (2014)	X		X	X	
Rancourt, Cordeau, Laporte (2013)	X		X	X	
Rancourt and Paquette (2014)	X		X	X	
Archetti and Savelsbergh (2009)		X		X	
Goel and Kok (2012)		X		X	
Shah (2008)		X		X	
Goel (2012)		X	X	X	X
Koc et al. (2016)		X	X	X	X
Proposed Model	**X**		**X**	**X**	**X**

Savelsbergh and Sol (1998), Zapfel and Bogl (2008), and Ceselli, Righini, and Salani (2009) define several approaches to solve a Vehicle Routing Problem that include working hours of a truck driver, but these working hours are not the most recent regulations. Salvelsbergh and Sol (1998) present a Dynamic Routing of Independent Vehicles which involves a branch-and-price algorithm for the general pickup and delivery problem. In the General Pickup and Delivery Problem a set of routes is constructed to satisfy transportation requests which specifies the size of the load, where it is to be picked up, where it is to be delivered, and time windows when the delivery can be picked up or dropped off (Salvelsbergh and Sol, 1998). This problem is similar to the Vehicle Routing Problem but does not have a central location or depot where all trucks start and end their trip. Zapfel and Bogl (2008) solve a vehicle routing and crew scheduling problem with a two-phase heuristic. The vehicle routing and crew scheduling problem is an extension of the VRP that also includes pre-specified arrival times at nodes and/or arcs (Bodin & Golden, 1981). Cesellini, Righini, and Salani (2009) develop an optimization algorithm based on column generation and dynamic programming for a rich vehicle-routing problem with multiple capacities, time windows, and characteristics associated with different elements of a vehicle such as weight of the truck and number of pallets on a truck. A Rich VRP simply adds constraints to the VRP in order to solve more realistic problems.

Xu et al. (2003), Goel and Irnich (2014), and Goel (2014) solve types of Vehicle Routing Problems while including the 11-Hour Rule in their models (Rule 1 from Section 2.1). Xu et al. (2003) solves a pickup and delivery vehicle routing problem involving multiple carriers, vehicle types, and multiple pick-up and delivery time windows. The proposed problem is solved using a column generation based solution approach wherein they solve the subproblem with a heuristic. Goel and Irnich (2014) develop an exact column generation based algorithm for vehicle routing and truck driver scheduling problems (VRTDSP) by using a branch-and-price algorithm. The VRTDSP generalizes the VRP with time windows by considering working hour constraints. Goel (2014) proposes a simulation-based methodology for assessing the impact of U.S. HOS regulations. He gives a formal model of scheduling duty and rest periods that minimizes the total duration of a trip. In addition, Goel restricts the time horizon to one week.

The factor that is not incorporated into many solution procedures is the 70-Hour Rule (Rule 4 from Section 2.1). At first glance, Goel and Vidal (2014), Rancourt et al. (2013), and Rancourt and Paquette (2014) solve a Vehicle Routing Problem while incorporating the 11-Hour Rule and the 70-Hour Rule. However, these solution methods do not explicitly track a rolling cumulative count of hours in the 7/8 days to implement this rule. Goel and Vidal (2014) use the 60 hour in 7 day rule rather than the 70 hour in 8 day rule. However, this rule is not explicitly stated in a formulation for U.S. HOS regulations. Goel and Vidal (2014) use an optimization algorithm to solve a VRP that minimizes transportation costs for a fleet of vehicles with hours of service regulations and customer time windows. The algorithm uses a population-based metaheuristic that incorporates local search heuristics and tree search procedures. Rancourt et al. (2013) solve a Long-Haul Vehicle Routing and Scheduling with Working Hour Rules Problem, which is an extension of the Vehicle Routing with Multiple Time Windows (VRPMTW) problem. The VRPMTW is a VRP that gives several time windows at each customer location that specifies when a truck can deliver or drop off freight (Cordeau et al., 2002). The Long-Haul Vehicle Routing and Scheduling with Working Hour Rules Problem is designed for the less-than-truckload industry that involves long-haul transportation and therefore incorporates work and rest hours. Rancourt et al. restricted the number of consecutive days during a planning horizon to be 8. In this sense, the 70-Hour Rule is not implemented in a way that reflects long-haul drivers' working constraints since these drivers tend to be on the road for weeks at a time. Rancourt and Paquette (2014) solve a Long-Haul Routing and Scheduling Problem with multicriteria optimization but also only consider a planning horizon of 8 consecutive days.

Several papers use a Path-based formulation to solve problems with working hour constraints on truck drivers. Archetti and Savelsbergh (2009), Goel and Kok (2012), and Shah (2008) all solve a path-based problem incorporating the 11-Hour Daily Rule. Archetti and Savelsbergh (2009) present a polynomial-time algorithm for the trip scheduling problem. The Trip Scheduling Problem determines whether a sequence of transportation requests with a dispatch window at the origin can be executed by a driver. Goel and Kok (2012) create a scheduling method for the Truck Driver Scheduling Problem in polynomial time. The U.S. Truck Driver Scheduling problem is the problem of visiting a sequence of locations within given time windows in a way that driving and working activities are in compliance with U.S. HOS regulations. Goel and Kok (2012) also assume that "no more than 60 or 70 hours of on-duty time are assigned to a driver within the planning horizon". Thus they enforce the rule, however only through a limited time horizon. Shah (2008) solves a Time Dependent Truck Routing and Driver Scheduling Problem with a metaheuristic. This metaheuristic involves a Time Dependent Dijkstra's algorithm to construct an initial tour and Simulated Annealing heuristic to improve the solution. Shah also assumes that a trip is less than a week.

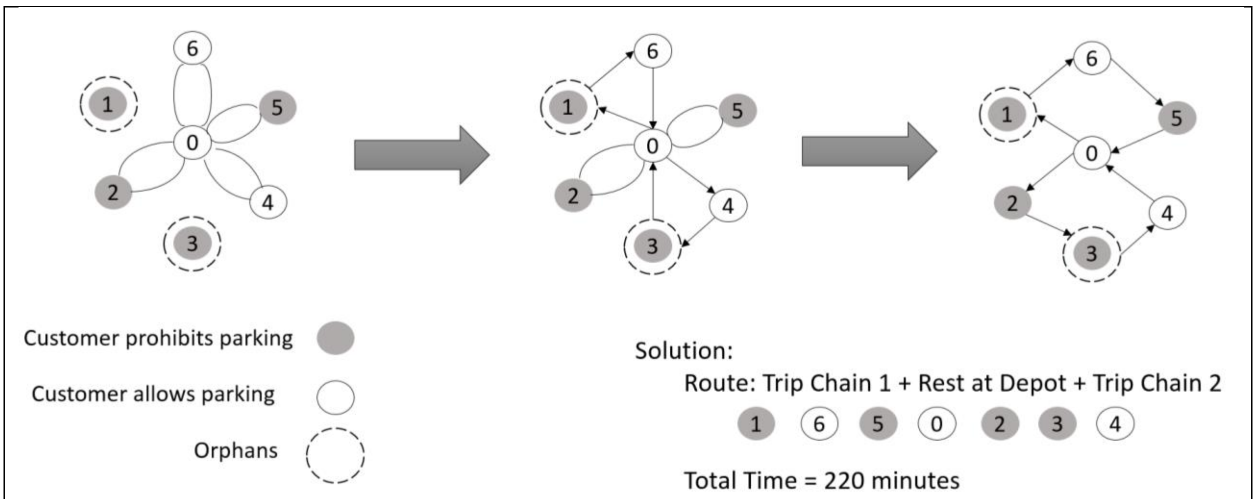
Finally, Goel (2012) and Koc et al. (2016) solved a path-based problem that includes both the 70 Hour Weekly Rule, 11 Hour Daily Rule, and parking policies. Goel (2012) presents a mixed integer programming formulation for a variant of the truck driver scheduling problem with minimum duration, where truck drivers may only rest at customer locations and suitable rest areas. Although Goel seemingly uses the 70 Hour Rule, it is not clear that his implemented rule accurately models the real-world regulation. Goel limits the "accumulated amount of driving or the accumulated amount of driving and working in between rest periods". The 70 Hour Rule does not just apply between two subsequent rests, it is over the entire time horizon that a driver is working. In addition, from talking with industry stakeholders we know that not all customer locations will allow drivers to take breaks or rests at their locations. Koc et al. (2016) look at the Truck Driver Scheduling Problem with Idling Options that involves driving cost, fuel and CO_2 emissions, and idling costs. Furthermore, they do consider real parking locations, but only consider interstate rest areas, not truck stops. In addition, they "assume that the truck driver has been off-duty and off-the-road for at least 34 consecutive hours before departure from the starting depot, and each trip has a maximum duration of 7 days". Our long term research goal is to be the first to implement the 70 Hour Weekly Rule for a trip duration of longer than 8 days, as well as real truck stop and interstate rest areas that drivers may rest at if there is space at the time needed. The work presented in this thesis is a step towards this goal by including the 70 hour rule and parking at select locations.

3. Problem Statement and Methodology

The proposed model is formulated as a Vehicle Routing Problem solved with a modified Clarke-Wright Savings Heuristic. We seek to determine the minimum duration route for a truck driver while adhering to the parking availability and HOS regulations. Following the problem definition, a description of the Clarke Wright Savings Heuristic and our proposed model is presented.

3.1 Problem Formulation

The proposed model defines nodes, routes, and trip chains. First, a set of nodes, numbered from 0 to n, is defined such that '0' is the depot node and all other nodes represent customer locations. In the example provided in Figure 3C, the depot is represented by node 0. The depot is the location where the truck will start and end its route. In the proposed model, a 'route' is defined differently than the typical VRP definition. For the proposed model a "Trip Chain" defines a cycle which a truck driver will take that starts and ends at the depot. A 'route' is comprised of all the trip chains such that the entire set of nodes are visited with each starting and ending at the depot. From Figure 3C, the illustrated route is comprised of two different trip chains, each starting and ending at the depot. Trip Chain 1 starts at the depot, visits node 1, 6, 5, and returns back to the depot. Trip Chain 2 starts at the depot and visits node 2, 3, 4 and ends back at the depot. The route in this example starts at the depot, visits nodes 1, 6, 5, 0(depot), 2, 3, 4, and finishes back at the depot.



A	B	C

Figure 3. Problem Illustration

For the proposed model, the set of customer nodes can either allow or prohibit parking while the depot node always allows and has available parking. In addition, there are no parking locations which are not a customer (e.g. there are no truck parking facilities), and therefore all nodes must be visited. It is also assumed that there is one truck and one driver that will complete the entire route if feasible.

The goal of the problem is to determine where and for how long a driver should park at each customer location. If the driver has not reached their HOS limits and can make it to the next customer without resting, then the driver will not rest at the current customer location. After all trip chains are determined, they are ordered into a single route. The objective function minimizes the total drive and rest time of the route, and the constraints deem that the truck driver must visit all of the customers while adhering to HOS regulations and truck parking availability. An example is given in Figure 3A to illustrate the proposed model. This example includes six nodes and the depot. Shaded nodes are locations that prohibit parking while white nodes are locations that allow parking. This example will be further explained in the Modified Clarke Wright section where we provide how we are solving our problem.

3.2 Clarke Wright Savings Heuristic

The Clarke Wright Distance Savings Heuristic is adopted to solve the defined VRP (Clarke and Wright, 1964). First, the Clarke Wright Heuristic forms a trip chain with each node in the set: 0-i-0 for i=1..n. In this way, a trip chain is created from the depot to node 1 and back, then from the depot to node 2 and back and so forth, such that the route is a series of single customer trip chains. The heuristic then merges trip chains if there is a distance savings associated with merging these trip chains and capacity constraints are not violated. Capacity constraints are interpreted as the maximum amount of demand that can be satisfied at customers on the same route. The distance savings is defined according to equation 1.

Eq. 1 $s_{ij} = c_{0i} + c_{0j} - c_{ij}$

Where s_{ij} is the savings between nodes i and j

c_{0i} is the cost from the depot to node i

c_{0j} is the cost from the depot to node j

c_{ij} is the cost on the arc between nodes i and j

Next, the node pair with the highest savings (s_{ij}) will be selected and a new trip chain is created by connecting nodes i and j and deleting arcs (i,0) and (0,j). There are n+1 nodes. We designate node 0 as the depot from which every node i we can get to all other nodes j via arc (i,j) with cost c_{ij}. This process of creating new trip chains by connecting nodes and deleting arcs continues until there are no further savings.

3.3 Modified Clarke Wright

We use the foundation of the Clarke-Wright heuristic and modify it for the proposed truck routing problem with HOS regulations and parking availability. The modified Clarke-Wright used in this study differs from the original in several ways. Table 3 outlines the differences of each approach. First, in the original Clarke-Wright there are a set of customers and a depot. In the proposed modification, the set of customers either allow or prohibit parking while the depot always allows parking. Next, the modified Clarke Wright interprets capacity as adhering to HOS given parking availability while the original Clarke-Wright defines capacity as the maximum demand satisfied at customer locations on the route. In addition, the original heuristic merges routes based on an associated distance savings while the proposed modified version merges trip chains if there is a total time savings that includes necessary rest periods. Finally, the original heuristic uses an objective function that minimizes distance while the proposed modification aims to minimize route duration defined as the total rest and drive time of the route.

Table 3. Comparison of Original and Our Modified Clarke-Wright

Characteristic	**Clarke-Wright**	**Modified Clarke-Wright**
Node Definition	Set of customers + Depot	Set of customers, some which allow parking + Depot always allows parking
Capacity Interpretation	Maximum amount of demand that can be satisfied at customers on the same route	Adhere to HOS rules and parking availability
Merge Rules	Distance Savings	Time savings that includes driving and necessary rest periods
Objective Function	Minimize distance	Minimize route duration (rest + drive time)

To demonstrate the modified Clarke-Wright, we revisit the network shown in Figure 3. In the example shown in Figure 3 white nodes allow parking while shaded nodes prohibit parking. The modified heuristic begins with forming individual trip chains from the depot to each node. In this example there are two nodes that do not form an initial trip chain, nodes 1 and 3, indicated in Figure 3 by a dashed line. Nodes not included in initial trip chains are referred to as orphans. An orphan is created when a driver cannot make a round trip from the depot to a node within the allowable HOS regulations. For example, if the drive time from the depot to the node is six hours (e.g., 12 hours round trip) and node 1 prohibits parking, then the driver would violate HOS daily driving limits (e.g., 11 hours) by traveling to node 1 and back in a trip chain. Thus, the driver cannot complete this trip chain. After forming all initial feasible routes and identifying the set of orphans, the heuristic searches to see if the orphan nodes can be joined with a trip chain. In this example, the trip chain containing node 6 was merged with node 1 to form a new trip chain that starts at the depot, continues to node 6, on to node 1, and returns to the depot. An important aspect to point out is that even though a node may allow parking, it does not mean that the driver must stop and rest at this node. The driver only has to rest at a node if necessary to finish the trip chain. Finally, the formulation merges trip chains to reduce the total drive and rest time.

Upon completion of the algorithm all trip chains are combined to form a route. The example in Figure 3C includes two trip chains to form the route. Trip chain 1 starts at the depot, goes to node 1, 6, and 5, and then back to the depot, in that order. The driver then rests at the depot and then begins the second trip chain which goes from the depot to node 2, 3, and 4, and back to the depot. These two trip chains form a final route which starts at the depot, goes to node 1, 6, 5, 0(depot), 2, 3, 4, and back to the depot. As stated above, a driver only needs to rest at a parking location if it is not possible to make it to the next parking location under HOS regulations. In this example, the driver only needed to rest at the depot between the trip chains, meaning he could complete the individual trip chains under HOS regulations. The algorithm calculates the total drive, total rest, and total drive and rest time for the routes. The modified Clarke-Wright is summarized in Algorithm 1.

Algorithm 1: Modified Clarke-Wright

1. Load Data

    1.1 Load Node Data with node ID and parking availability

    1.2 Load Arcs Data with start node, end node, distance and traversal time

2. Build individual trip chains as you can

    2.1 For all nodes n, identify out and back trip chain

    2.2 If trip chain to node and back is < 11(HOS drive regulations), then add trip chain

      Else leave node as orphan

3. For each orphan, merge with cheapest feasible trip chain

    3.1 For each orphan, find closest node

    3.2 If closest node is NOT a parking location check if orphan can be added to trip chain within HOS regulations

If true insert orphan in least total time location within trip chain

3.3 If closest node is a parking location, check if orphan can be added to trip chain within HOS regulations

If true insert node in trip chain in least time consuming way

ELSE do not add orphan

3.4 If orphan cannot be added to a trip chain it is an infeasible solution

4. For each trip chain

4.1 Calculate total time of trip chain with and without rest

4.2 Make parking decisions at available parking nodes

4.3 Combine trip chains together if it results in a time savings until no further merges can be done

4.3.1 Recalculate total time of trip chain with and without rest

4.3.2 Recalculate parking decisions at nodes along trip chain to ensure HOS feasibility for entire trip chain

5. Create route comprised of all trip chains

6. Calculate route information

6.1Recalculate parking decision at all nodes along route to ensure HOS feasibility for the entire route

6.2 Calculate total daily driving time, cumulative driving time, and number of hours in driven in past 8 days

4. Case Study

In this section, two case studies are presented to evaluate the impacts of varying HOS regulations and parking availability with the proposed problem. Solomon instances of 25 nodes ("Capacitated VRP with Time Windows Instances | Vehicle Routing Problem", 2017) were used to define customer and depot locations. The first case study (Solomon instance C101) represents a clustered customer network as shown in Figure 4. The second case study (Solomon instance R101) represents a more dispersed customer network as shown in Figure 5. The depot for each instance is labeled as a white node with a black outline while the customer locations are the black nodes. These particular Solomon instances were selected to show how network configuration can lead to varied routing solutions, insights on parking availability needed, and insights on the impact of HOS.

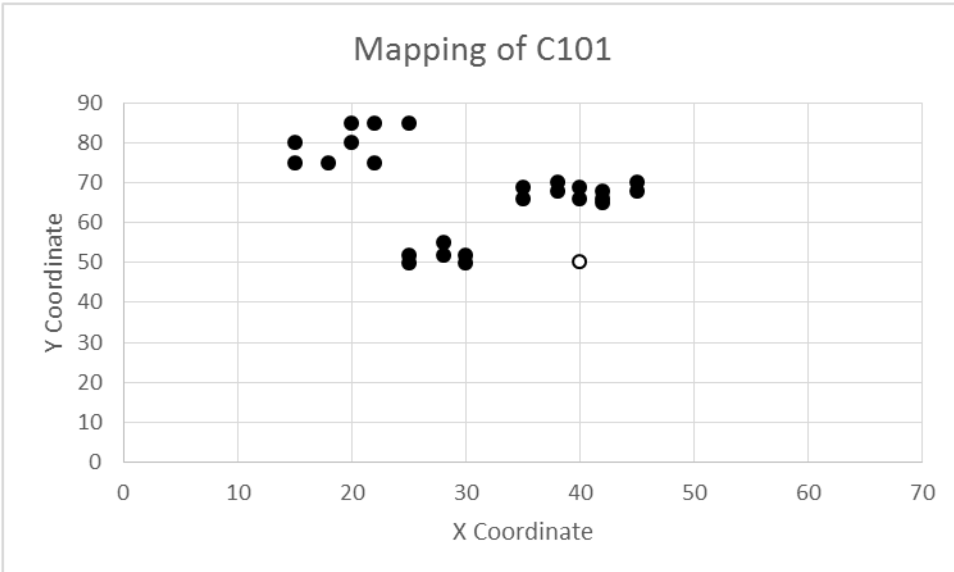


Figure 4. Network Mapping of Solomon Instance C101

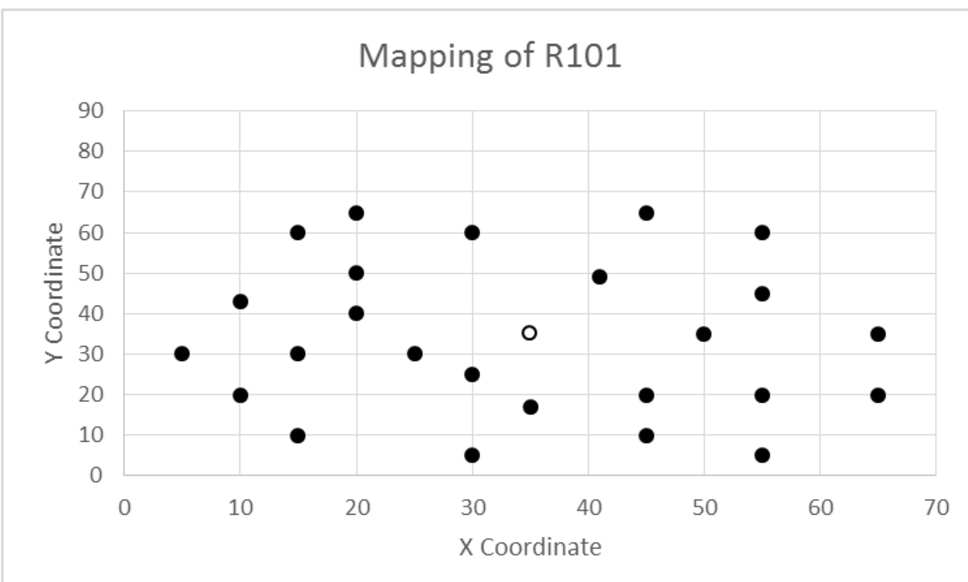


Figure 5. Network Mapping of Solomon Instance R101

Each of the Solomon instances provided a complete network or include arcs that connect each pair of nodes. The distances between the nodes were converted to a traversal time using an assumed truck speed. Since the Solomon instances only specify customer and depot locations, parking availability was assumed for each customer location. Parking was assigned by varying the percentage of customer locations that allow parking and creating instances by randomly selecting which locations allowed parking. The percent of customer locations allowing parking ranged from 20 to 80 percent. In addition, HOS regulations were varied: the daily allowable driving varied between 10, 11, and 12 hours and the required rest varied from 8 to 11 hours. For each of the parking percentages, 30 random instances were created such that the customer locations that allowed parking changed between each instance. For example, one instance for 20 percent parking availability might have parking available at nodes 1-5. The second instance then might have parking available at nodes 5-10.

Thus, each instance is defined by a level of parking availability (20, 40, 50, 60, or 80%) and random distribution of nodes that allow parking. Allowable drive time (10, 11, or 12 hours), and required rest time (8, 9, 10, and 11 hours) is also varied within each of these instances. The design of the experiment is shown in Table 4. Analysis for each Solomon case under each instance are provided in the next section.

Table 4. Design of Experiment

Factor	**Levels**	**Detail**
Parking Availability	5	20%, 40%, 50%, 60%, 80%
Drive Time	3	10, 11, 12 hours
Rest Time	4	8, 9, 10, 11 hours
Node Graph	2	C101, R101

4.1 Case 1-C101

For Case 1, results of the heuristic under the normal HOS regulations (max 11 hours consecutive driving, required 10 hours rest) and every instance under varied parking availability percentages are presented. In total there were 30 instances for each parking percentage scenario, leading to a total of 150 instances.

Figure 6 shows the number of feasible instances and the average total time for the route for each parking percentage under the normal HOS regulations. Infeasible scenarios occur when an orphan node cannot be added to an initial route. This might be possible depending on the distance between customer locations and the depot because of unavailable parking. The bars on the graph show how many instances were feasible for each parking percentage and the line shows the average total time (drive plus rest time) required to complete the route under each parking scenario. For parking percentages 20 and 40, only eight of the 30 instances were feasible. Parking percentages 50, 60, and 80 resulted in 11, 16, and 24 feasible instances, respectively. Figure 6 shows that, overall, as the amount of available parking increased, the number of feasible instances increased as well. In this case the number of feasible instances from 20 to 40 percent did not increase. This is due to the mix of parking locations in the instances for each of these percentages. The instances for 20 percent parking availability had the same mix of well placed parking locations as with the 40 percent parking availability instances. In addition, the overall average total time decreases as the number of available parking locations increases.

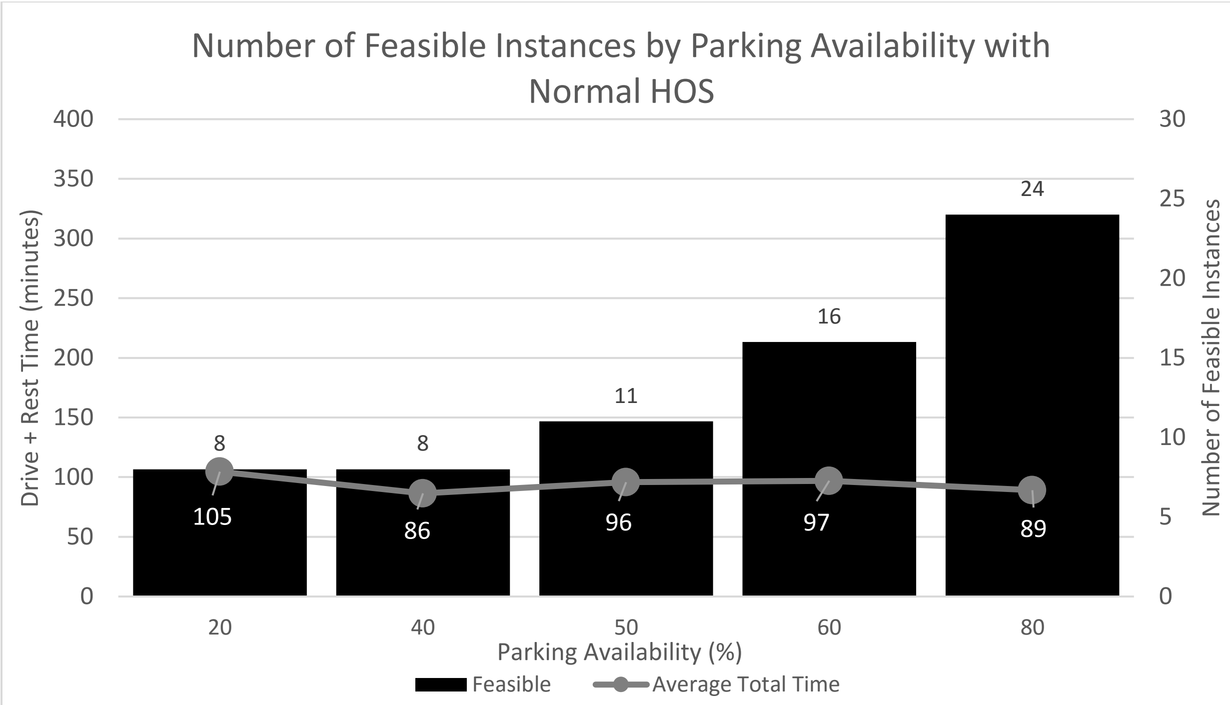


Figure 6. Average Total Time and Number of Feasible Instances for Case 1

Figure 7 shows a boxplot of the feasible instances related to the total drive and rest time of the route. Similar to Figure 6, the mean drive and rest time changes as parking availability changes. While a clear upward or downward trend is not apparent, results indicate that parking availability has an effect on the total drive and rest time of the route. Figure 7 also shows the range of solutions for each scenario. The upper bounds or top of the lines on the graphs differ across the different parking availability scenarios indicating that the location of parking affects the required drive and rest time. The lower bounds however, are similar across the parking scenarios. This is due to the fact that there is a unique set of customer locations for which, when included in the scenario to allow parking, a minimum drive and rest time is possible.

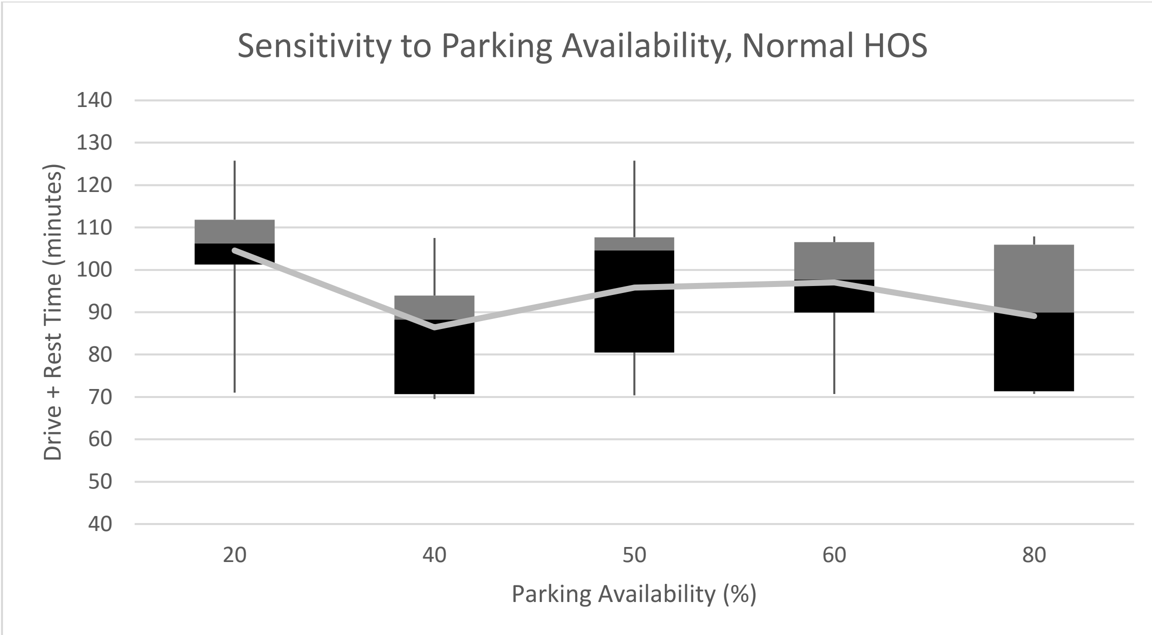


Figure 7. Sensitivity to Parking Availability with Normal HOS, Case 1

Next, allowable driving hours were varied from 11 and 12 and the required rest was varied from 8, 9, 10, and 11. We vary HOS regulations in order to assess its impact on route duration and feasibility. Varying the HOS in the case study also allows us to quantitatively link changes in HOS to parking. For each combination of drive and rest time, two parking availability scenarios, 50% and 80%, were evaluated. Figures 8 and 9, show that under the 50% parking availability scenario, the longer the required rest, the greater the drive and rest time of the route, as one would expect. A comparison of the 11 hours to 12 hours allowable drive time shows that the more driving time allowed, the lower the total drive and rest time of the route. This coincides with the hypothesis that with less restrictive HOS under the same parking availability, the timeliness of the route improves due to a lower total time. For the 80% parking availability shown in Figures 10 and 11, similar conclusions can be drawn. However, there is much less variability in the total drive and rest time of the route when compared to 50% parking availability.

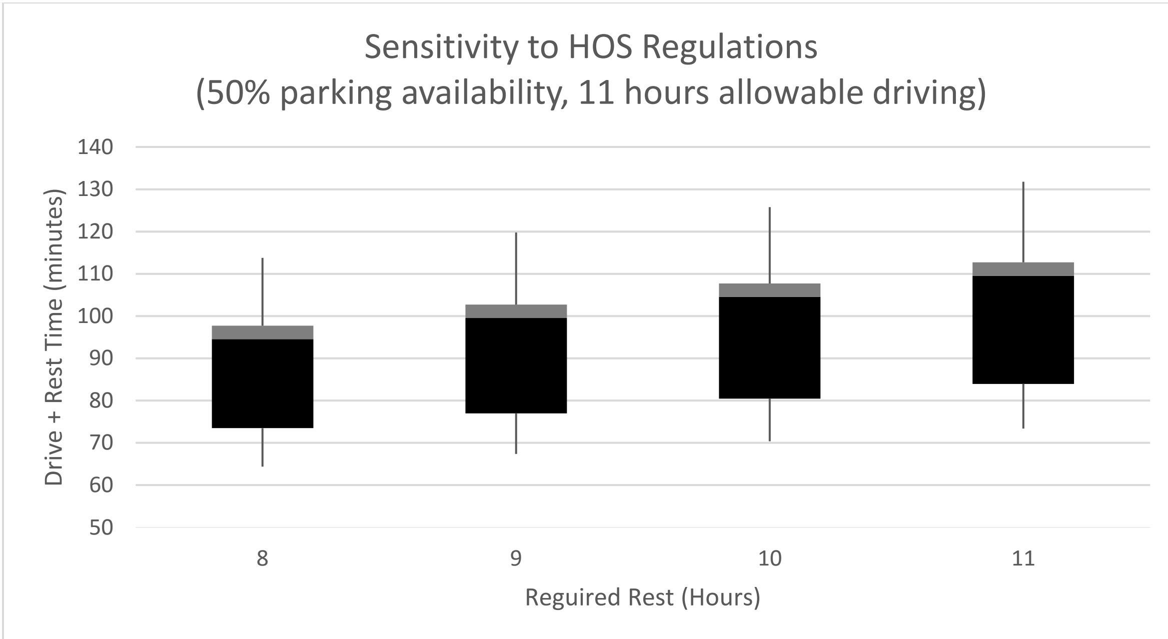


Figure 8. Sensitivity to varying rest requirements and 11 hours allowable driving with 50% parking availability, Case 1

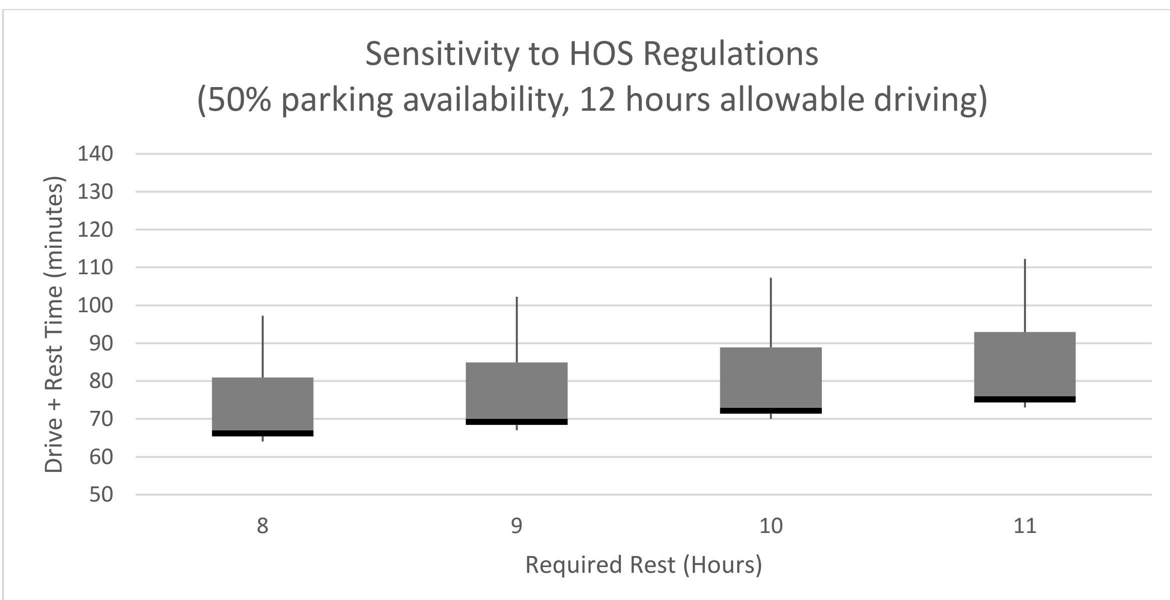


Figure 9. Sensitivity to varying rest requirements and 12 hours allowable driving with 50% parking availability, Case 1

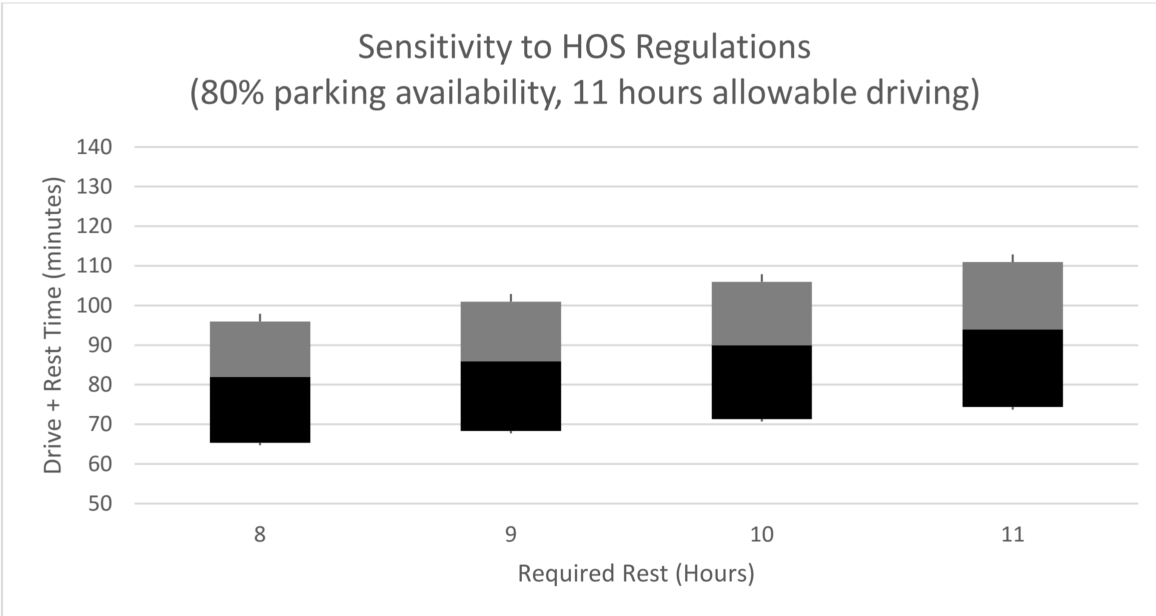


Figure 10. Sensitivity to varying rest requirements and 11 hours allowable driving with 80% parking availability, Case 1

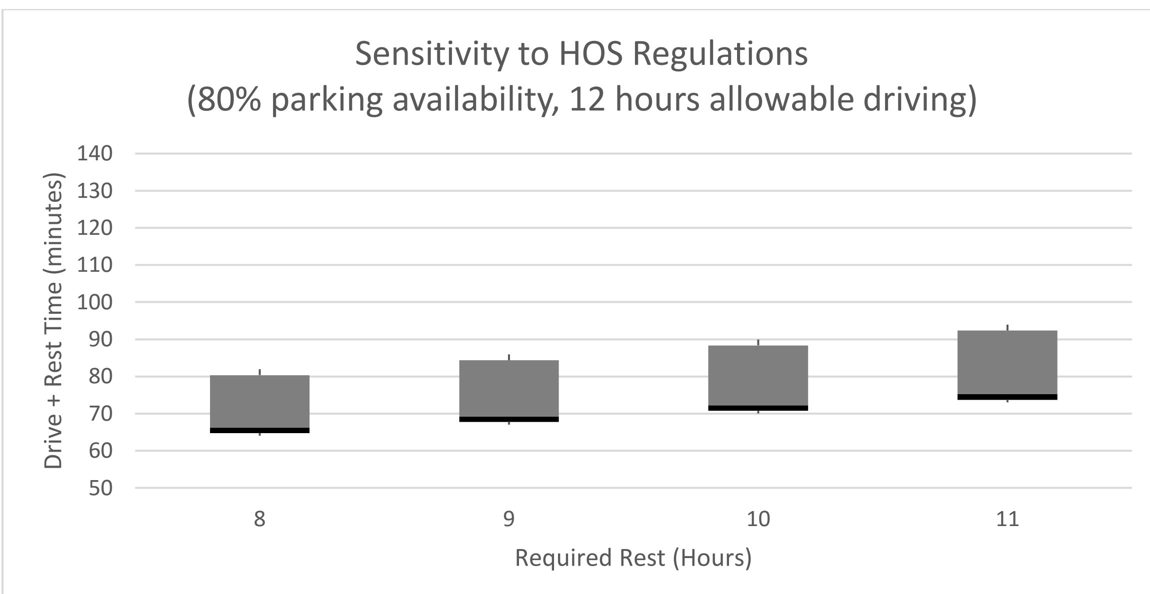


Figure 11. Sensitivity to varying rest requirements and 12 hours allowable driving with 80% parking availability, Case 1

4.2 Case 2-R101

We perform a second analysis to see how the location of customers impact the findings. As with Case 1, each instance for Case 2 is defined by a level of parking availability (20, 40, 50, 60, or 80%) and random distribution of nodes that allow parking. Allowable drive time (10, 11, or 12 hours), and required rest time (8, 9, 10, and 11 hours) is also varied within each of these instances. For Case 2, the normal HOS regulations were applied to the varied parking availability scenarios. Figure 12 shows the number of feasible instances for each parking scenario. Under 20 and 40% parking availability, no instances were feasible for Case 2. For 50, 60, and 80 percent parking availability, 2, 2, and 11 instances were feasible. These numbers are very low compared with the number of feasible instances across the parking percentages in Case 1. This signifies that the location of nodes or customer locations across the network has a significant impact on the feasibility due to the link between HOS and parking. Figure 12 also shows that as parking availability increased, so did the number of feasible instances. However, a much higher amount of parking is necessary to enable feasible instances.

Furthermore, Figure 13 shows the difference in the available parking locations in Case 2 for one instance that was feasible and one instance that was not feasible at 50% parking availability. The white nodes are customer locations that allow parking and black nodes are the customer locations that don’t allow parking. From the two graphs it is hard to tell a major difference in the positions of the customers that allow parking. For the most part, the two graphs look very similar in the dispersion of parking and non-parking nodes. There are eight similar nodes between both of the instances, meaning there only four locations that are different for allowing parking. The orphan node that could not be added to a trip chain, therefore making this instance infeasible is outlined in a black box. This single node had an effect on whether the instance was feasible or not depending on if the node allowed parking. This means that the location of available parking is extremely important in a network. Figure 14 outlines the route for the feasible instance in Case 2. If the customer location outlined in the black box had not been an available parking location, the entire trip chain that the node sits on would be infeasible. However, if you look at the configuration of parking and non-parking nodes on the infeasible instance, it looks as if it may be possible to add the orphan node in a trip chain. The heuristic used to add orphans looked at only adding the orphan to a single node trip chain. It may have been possible, however, in the infeasible instance in Figure 13 to add the orphan node to a multi node trip chain. Therefore future work could include a different procedure for adding orphans to trip chains to determine in the instance is feasible or not.

Looking at a feasible and infeasible instance for Case 1 a similar conclusion on the importance of parking locations can be drawn. Figure 15 displays both a feasible and infeasible instance for Case 1. Seven of the nodes have the same customers allowing parking while five of them are different. In the cluster in the upper left corner for the feasible instance, there were 6 of the 8 nodes that allowed parking. In the same cluster for the infeasible instance, only 4 of the 8 nodes allowed parking. The node outlined in a black box was the orphan node that could not be added to a trip chain, thereby making the instance infeasible. There was a difference in 2 nodes that allowed/ did not allow parking in the upper left-hand cluster that could determine if the instance was feasible or not. Only one of these nodes was the reason for the instance being infeasible. Again, we can see that the location of parking, even in clustered networks where nodes are close is important. Figure 16 shows the route that was formed from the feasible instance in Case 1. Again, the node outlined in a black box was the node that did not allow parking in the infeasible instance, thereby making it infeasible. If this node had been added to a multi node trip chain it seems a trip chain could be formed with the orphan.

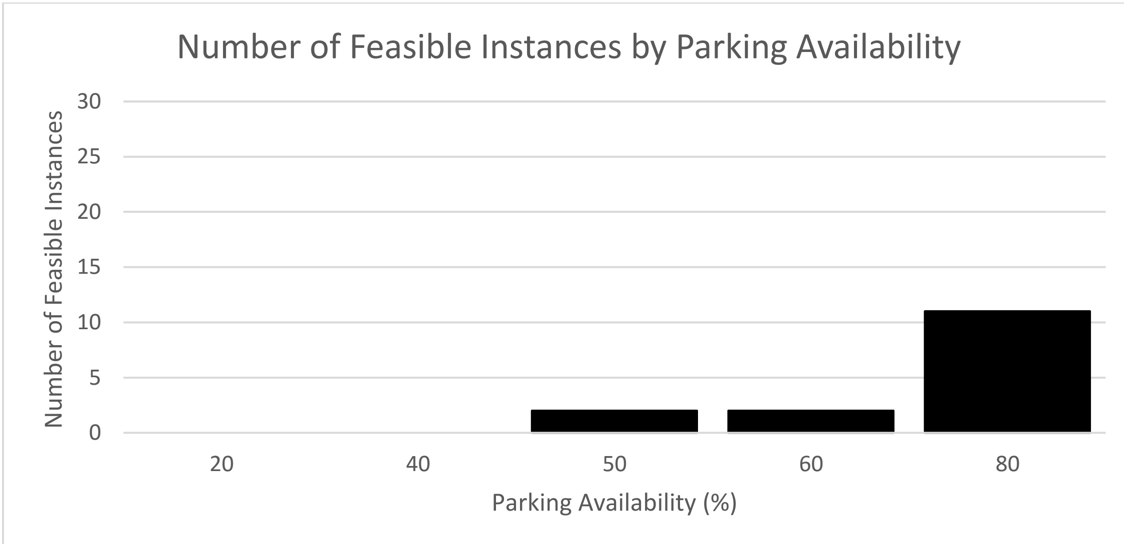
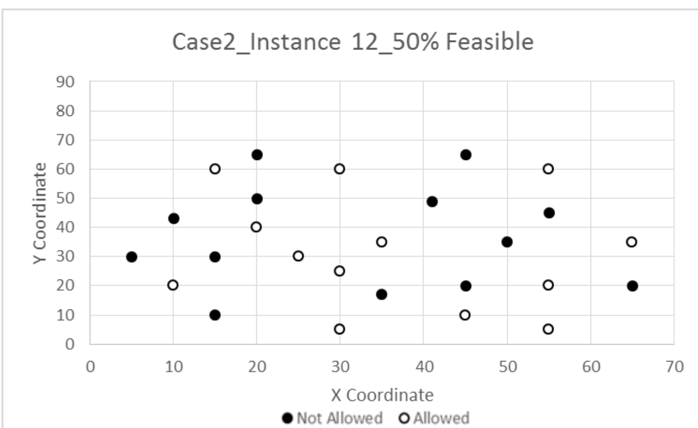


Figure 12. Number of Feasible Instances for Case 2



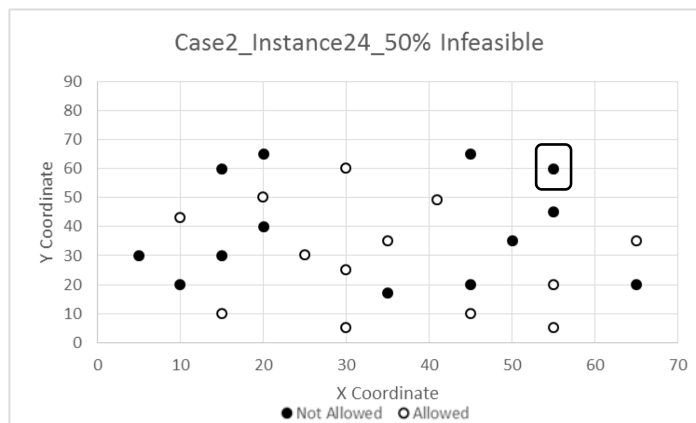


Figure 13. Case 2 Feasible and Infeasible Instance at 50% Parking Availability

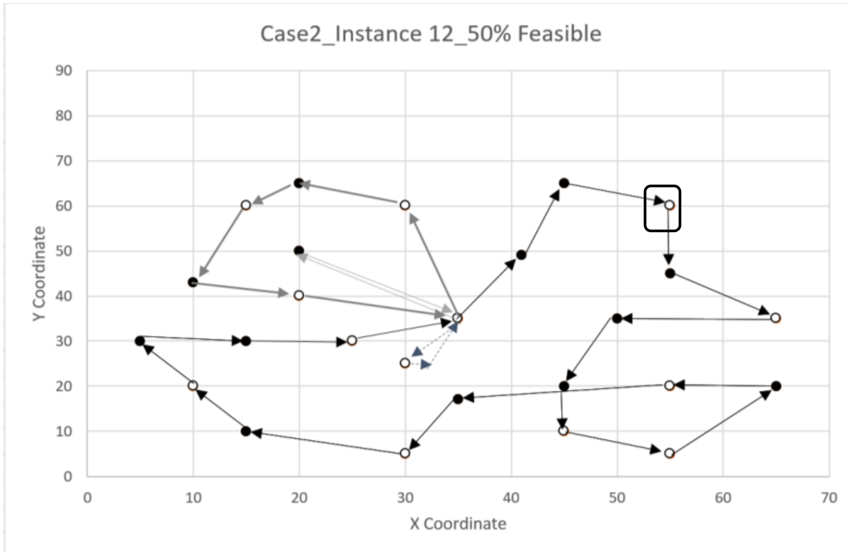


Figure 14. Route for Feasible Instance 12 Case 2

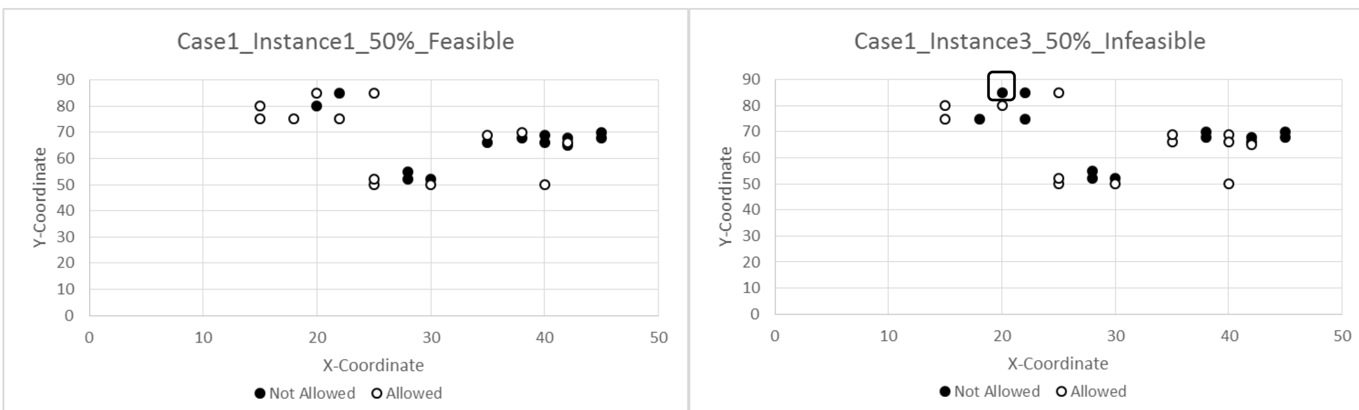


Figure 15. Case 1 Feasible and Infeasible Instance at 50% Parking Availability

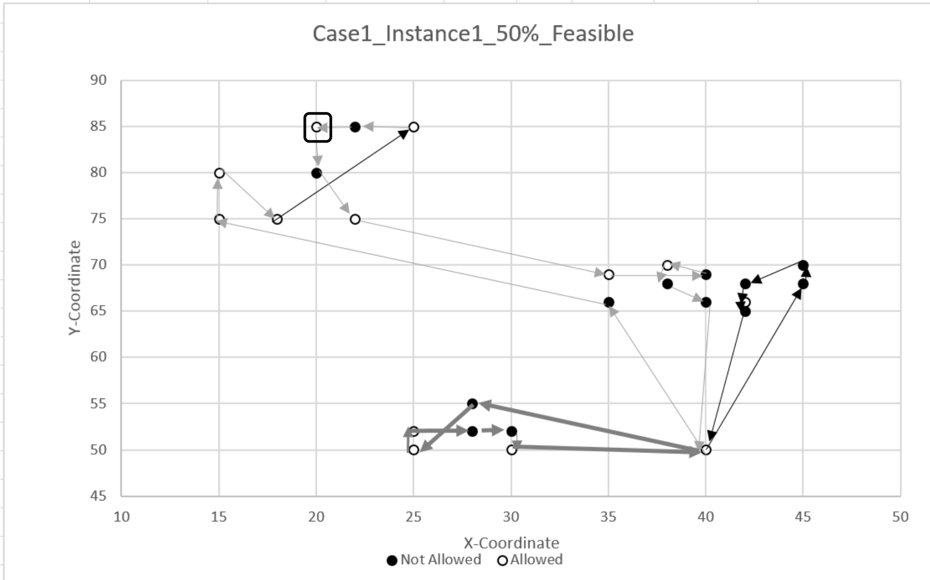


Figure 16. Route for Feasible Instance 1 Case 1

5. Extensions to Work

The work presented in this thesis is aimed to solve current real world problems for long haul truck drivers. Although the modified Clarke-Wright has been modeled to take into consideration real world scenarios (HOS weekly driving limitations and parking availability), it has not yet been applied to real data. Rather, Solomon instances have been used to see the effects of varying HOS regulations and parking availability. The ultimate goal is to evaluate the proposed modified heuristic with real world data including observed truck travel patterns discerned from on-board GPS units, public rest stop and commercial truck stop locations and availability, and network demands. To do this, there are several different data sets that have been obtained.

In the case studies, parking was randomly assigned to customer locations. In order to model real world characteristics of the problem, the locations of truck stops (private parking) and rest areas (public parking) will be used. Through an Honors Technology Grant, the research team was able to purchase truck stop data from a company called ‘Trucker’s Friend’. Figure 17 provides a mapping of the parking locations across the U.S. This figure shows that there are more parking locations in the central and eastern part of the U.S. than in the West. This could mean that it may be harder for truck drivers to find available (vacant) parking in the central and eastern US while it may be harder to simply find parking facilities in order to meet the HOS regulations in the West since the parking locations are not as densely spaced. In addition, the data set also provides further information on the truck stops and rest areas such as number of available spaces, operating hours, etc. Tables 5 and 6 summarize the data available in the Trucker's Friend dataset. Information such as the number of truck parking spots is important to consider because depending on the time of day, a truck stop or rest area could be at capacity and the truck driver would not be allowed to park there. This leads to a second problem needing to be considered.

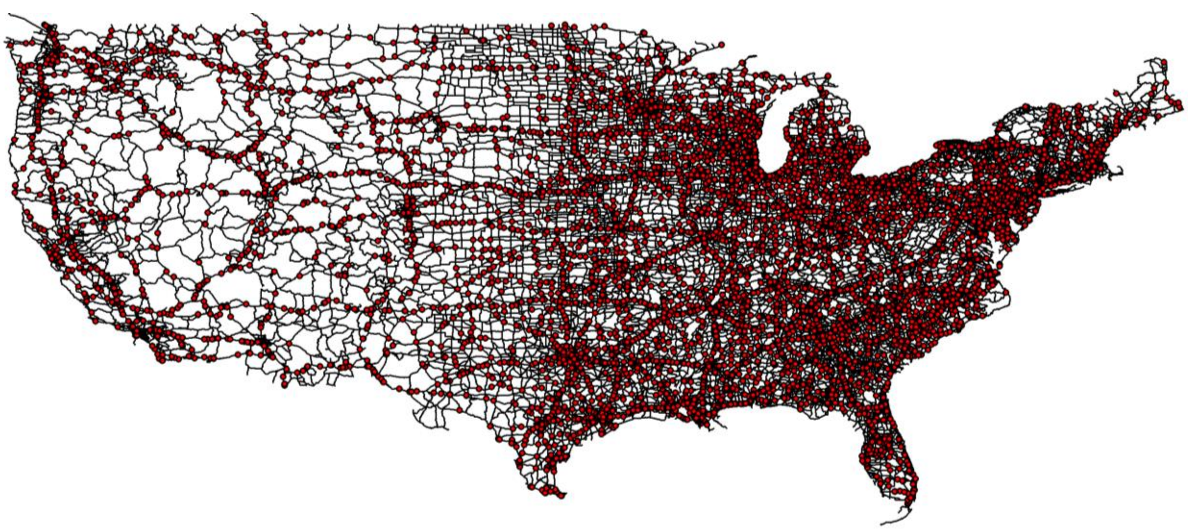


Figure 17. Map of Parking Locations Across U.S.

Table 5. Information for Truck Stops

Column Name	Description
ID Number	A unique number associated with one and only one truck stop
Name	A unique name of a truck stop
Highway Location	Address of truck stop
LocationCity	City that truck stop is located in
LocationState	State that truck stop is located in
LocationZipCode	Zip code that truck stop is located in
TruckDiesel	Yes/ No column for if the truck stop has a diesel pump
24HrDiesel	Yes/No column for if truck stop has 24 hour access to a diesel pump
OvernightTruckParkingSpaces	Number of overnight parking spaces for trucks
Restaurant	Yes/No column for if truck stop has a sit- down restaurant
FastFood	Yes/No column for if truck stop has a fast food restaurant
C-Store	Yes/No column for if truck stop has a convenience store
TruckerStore	Yes/No column for if truck stop has Trucker Store
Showers	Number of showers that truck stop has
GEOLOCATION	Latitude and Longitude of Truck Stop

Table 6. Information for Rest Areas

Column Name	Description
FID	A unique number associated with one and only one rest area
State	State the facility is located in
Rest_Area	The name of the rest area
Route	The interstate or highway the rest stop is located on
MilePost	Mile Post Number where rest stop is located
Municipality	Municipality where rest stop is located
County	County in which the rest area is located
Latitude	Latitude coordinates of rest stop
Longitude	Longitude coordinates of rest stop
Total Spaces	Total number of parking spaces
Truck Spaces	Number of truck spaces
Hours	The hours that the rest stop is open
Limit	The maximum allowable time to park/rest at the rest stop

In order to model the real world characteristics of the problem, capacity and time of day constraints need to be considered. In order to determine the truck volume flow and time of day patterns to evaluate if a parking location is at capacity or not, the Freight Analysis Framework (FAF) (Freight Analysis Network, 2016) will be used. The FAF network shows the movement and flow of trucks on the highway network. This information is critical because as explained earlier, many truck stops and rest areas are overcapacity. Data on freight truck volume will allow us to account for the time-of-day demand for parking in the problem formulation.

Lastly, rather than Solomon instance, the research team plans to derive actual customer locations from a truck GPS dataset obtained from a national trucking company. The dataset provides characteristics of truck drivers' routes and their duty status (driving, off-duty, etc.). Specifically, the data includes Driver ID, Truck ID, Latitude, Longitude, Date Time, Duty Status, and MPH. The description of each of these is provided in Table 7. This information is recorded every 15 minutes for each truck driver. Since the status of the driver at each data point is recorded, it is possible to infer when a truck is stopped to service a customer or complete required rest. This data will allow us to track the drive and rest time of the driver as well as when the driver is using the sleeper berth rule or completing required rest at another location. In addition, information on the driver's duty status could allow us to determine when the driver arrives at a customer location. If a driver is 'on duty' for a period following a report of 'driving' status, we could infer that the driver has arrived at a customer location and is performing a pick-up or delivery.

Table 7. National Truck GPS Dataset Information

Column Name	**Description**
Driver ID	A unique identifier for a truck driver
Truck ID	A unique identifier for a truck
Latitude	The latitude of the truck at the Date Time associated with it
Longitude	The longitude of the truck at the Date Time associated with it
Date Time	The date and time
Duty Status	Whether the driver is driving, on duty (not driving), off duty, in the sleeper berth, or unknown/ unavailable
MPH	The truck's speed in miles per hour at the Date Time recorded

6. Conclusions

This thesis presented a problem and method for solving a VRP that incorporates parking availability and HOS regulations. The proposed method is the first to explicitly take into consideration the 70-Hour Rule and parking availability to better replicate real world parking restrictions. This approach assesses the impact of parking availability as well as HOS regulations and how these interact. The results show that not only do HOS regulations impact the timeliness of a trip, but parking availability plays a major role as well. Furthermore, the case studies presented in this paper show that both the location of parking and structure of the customer network are critical in determining whether a sequence of customers can be served without violating HOS regulations. For customer networks whose locations are dispersed (larger distances between customer locations), parking availability plays a crucial role in determining the feasibility of a route. Clustered networks, on the other hand, tend to have more feasible routes since the smaller distance between customer locations allow drivers to select from multiple parking locations on each route. This work can be expanded to incorporate real-world data including actual customer locations rather than simulated locations, actual parking locations instead of restricting parking to customer locations only, and actual parking availability/demand instead of random availability. By developing a model from real-world data, we can help decision makers tasked with creating transportation policies to more effectively determine where improvements should be made to existing parking capacity.

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