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EVALUATING RAMP METER WAIT TIME IN UTAH

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RESEARCH



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LIST OF ACRONYMS

AIMD	Additive Increase Multiplicative Decrease
ALINEA	Linear Feedback Control (Asservissement Linéaire d'Entrée Autoroutière)
Caltrans	California Department of Transportation
CRM	Corridor Responsive Metering
EQ	Excessive Queue
FHWA	Federal Highway Administration
HCM	Highway Capacity Manual
HERO	Heuristic Ramp Metering Coordination
HOV	High Occupancy Vehicle
IQ	Intermediate Queue
ISTEA	Intermodal Surface Transportation Efficiency Act
ITS	Intelligent Transportation System
MnDOT	Minnesota Department of Transportation
NB	Northbound
PQ	Passage Queue
RMSE	Root Mean Square Error
SB	Southbound
SWARM	Systemwide Adaptive Ramp Metering
SZM	Stratified Zone Metering
UDOT	Utah Department of Transportation
VicRoads	Roads Corporation of Victoria
WSDOT	Washington State Department of Transportation

EXECUTIVE SUMMARY

The purpose of this research was to develop an algorithm that can accurately predict wait times at metered freeway on-ramps throughout the state of Utah using existing loop detector systems on the ramps. The loop detectors provide data in 60-second increments that include volume, occupancy, and the ramp meter discharge rate. The methods proposed in this research would allow for the Utah Department of Transportation (UDOT) to publish live queue length and associated wait time estimates to a website (not part of this research), and thus communicate to the public whether long wait times can be expected at a particular metered on-ramp. The model results would also more broadly aid in traffic operations management.

Five days of data were collected during the PM metering period at four on-ramps to I-15 throughout Davis, Salt Lake, and Utah counties, including the northbound on-ramp at Layton Parkway in Davis County, the southbound on-ramp at Bangerter Highway in Salt Lake County, the southbound on-ramp at Pleasant Grove Boulevard in Utah County, and the southbound on-ramp at University Avenue in Utah County. These ramps were chosen because they cover a broad region of the metered on-ramps in Utah and they each possess unique characteristics that allow the research to cover a wide range of ramps that may be representative of all metered on-ramps throughout the state. Data collected for each ramp included the queue length and the number of vehicles entering the ramp in each minute, which were then paired with the relevant detector data for occupancy, density, and flow rate.

The ramp queues were modeled using several methods, including a traffic conservation model and multiple variations of a Kalman filter model. The conservation model would be the ideal model were the detector data perfect. However, because of detector imprecision, this method is often inaccurate. The Kalman filter model attempts to account for this error by introducing occupancy data, ramp characteristics, and a Kalman filter constant K which is typically between 0 and 1. For each 15-minute period in the collected data, an optimal K value for that period was determined using a non-linear maximization procedure. This cannot be used for queue length prediction however, as it relies on manually observed queue lengths. A model developed by Vigos et al. (2006) assumes a constant K equal to 0.22. This research developed and considered two additional methods to estimate an appropriate K value for a given ramp or a

given performance condition: first, a linear regression model predicting K using density, occupancy, and a variable representing each ramp as predictors; and second, a heuristic model that applies an average value of K based on density and volume patterns determined through cluster analysis. The research demonstrates that although the accuracy occasionally varied, the heuristic and Vigos models were both generally within approximately 10 vehicles of the observed queue length at each ramp.

Following the results of the queue length analysis, the queue lengths were converted into wait times by dividing the modeled queue lengths by the observed metering rate. This method allows for the estimation of wait times to be fully automated at each ramp, relying solely on the detector data and general characteristics of the ramp, such as the number of lanes and the length of the ramp. This method was analyzed to ensure it represented the observed wait times, which was verified to be an accurate method of establishing wait times. The heuristic and Vigos models proved to be most accurate in predicting the wait time at the four ramps, while the linear regression model and the conservation model performed much more poorly. The wait times provided by the heuristic and Vigos models were generally within approximately 45 seconds of the observed wait times.

Based on the results of this analysis, it is recommended that the Vigos model be implemented by UDOT, as it is nearly as accurate as the heuristic model, but is much simpler to implement, as it requires a single unvarying K value for all ramps and traffic conditions. The current method employed by UDOT to estimate wait times involves extensive field data collection on a ramp-by-ramp basis and using arbitrary occupancy values to assess wait times. The implementation of the Vigos model will significantly reduce the amount of time required by UDOT as this method can easily be applied to any metered on-ramp throughout the state.

There are several limitations and challenges that were experienced throughout this project. The COVID-19 pandemic caused traffic to decline significantly, delaying the data collection period and overall project schedule. Additionally, the detector data does not predict volumes or occupancies consistently and occasionally fails to produce any data, so wait time estimates are not as accurate as they may otherwise be. However, the Vigos model will provide UDOT with additional insight of what wait times are expected to be at metered on-ramps.

1.0 INTRODUCTION

1.1 Problem Statement

Ramp metering involves the deployment of a traffic signal on a freeway on-ramp to control the rate at which vehicles enter the freeway facility. Controlling the rate at which vehicles can enter the facility allows traffic to flow in a more consistent manner. Ramp metering has been used since the late 1950s and early 1960s. Though the primary goal of ramp metering is to improve traffic flow on the primary expressway facility, the delay caused by the ramp meters is of interest to traffic operations as well. The Utah Department of Transportation (UDOT) is interested in taking an active role in evaluating and monitoring ramp meter delays across the state to provide better information to the public regarding wait times at metered on-ramps.

1.2 Objectives

The primary objective of this research was to evaluate ramp meter wait time using existing detector data and to develop a method that can reliably predict wait time at any metered on-ramp throughout the state.

UDOT will benefit from this research by gaining a better understanding of the performance of ramp meters. Using the results of the research, ramp meter wait times will be provided to communicate system performance to UDOT managers, operational staff, and the public. The results can then be published to the web (by UDOT) to help provide situational awareness and context of ramp meter delays. UDOT can also use the data to balance freeway performance with ramp meter wait times with the eventual goal to implement a managed motorways system.

1.3 Scope

This report is intended to provide a thorough understanding of metering at freeway on-ramps both individually and within the system. The current ramp metering algorithm is based on the Seattle Bottleneck methodology (UDOT, 2013b). This research investigates this

methodology as well as proposed improvements to ramp metering which could further utilize existing research for practical application.

Four on-ramps were studied in this research and the recommendations provided are based on the results observed at these ramps. Although the ramps were chosen to cover a broad range of ramp configurations and locations, this research does not provide comprehensive analysis for all metered on-ramps throughout the state of Utah. This research also does not provide the methodology by which UDOT may publish these results to a website.

1.4 Outline of Report

The report is organized into the following chapters:

- Chapter 1 includes an introduction to the research, project objectives, and the outline of the report.
- Chapter 2 includes a literature review of ramp metering design, selected ramp metering algorithms used throughout the world, UDOT's current performance measures and wait time estimation methods, and existing literature available regarding estimating queue lengths and wait times at metered on-ramps.
- Chapter 3 includes a discussion on the methods used to model queue length and wait time and how the data were collected.
- Chapter 4 includes a discussion on the data analyses conducted on each of the on-ramps used in this research and the various models used to predict queue lengths and wait times on these ramps.
- Chapter 5 includes a summary of the findings of this research study, limitations and challenges, recommendations for future research, and concluding remarks.

2.0 LITERATURE REVIEW

2.1 Overview

This chapter provides a review of literature that relates to the research presented in this report. The review focuses on ramp meter operation and evaluation, methods utilized in ramp meter control to measure performance, as well as existing ramp meter queue length and wait time algorithms. First, the review discusses the rationale used in designing and implementing various ramp metering systems in different areas throughout the world. This will help UDOT to anticipate and prepare for population growth and to accommodate growing traffic volumes on local roadways by increasing understanding of ramp metering theory and practices. Next, the review will discuss the work UDOT has done prior to this project in analyzing freeway and ramp performance, which includes the existing ramp meter wait time estimates. A brief review of data collection methods and technologies used by UDOT will follow. Understanding automatic data collection will provide important context for the next section of the literature review, which covers both freeway and ramp performance measures and their connection to ramp metering. Following the discussion on performance measures, a discussion of existing literature on queue length and wait time estimation algorithms will be presented. Finally, the review will conclude with a summary of all items discussed.

2.2 Ramp Metering Design and Implementation

Ramp meters have been employed in many urban locations in the United States and around the world as a means of mitigating congestion caused by growing demand. By controlling the flow of traffic onto freeways—particularly around peak usage times—ramp meters allow freeways to operate at a higher volume while lowering the likelihood or severity of decreases in level of service. Additional observed benefits of ramp metering include decreases in crash rates, lower emissions, and improved safety (Papageorgiou and Kotsialos, 2002).

Several approaches may be taken to implement a ramp metering program depending on transportation needs and the goals of the transportation agency. Meters are generally classified into two different types: pre-timed and traffic-responsive. Pre-timed ramp meters are generally

based on historical data, whereas programmed traffic-responsive meters use real-time data to detect and react quickly to changing traffic conditions. Controls may be implemented at a local level based only on conditions immediately surrounding the ramp or on a systemwide level based on conditions of a freeway corridor including multiple on-ramps (Jacobson et al., 2006).

Pre-timed metering at both the local and systemwide level is determined based on historical data, making it simpler to implement than traffic-responsive metering. When congestion problems are predictable, pre-timed meters can generally meet needs for managing flow onto the freeway. However, pre-timed metering rates must be regularly monitored and periodically updated to accommodate changes in traffic patterns, which may result in additional long-term expenses. Furthermore, pre-timed meters cannot adjust to traffic conditions in real time, which may employ rates that are either too restrictive or too free for the actual conditions (Jacobson et al., 2006).

Traffic-responsive metering depends on real-time data collection. This often makes initial programming for the meters more difficult but reduces the number of required updates long term once the meters have been tuned in the field. Local traffic-responsive metering can be used to mitigate congestion based on data collected on the freeway near the ramp. These meters rely on data collected via sensors to determine an acceptable rate at which vehicles can be released onto the freeway from a specific on-ramp. Systemwide traffic-responsive metering coordinates metering rates across the entire freeway section to effectively manage entry onto the freeway for optimal use (Jacobson et al., 2006).

Although ramp metering has proven to considerably improve freeway service, it also has some drawbacks. Ramp meters tend to favor those who commute longer distances on the freeway, as the time spent waiting on the on-ramp is more than made up for by the travel time saved on the freeway. Those who travel shorter distances may not benefit or may even be negatively affected by wait times at on-ramps, which may exceed time savings on the freeway. If queueing on the ramp is not properly managed, ramp metering can have negative effects on the larger road network. While freeway travel times may improve, ramp delay may become too high, and in some cases spillback onto arterial roads can lead to serious disruptions (Liu et al., 2007). Public acceptance of ramp metering is valuable to its overall success; excessive wait times or

slow metering rates may lead drivers to ignore the meters or lobby for other methods of traffic management (Jacobson et al., 2006).

Several metering approaches are available for ramp meter control. These approaches generally use a mixture of local and systemwide traffic-responsive metering rates to optimize traffic flow during peak periods. Due to the wide variety of existing metering algorithms in use around the world, an exhaustive list is not practical in this literature review. Rather, some of the more common metering strategies are briefly explained in the following subsection including the Seattle Bottleneck method, Additive Increase Multiplicative Decrease (AIMD), Fuzzy Logic, Stratified Zone Metering (SZM), Systemwide Adaptive Ramp Metering (SWARM), Linear Feedback Control (ALINEA), and Heuristic Ramp Metering Coordination (HERO).

2.2.1 Seattle Bottleneck Algorithm

UDOT's Coordinated Ramp Metering system currently utilizes the Seattle Bottleneck algorithm to determine ramp metering rates and will thus be discussed in greater detail than other ramp metering algorithms (UDOT 2013b). The Bottleneck algorithm calculates two different metering rates, one based on local conditions, and one based on systemwide conditions. Additional adjustments are made based on conditions at the on-ramp (Jacobson et al., 1989). These calculations are made in real time using data collected by sensors on the freeway and the on-ramp. The algorithm is designed to operate such that it maintains volume on the mainline below its capacity to avoid bottlenecking and congestion. By measuring the flow of traffic upstream of the ramp and monitoring conditions downstream, the algorithm determines an appropriate metering rate to maximize freeway use without causing congestion. This is commonly referred to as a "demand-capacity" strategy, as it aims to decrease the freeway demand as capacity is approached (Hadj-Salem et al., 1994).

The local metering rate is determined based on historical data collected from mainline stations. Volumes are correlated with historical occupancy data, which gives an approximation of traffic volume from real-time occupancy data during operations. Occupancy refers to the percent of time a point on the road is occupied by a vehicle; for example, if no vehicle passes over the detector during a given time period, the occupancy would be 0 percent, whereas if vehicles were detected passing over the detector during half of that same time period, the time occupancy

would be 50 percent. The combined upstream volume and volume of entering vehicles is designed to meet capacity for that segment of freeway, and the metering rate is thus calculated such that the number of vehicles released from the on-ramp is the difference between the freeway capacity and the upstream volume. A set of control values are established based on the volume of entering vehicles needed to bring the freeway segment to capacity given a certain occupancy reading (Jacobson et al., 1989). Metering rates are calculated to provide that volume by interpolating between control values as shown in Equation 2.1:

$$A_i = A_x + (A_y - A_x) * (P_i - P_x) / (P_y - P_x) \quad (2.1)$$

where:

A_i = Calculated metering rate

A_x = Metering rate associated with P_x

A_y = Metering rate associated with P_y

P_i = Mainline occupancy at station i

P_x = Lower occupancy control value

P_y = Higher occupancy control value.

The systemwide metering rate, also referred to as the bottleneck metering rate, is triggered when the average mainline occupancy exceeds a certain threshold and detectors indicate that vehicles are being stored on the freeway section. The freeway section may be defined as beginning just before an on-ramp and ending just after an off-ramp further downstream. Vehicle storage is defined in Equation 2.2:

$$Q_{INit} + Q_{ONit} > Q_{OUTit} + Q_{OFFit} \quad (2.2)$$

where:

Q_{INit} = Upstream mainline volume for section i at time t

Q_{ONit} = On-ramp volume for section i at time t

Q_{OUTit} = Downstream mainline volume for section i at time t

Q_{OFFit} = Off-ramp volume for section i at time t .

Data are collected and the algorithm adjusts to that data in 1-minute periods. To prevent bottlenecks, an upstream ramp reduction is calculated using the relationship shown in Equation 2.3:

$$U_{i(t+1)} = (Q_{INit} + Q_{ONit}) - (Q_{OUTit} + Q_{OFFit}) \quad (2.3)$$

where:

$U_{i(t+1)}$ = Upstream ramp reduction for the next 1-minute period.

Freeway segments are assigned areas of influence based on their potential to be affected by other ramps. Operators can adjust the parameters governing areas of influence as needed. Weighting factors are also assigned based on the anticipated magnitude of the effect from different parts of the areas of influence. Based on the area of influence and the weighting factor, the upstream ramp deduction is distributed among the affecting upstream ramps as shown in Equation 2.4:

$$BMRR_{ji(t+1)} = U_{i(t+1)} * WF_j / \text{sum}(WF_j)_i \quad (2.4)$$

where:

$BMRR_{ji(t+1)}$ = Bottleneck metering rate reduction for ramp j on section i following time t

WF_j = Weighting factor for ramp j

$\text{sum}(WF_j)_i$ = Sum of weighting factors in section I .

The bottleneck metering rate can then be calculated as shown in Equation 2.5:

$$BMR_{ji(t+1)} = q_{ONjt} - BMRR_{ji(t+1)} \quad (2.5)$$

where:

$BMR_{ji(t+1)}$ = Bottleneck metering rate for ramp j on section i following time t

q_{ONjt} = Entrance volume from ramp j at time t .

The two key points to consider in bottleneck equations are the points before and after the bottleneck, where the cumulative flow of the freeway section is considered (Ni, 2016). Two variables at each of these locations are considered: time and flow. Each of these locations will record the traffic volume at a certain time, which can be identified as the creation of the

bottleneck. Holding flows at bottlenecks to capacity maximizes the ability of the ramp to reduce freeway congestion without causing excessive spillover onto local roadways.

Evaluations by several agencies, including the Washington State Department of Transportation (WSDOT) observed that the Seattle Bottleneck algorithm tends to be reactive, rather than proactive, meaning it does not address bottlenecks until they are detected. It also tends to react dramatically to on-ramp queueing, which can cause dramatic oscillations between freeway bottlenecking with short on-ramp queues and smooth freeway flow with long on-ramp queues (Taylor and Meldrum, 2000a).

Minimizing congestion caused by vehicles merging onto the freeway by controlling flow onto the freeway and breaking up entering platoons is one of the main benefits of ramp metering. If excessive queueing on the ramp leads to a dramatic decrease in metering restrictiveness, the subsequent high entry rate of vehicles will lead to congestion on the mainline. However, the Bottleneck algorithm is somewhat prone to causing long ramp queues because it is designed to always choose the most restrictive metering rate. The Bottleneck method's use of real-time sensor data carries some risk—while it facilitates quick adjustments to metering based on traffic conditions, if sensors fail to accurately communicate conditions, the calculated metering rate will not be appropriate (Jacobson et al., 1989). Despite these shortcomings, data generally show that the Bottleneck algorithm leads to improvements in freeway conditions including decreased crash rates and travel time (Jacobson et al., 2006).

2.2.2 Other Ramp Metering Algorithms

The Additive Increase Multiplicative Decrease (AIMD) methodology is modeled after a computer transmission congestion control algorithm of the same name (Perrine et al., 2015). Computer traffic is strategically increased and decreased in order to optimize the traffic of the entire system. It is designed to improve mainline traffic flowrates by aggressively responding to nonrecurrent congestion. When mainline congestion is detected in a ramp metering system which includes multiple ramps, upstream ramps are individually controlled at a multiplicatively (geometrically) reduced rate, reducing flow onto the freeway to a fraction of what would be typical. Simultaneously, downstream ramps are additively (linearly) increased to initial ramp demand. This metering strategy allows ramps to reach their prescribed storage capacity without

overwhelming the freeway system. By treating congestion quickly, delays on the freeway mainline are decreased. When performing as intended, the overall system is optimized as local streets remain below capacity while reducing overall delay on all roadways. However, this method appears to have primarily been used in simulation and thus far not applied in practice (Perrine et al., 2015).

The fuzzy logic metering algorithm is based on the computer programming principle of fuzzy logic, which deals with vague and uncertain information (Chen et al., 1990). In ramp metering, this provides flexibility in determining metering rates. Fuzzy logic has been used in a wide range of applications, with the first known use in ramp metering implemented by the California Department of Transportation (Caltrans) in 1990 at the San Francisco-Oakland Bay Bridge (Taylor and Meldrum, 2000b). Other early uses took place in locations such as the Netherlands and Washington, and fuzzy logic algorithms are now widely used for managing ramp meter operations (Taylor and Meldrum, 2000a). Using fuzzy logic for ramp metering can account for certain shortcomings faced by other metering approaches. For instance, most metering algorithms rely heavily on real-time data, even though detectors may fail to provide reliable data. While metering using fuzzy logic is not performed independent of data, it can be adjusted to deal with data collection deficiencies. Since a range of different inputs can be used simultaneously, fuzzy logic is not as heavily affected by data collection issues as some other metering algorithms, which depend on very few data sources (Taylor and Meldrum, 2000b).

SZM uses a method of overlapping zones, which are defined as a section of freeway bounded by two mainline detectors (Kondyli and Shehada, 2019). A zone may include several detectors between the two boundary detectors. Each zone belongs to at least one layer; a layer is a series of consecutive zones of equal length. Due to the variety of potential zone sizes and layer configurations, a given on-ramp may fall within several different zones and layers (Xin et al., 2004). The SZM algorithm is designed to maintain a consistent flow of traffic from one zone to the next by balancing traffic volumes entering and exiting the boundaries of the zone. Like the Seattle Bottleneck algorithm, SZM meters based on demand-capacity strategy. The Minnesota Zone Algorithm in the Twin Cities is an example of an SZM system (Jacobson et al., 2006).

SWARM was first developed in the 1990s by Caltrans; SWARM divides the freeway into contiguous segments, each bounded by the location of two bottlenecks, with multiple off-ramps and on-ramps in between (Belisle et al., 2019). Two separate algorithms are used in determining the metering rate globally and locally—SWARM1, the global metering rate, is based on forecasts of density using linear regression, and SWARM2, the local metering rate, is a traffic-responsive system—to determine the optimal metering rate. SWARM2 may be determined using any local traffic-responsive metering calculation. Once SWARM1 and SWARM2 are calculated, the more restrictive of the two rates is used as the metering rate (Kondyli and Shehada, 2019).

Asservissement Linéaire d'Entrée Autoroutière (ALINEA), which translates as “linear feedback control of a freeway entrance,” was introduced in France over 30 years ago (Belisle et al., 2019). Since then, several other ramp metering algorithms have been designed using the base algorithm from ALINEA. ALINEA is a local feedback strategy that determines metering rates using historical data as well as current and target occupancy of the freeway (Cho et al., 2020). A feedback strategy determines metering rates using downstream measurements, rather than the upstream measurements used by feedforward strategies like the Seattle Bottleneck algorithm. Unlike systemwide metering systems like the Seattle Bottleneck algorithm or SWARM, ALINEA functions as a local metering system (Papamichail et al., 2010). The metering rate adjusts itself over time to keep traffic on the merging segment downstream of the ramp at a desired density. Feedforward metering algorithms, which depend on upstream data rather than downstream data, sometimes perform poorly because they are designed to restrict metering once bottlenecking has begun. ALINEA is designed to prevent bottlenecks by controlling the flow of additional vehicles to the mainline such that capacity is not exceeded. The target density is often the critical density, rather than the maximum density. Achieving maximum density often leads to unstable flow, which may break down and lead to congestion. Critical density, however, allows for slightly lower traffic flow that is more stable and reliable (Papamichail et al., 2010).

In 2010, a new ramp metering methodology was developed and released by Prof. Markos Papageorgiou and Dr. Ioannis Papamichail at the Technical University of Crete in Greece (Belisle et al., 2019). The methodology proposed in their report, HERO, is a traffic-responsive feedback control strategy. The algorithm includes the individual ramp metering calculation from the ALINEA algorithm, but Papageorgiou and Papamichail argue it is improved as it is

coordinated, feedback based, rule based, and reactive (Belisle et al., 2019). Rather than operating at individual ramps as ALINEA does, HERO provides traffic-responsive metering rates systemwide (Papamichail et al., 2010). HERO places particular emphasis on the setting of minimum queue lengths at each on-ramp throughout the system; as an on-ramp exceeds that queue length, the algorithm reallocates congestion from that ramp to a cluster of ramps upstream until the queue drops below the preset value (Belisle et al., 2019). The algorithm is solely intended to be activated when the ALINEA algorithm fails to meet expectations; HERO is triggered when: 1) the mainline occupancy is over a threshold of the target occupancy, and 2) the queue on the on-ramp is over a threshold of the maximum queue length available at that ramp (Belisle et al., 2019). Any ramp in the system may become the “master” ramp, which will then use the upstream ramps’ extra storage length to alleviate the spillback on the master ramp. Once the master ramp either meets one of two conditions—1) mainline occupancy drops back below the threshold of target occupancy, or 2) queue on the master ramp is lower than a threshold of the maximum queue—the HERO algorithm will shut off and the ramp metering system will return to the ALINEA base algorithm. HERO was originally implemented at the Monash freeway in Melbourne, Australia. Successful results were obtained following careful calibration of the HERO system (Papamichail et al., 2010). Overall, since its implementation in Melbourne, HERO has been used in several locations in New Zealand, Amsterdam, and the United States (Belisle et al., 2019). HERO is still in use in Melbourne, where it is used as the metering algorithm for the Roads Corporation of Victoria (VicRoads) Managed Motorways program. These algorithms have been effective at determining the metering rate in varying conditions (Gaffney et al., 2019). The UDOT-established ramp metering algorithm, though, is a variation of the Seattle Bottleneck method. Therefore, it is imperative an algorithm for estimating queue length and wait time in Utah be able to use existing ramp conditions.

2.3 Utah Department of Transportation Existing Methods

UDOT currently uses the Seattle Bottleneck algorithm in conjunction with local metering operations to manage ramp metering throughout the state (UDOT, 2013b). The algorithm generally operates the same way the original Seattle Bottleneck algorithm does, as outlined in Section 2.2.1. The local metering operations are currently in practice at a number of ramps along

the I-15 corridor. Meters detailed in the Corridor Responsive Metering (CRM) report provided by UDOT are located at ramps from 3300 South to 5300 South northbound (NB) and southbound (SB), 9000 South to 12300 South NB and 7200 South to 12300 South SB in Salt Lake County (UDOT, 2013b). SB meters are active during the evening peak period, beginning at 3:30 PM and ending at 6:30 PM. All NB meters are active during the morning peak period from 6:30 AM to 9:15 AM. NB meters from 9000 South to 12300 South are also active during the evening peak period from 3:30 PM to 6:30 PM. Throughout the state, I-15 has ramp meters from 400 South in Springville, Utah County in the south, to Hill Field Rd. in Layton, Davis County in the north, as shown in Figure 2.1. Depending on the ramp, fixed-rate metering or traffic-responsive metering may be used. Where traffic-responsive metering is used, rates are calculated every 60 seconds, although they may be calculated as frequently as every 20 seconds.

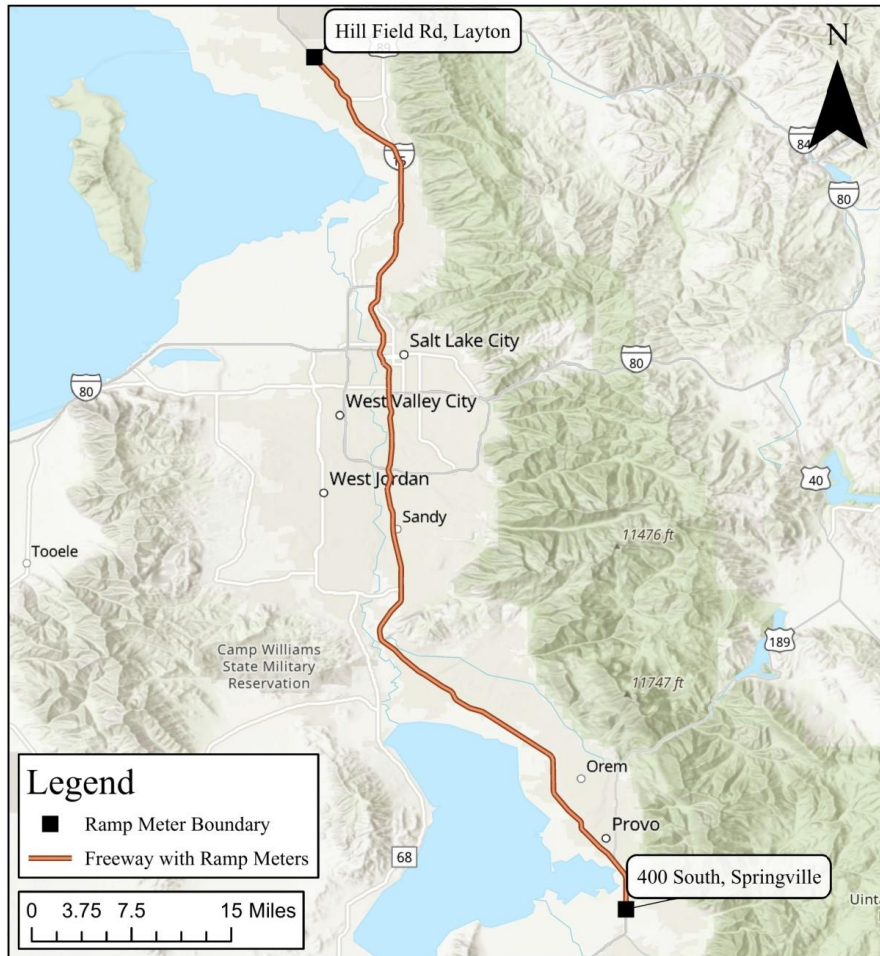


Figure 2.1 Extents of metered on-ramps to I-15 in Utah.

This section will explain UDOT modifications and improvements to the Seattle Bottleneck method to pertain to I-15, provide a description of the current method used to portray ramp meter wait time, and provide a description of UDOT’s goals of implementing a managed motorways and the importance of accurate ramp wait time estimation.

2.3.1 Modifications from the Seattle Bottleneck Algorithm

Although UDOT’s CRM system closely follows the original Seattle Bottleneck methodology, certain adjustments were made for its implementation on I-15. The local metering rate does not interpolate between the base volume-occupancy relationships. Instead, there are six “levels” of volume-occupancy relationships, with a certain metering rate attached to each relationship. If mainline occupancy reaches the occupancy threshold for a volume-occupancy relationship, that metering rate is used without interpolating with a higher level (UDOT, 2013b). A second difference is the fact that the local queue override specifies the calculation for the metering rate adjustment, while the original Seattle Bottleneck algorithm does not specify the means by which the metering rate is increased to avoid spillback. The metering rate adjustment is shown in Equation 2.6:

$$IOR_{i,t} = \min[AMR_{i,t} + IRA_i, RL_i] \tag{2.6}$$

where:

$IOR_{i,t}$ = Intermediate queue override metering rate for ramp i at time t

$AMR_{i,t}$ = Metering rate calculated by the algorithm for ramp i at time t

IRA_i = Rate adjustment for an intermediate queue override at ramp i

RL_i = Rate limit for the queue override at ramp i .

The inclusion of a minimum bottleneck metering rate limit can help mitigate the risk of the on-ramp queue spilling back onto the arterial by ensuring that freeway conditions have a limited effect on vehicle wait times. However, this does increase the risk of the freeway exceeding capacity, which could lead to bottlenecks.

2.3.2 UDOT's Current Ramp Wait Time Estimation Methods

UDOT freeway performance metrics provide an example of real-time analysis of ramp conditions. Ramp performance is rated on a 3-tier scale, which aims to characterize each ramp in real time as having below average, average, or above average wait times. The current definition of “average” does not necessarily correlate with wait times but rather is based on past history specific to each ramp during the PM metering period. A ramp experiencing heavy traffic may still indicate “average” wait times, which could mislead a user evaluation of the ramp. Some ramps cannot indicate a “below average” wait time because the average wait time assigned to the ramp falls in the lowest wait time range. Currently a system of 15 ramp meters along I-15 have published data pertaining to ramp performance. Wait times are estimated based on real-time data collected from intermediate and excessive queue detectors. Occupancy values are correlated with wait times estimated by manually collected historical data. These occupancy values are also compared with historical occupancy data to determine whether the wait is “above average,” “average,” or “below average.” Figure 2.2 shows UDOT’s ramp wait time dashboard on the Freeway Performance Measures website.

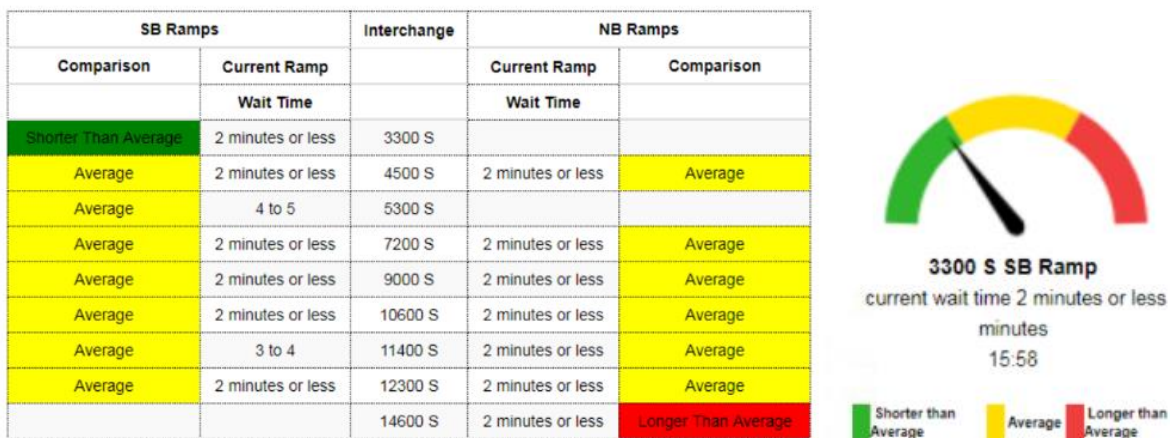


Figure 2.2 UDOT ramp meter wait time web page (UDOT, 2020).

The table on the left side of the dashboard lists estimated maximum wait times and their comparison to the average wait times for each ramp where metering is active and historical data has been analyzed. Individual ramps can be chosen to compare the current wait time to the average wait time for the selected ramp. This comparison is illustrated by the dial on the right,

which lists the estimated maximum wait time, the time at which the data were collected, and the comparison of the current wait time to the estimated average wait time. This method of estimating wait times, although it does provide a useful interface for UDOT employees and Utah residents to view, requires significant time commitment and calibration on UDOT's part.

2.3.3 Managed Motorways

In relation to the development and improvement of ramp metering in Utah, UDOT has the goal of achieving a more efficient and intelligent freeway network by implementing practices used on some Australian roads in the "Managed Motorways" program. Managed Motorways is an intelligent transportation system (ITS) that incorporates multiple communications and control technologies and information both in and around the road (Bennett and Faber, 2014). The system used on managed motorways includes the HERO coordinated ramp metering system as well as variable speed limits, lane control, incident detection, real-time traffic flow data, and other forms of ITS tools to prioritize mainline speed and flow. By implementing these practices first used in Australia, UDOT aims to optimize mainline speed and flow and improve the overall quality of the freeway system along I-15. The development of an accurate and efficient method to view wait times on freeway on-ramps may also aid UDOT in implementing a managed motorways system.

2.4 Data Collection

Data collection is essential to accurate and efficient evaluation of ramp meter performance measures. Although manually collected data and traffic simulations are valid options for evaluating ramp meter behavior, automated data collection is the most effective means of analyzing actual ramp service over an extended time period (UDOT, 2013b). Collecting data manually is extremely labor intensive, while simulations are primarily used for isolating and comparing variables rather than analyzing what is occurring in the field (Vigos et al., 2006). A variety of technologies may be used to collect real-time data for algorithm use and performance evaluation. This section will briefly discuss the automatic data collection devices in use at Utah on-ramps, which will assist in understanding the performance measures discussed in Section 2.5.

Automated data collection devices are classified as intrusive or nonintrusive depending on the means by which the devices are installed. Intrusive detection devices are those that are placed on or inside the roadway to collect data. This includes inductive loop detectors, magnetic detectors, and pneumatic tubes. Intrusive detection devices are more difficult to install, as they place workers in dangerous areas, and in the case of inductive loop detectors and magnetic detectors, closing portions of the road for installation may be necessary (Mimbela and Klein, 2000). Nonintrusive detection devices can be mounted on traffic signals or in similar areas to collect data. Examples of nonintrusive detection devices include microwave detectors, infrared sensors, and ultrasonic sensors.

Inductive loop detectors utilize wires embedded in the pavement. Vehicle passage over the detector decreases an inductive current, which allows the controller to identify information such as vehicle passage, presence, occupancy, and count. Overall, these data can function in a wide variety of uses, and the detectors can assist in regular operations for long periods of time. The main drawback is the inconvenience associated with installation and maintenance (Mimbela and Klein, 2000).

Freeway on-ramps in Utah generally use loop detectors to collect data and manage traffic-responsive operations. Sensor configurations across Utah are generally similar to each other, with the main variations occurring due to capacity needs and the layout of adjacent arterials. Figure 2.3 provides an example of the general positioning of detectors pertinent to a three-lane metered ramp (UDOT, 2013a). Loops 1-10 calculate the traffic flow approaching the merge area on the freeway with the ramp. Loops 20-22 are used to determine when vehicles have passed the meter and are called passage queue (PQ) detectors. Loops 17-19, the demand loops, are used to identify vehicle presence at the meter. Loops 23-25 are the intermediate-queue (IQ) loop detectors, located approximately one-third of the length of the ramp from the arterial. Loops 26-28 are the excessive queue (EQ) loop detectors, which are positioned at the entrance of the ramp, adjacent to the arterial. These loop configurations collect the necessary data to allow the Seattle Bottleneck algorithm to operate the ramp meters (UDOT, 2013b).

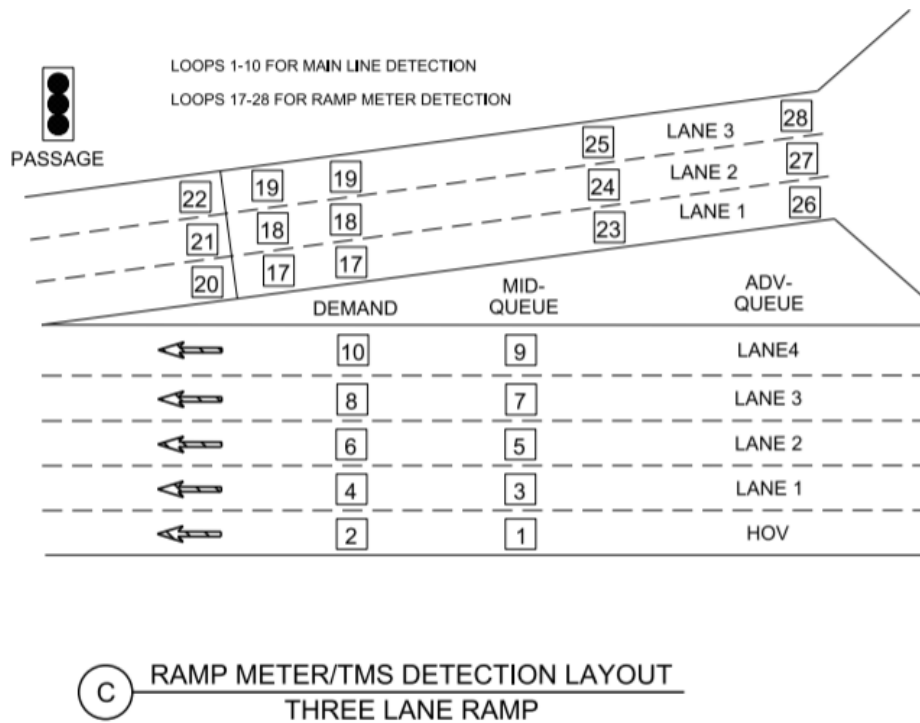


Figure 2.3 Ramp meter detectors (UDOT, 2013a).

2.5 Performance Measurement

During the 1990s, performance measurement became widely adopted by state transportation agencies and metropolitan planning agencies across the United States following the Intermodal Surface Transportation Efficiency Act (ISTEA) (Shaw, 2003). Performance measures are calculated based on data collected on roadways and when properly designed, they help decision makers identify deficiencies in the system such as excessive congestion. Properly designed performance measures can help a transportation agency improve accountability, efficiency, effectiveness, and clarity of communication, all of which assist decision makers in improving the system. Conversely, poorly designed performance measures will lead agencies to expend resources pursuing matters of little benefit (Jacobson et al., 2006). The Federal Highway Administration (FHWA) recommends using as few performance measures as possible and making those performance measures simple, as performance measures are most useful in decision-making when they concisely and clearly provide analyses of essential data (Jacobson et al., 2006).

This section will first review the existing performance measures employed by UDOT. Measures for evaluating ramp conditions as they are affected by metering will then be reviewed. Since ramp meters are usually a means of improving freeway performance, ramp meter effectiveness is generally evaluated based on mainline conditions. However, ramp wait times, ramp spillback, and other measures are useful when evaluating the overall effect of metering. Understanding the effect on both the on-ramp and the freeway mainline can enable a more comprehensive study of the effects of a metering system.

2.5.1 Measures Employed by the Utah Department of Transportation

UDOT currently uses a range of freeway and ramp performance measures which are available for public access on the UDOT website. Performance measures posted on the site include travel time, speed, mobility, delay, reliability, wait time, and detector health. This section will explain the most applicable performance measures to ramps, being travel time, speed, delay, and wait time (UDOT, 2020).

2.5.1.1 Travel Time

The travel-time performance measure is calculated for different freeway segments in the Salt Lake City area. Based on data collected within a time range and location specified by the user, the maximum amount of time required to traverse the selected segment 15 percent of the time, 50 percent of the time, and 85 percent of the time is shown. In addition to providing travel time, comparison between the 15th, 50th, and 85th percentiles allows for a determination of the travel-time reliability in the freeway segment. Figure 2.4 shows the base display of the travel-time page on the UDOT website.

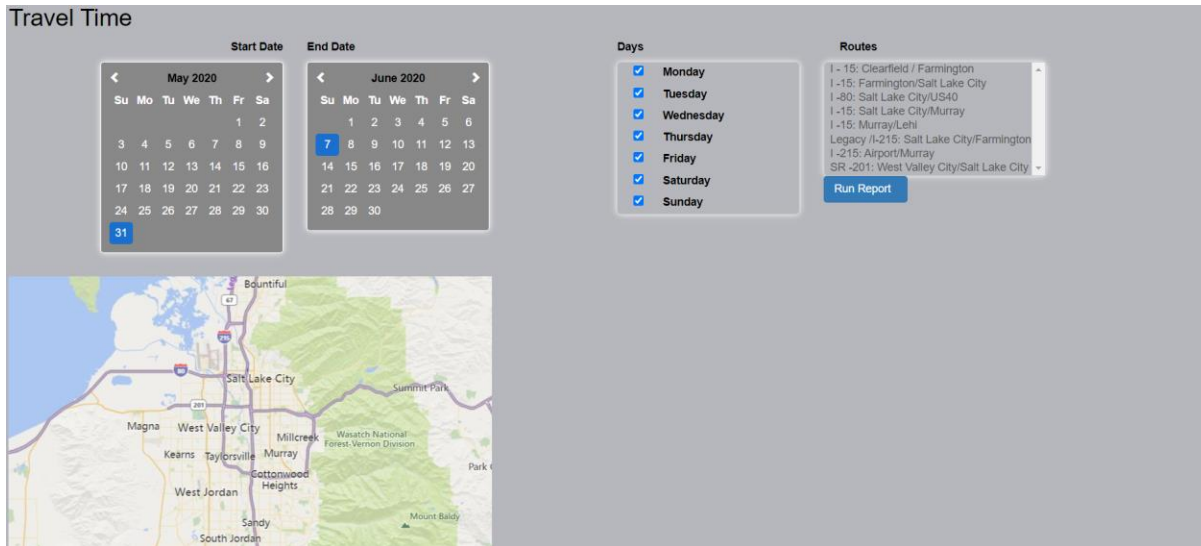


Figure 2.4 UDOT travel-time dashboard (UDOT, 2020).

2.5.1.2 Travel Speed

The speed performance measure functions similarly to the travel-time measure but allows for greater control in analyzing the data. In addition to allowing the user to specify the time range, options are provided to differentiate between morning (7:00 AM to 8:00 AM) or evening (5:00 PM to 6:00 PM) speeds, the directions of traffic flow, and high-occupancy vehicle (HOV) lanes versus general purpose lanes. The user can also define the segment of freeway that is studied rather than picking from a stock list of segments. Like the travel-time performance measure, as a means of analyzing reliability, comparisons between the 15th, 50th, and 85th percentile speeds are available as well as comparisons between the 10th, 50th, and 90th percentiles. The dashboard for the freeway speed report is shown in Figure 2.5 (UDOT, 2020).

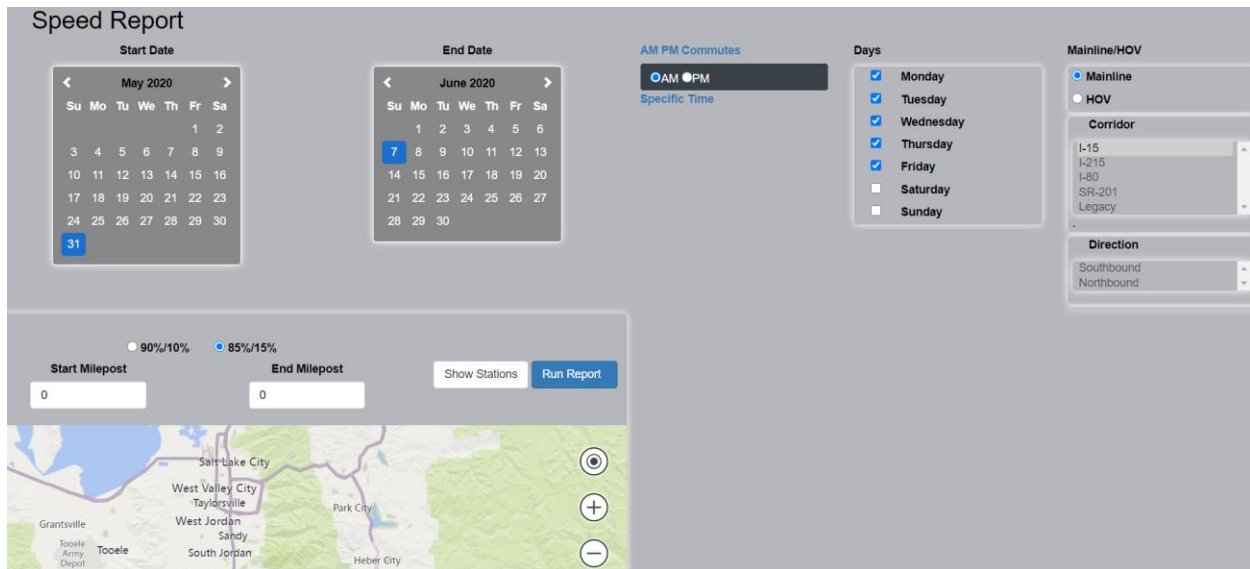


Figure 2.5 UDOT speed report dashboard (UDOT, 2020).

2.5.1.3 Freeway Delay

Several different performance measures are used to evaluate delay. One compares actual total delay per month to a target total delay per month for different corridors. Another delay performance measure allows for comparison between two time periods for specified segments of different freeways in the state. The last delay performance measure breaks down corridors by county and compares the amount of delay experienced each month of each year in the specified range in vehicle-hours. Figure 2.6 gives an example of freeway delay per month beginning in January 2019 to the most recent available data (May 2020 at the time that this figure was prepared).

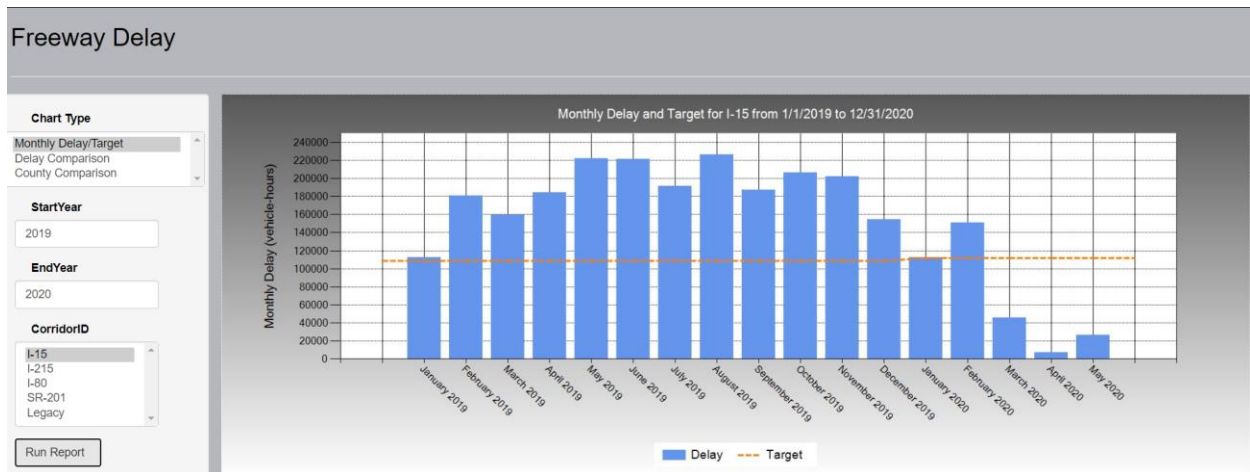


Figure 2.6 UDOT freeway delay dashboard (UDOT, 2020).

2.5.1.4 Ramp Meter Wait Time

Ramp meter wait time was previously introduced in Section 2.3.2 as UDOT’s estimation of the wait time required at ramp meters. Ramp meters along I-15 are mainly only used during peak AM and PM periods, and at other times are not activated. However, when activated, the existing website displays the average expected wait time for each previously configured on-ramp, which include ramps from 12300 South to 3300 South.

2.5.2 Metering Effects at On-Ramps

Ramp meters are generally considered part of the larger freeway system, and as such, most ramp meter performance measures pertain to the performance of the freeway rather than conditions on the on-ramp. In practice, freeway performance depends on a wide range of factors, making isolating the direct influence of ramp metering impossible. This is exacerbated by the fact that data collection for peak periods under “normal” conditions can take a significant amount of time. However, certain trends influenced by metering can be observed based on freeway data. A few performance measures, such as ramp wait times, specifically focus on conditions on the ramp, but are not as widely used.

WSDOT implemented the Seattle Bottleneck algorithm after several years of using other metering methods. After adjusting the algorithm for higher performance following its initial installation, WSDOT carried out an evaluation to determine the effectiveness of the new

algorithm (Jacobson et al., 1989). Performance measures included ramp delay times, signal violations, mainline volumes and travel times, crash rates, and relative crash rates. Ramp delay was calculated by subtracting free-flow ramp travel time (with no meter) from the amount of time spent on the ramp with the meter running, with the latter values determined by manual data collection. On average, delays were below 2 minutes, although ramps that had historically experienced higher delays (up to 8 minutes) still experienced above-average delays when compared to other ramps. Signal violations were observed as occurring from 0.8 percent to 6.8 percent of the time. Most violations occurred when metering during the peak period was beginning, and violations decreased as queues formed on the ramps.

As WSDOT began phasing out its Bottleneck metering algorithm in favor of the Fuzzy Logic metering algorithm, multiple performance measures pertaining specifically to ramp conditions were experimented with to provide a more in-depth comparison of the two algorithms (Taylor and Meldrum, 2000a). Most of the performance measures were ultimately discarded due to problems with reliability. Loop detectors embedded in the pavement provided the data used for performance measures. Issues with detector positioning and the accuracy of readings were the main causes of problems with providing reliable data. The two performance measures that were used were aggregates of the total number of minutes per day that the medium and advance queue loop detectors had occupancies exceeding 35 percent. The researchers observed that smoothly flowing traffic on the ramps would result in occupancies well below 35 percent, while stagnant traffic would result in occupancies well above 35 percent. Selecting a cutoff point of 35 percent occupancy at the two detectors thus allowed the researchers to determine whether queueing on the ramp was reaching the medium or advance detectors. A medium detector occupancy below 35 percent indicated that queueing had not reached the medium detector and that the ramp was operating below capacity. A medium detector occupancy above 35 percent coupled with an advance detector occupancy below 35 percent indicated that queueing had reached the medium detector and the ramp was approaching capacity. An advance detector occupancy above 35 percent indicated that the ramp had reached capacity and risked interfering with operations on the adjacent arterial (Taylor and Meldrum, 2000a).

Like WSDOT, the Minnesota Department of Transportation (MnDOT) attempted to calculate wait time at the ramp by determining the difference between rates of vehicles arriving

at and departing from the ramp. Time data were collected manually, as the existing detectors were unable to reliably collect data (Levinson and Zhang, 2004). Since the Minnesota ramp metering study, MnDOT has conducted further research on ramp meter wait times to assist in ramp meter operations. Due to the SZM algorithm's maximum wait time constraint, accurate wait time measurement was necessary. To account for detector failures, separate calculations for volume were designed for ramps with minimal problems (Class I), ramps with PQ detector problems (Class II), and ramps with queue and PQ detector problems (Class III). At Class I ramps, when queue occupancy is below 25 percent, the volume is calculated by summing the number of vehicles entering the ramp and the number of vehicles already on the ramp, then subtracting the number of vehicles leaving the ramp. If that total produces a negative number, the volume is set as 0. When queue occupancy exceeds 25 percent, the volume is the maximum capacity of the ramp. Class II ramps use the same calculation with the exception that the maximum number of vehicles leaving the ramp based on the metering rate is subtracted instead of the number of vehicles leaving the ramp reported by the PQ detector. At Class III ramps, Kalman filtering is used to estimate queue size from the inaccurate data. The Kalman filter uses a combination of historical and real-time data to automatically interpret the detector data. Comparing historical and real-time data enables the filter to correlate inaccurate values to accurate ones, after which the calculation for Class I may be used. Once volume calculations are complete, the metering rate can be used to determine the wait time for the vehicles at the end of the queue (Liu et al., 2007).

As mentioned in Section 2.3.2, one of the freeway performance measures UDOT publishes is the estimated ramp meter wait time. Based on statistical analyses performed by UDOT at various meters located at on-ramps to I-15 south of Salt Lake City, a set of average wait times at different ramp meters were calculated to correspond to certain occupancy thresholds as measured by loop detectors embedded in each lane of the metered on-ramps (UDOT, 2020). Once a given loop detector reached a certain occupancy value, the estimated maximum wait time was increased to the corresponding stock wait time. This wait time is compared against historical data for the ramp and labeled as "average," "above average," or "below average." These two pieces of information shared by UDOT regarding ramp meter performance could be classified as measures of mobility and reliability.

2.6 Queue Length and Wait Time Estimation Methodologies

While there are many performances measures that pertain to the freeway, there are few that directly evaluate freeway *ramp* performance. The goal of this project is to be able to utilize existing ramp sensor design to develop an algorithm that calculates ramp wait times while the ramps are being metered. This section discusses existing methodologies to estimate ramp queue length and wait time.

2.6.1 Estimating Ramp Queue Length

Occupancy and traffic volume data are often gathered by loop detectors on an on-ramp, as was presented in Figure 2.3. Using the loop detector data, several ramp queue length estimation algorithms have been developed and analyzed, including a conservation model, a Kalman filter, and the Highway Capacity Manual (HCM) back-of-queue method. The HCM back-of-queue method proved to be ineffective, as it substantially underestimated actual queue lengths, thus it will not be discussed in detail in this literature review (Wu et al., 2008). However, some variations of the conservation model and Kalman filter equation have been developed, which will also be discussed in this section.

2.6.1.1 Conservation Model

The conservation model for estimating queue length has been used for several decades but appears to have been first applied to metered on-ramps by Vigos et al. (2006). The conservation equation that they developed (with some minor naming modifications for clarity) is shown in Equation 2.7:

$$Q_n = Q_{n-1} + T(V_{in} - V_{out}) \quad (2.7)$$

where:

Q_n = number of on-ramp queued vehicles in the current period (veh)

Q_{n-1} = number of on-ramp queued vehicles in the previous time period (veh)

T = time period (min)

V_{in} = number of vehicles entering the on-ramp during a given time period (veh/min)

V_{out} = number of vehicles exiting the ramp during a given time period (veh/min)

This equation has also been used and evaluated by Wu et al. (2008) and Wu et al. (2009). The original equation developed for the conservation model in Equation 2.7 required the volume entering and exiting the ramp to be equal, but through analysis, it was found that the detectors introduced error when compared with field-recorded traffic volumes. Many difficulties are introduced when relying solely on the detector data, particularly that vehicles can be double-counted or missed altogether (Wu et al., 2008). Because of this potential for error, the original conservation model equation was modified to balance the volumes entering and exiting the ramp, which is shown by a volume-balancing ratio C in Equation 2.8:

$$Q_n = Q_{n-1} + T(CV_{in} - V_{out}) \quad (2.8)$$

where:

C = volume-balancing ratio to account for miscounting of the detectors

All other variables as defined previously.

By using this volume-balancing ratio, it is presumed the conservation model will produce more accurate queue length estimates. Wu et al. (2009) explain that the volume-balancing ratio may be set as a constant value or may be calculated in real time. Prior to incorporating this volume-balancing ratio, when Wu et al. (2009) utilized Equation 2.7 to find the queue length estimate based on the occupancy data, they found the correlation between the estimated queue length and the time occupancy to be only 0.63. This research also concluded that the relationship between volume data from the detector and the estimated number of vehicles is nonlinear, as the results gave a correlation coefficient of merely 0.18 between the two variables. Therefore, it is likely there are other factors outside the capability of this equation that affect the queue length such as detector error, driver distraction, poor weather, and traffic incidents.

However, in analyzing 20 datasets from ramp meters in Milwaukee, Wisconsin, Wu et al. (2009) found that the volume-balancing ratio improved the conservation model considerably in nearly every case. Therefore, it appears that the use of the volume-balancing ratio will improve the reliability of queue length estimates.

2.6.1.2 Kalman Filter Model

The Kalman filter model for estimating queue length at on-ramps was introduced by Vigos et al. (2006). A Kalman filter is an algorithm that can combine multiple data measurements to produce more accurate estimates. In the case of traffic flow, the conservation model presented in Equation 2.8 is enhanced by the addition of occupancy data and ramp characteristics as inputs that are also used to predict queue length as shown in Equation 2.9:

$$Q_n = Q_{n-1} + T(V_{in} - V_{out}) + K(\hat{Q}_{n-1} - Q_{n-1}) \quad (2.9)$$

where:

K = Kalman filtering constant (generally $0 < K < 1$)

\hat{Q}_{n-1} = number of on-ramp queued vehicles calculated from detector time occupancy data
(veh)

and \hat{Q}_{n-1} is calculated as outlined in Equation 2.10:

$$\hat{Q}_{n-1} = O_{n-1} \frac{L_R \times N}{L_E} \quad (2.10)$$

where:

O_{n-1} = time occupancy collected by loop detectors (percent)

L_R = length of the on-ramp (ft)

N = number of lanes

L_E = effective vehicle length, (vehicle length + safety distance between vehicles) (ft).

With the inclusion of detector occupancy and ramp characteristics, such as the length of the on-ramp, the number of lanes, and the vehicle length, the Kalman filter algorithm uses these known measurements to estimate unknown parameters—the ramp queue length in this case—with greater accuracy. The Kalman filter constant K can update in real time to account for “noise” in the data from the detector. The Kalman filter equation can further be improved by the inclusion of the volume-balancing ratio C , as proposed by Wu et al. (2009) in Equation 2.11:

$$Q_n = Q_{n-1} + T(CV_{in} - V_{out}) + K(\hat{Q}_{n-1} - Q_{n-1}) \quad (2.11)$$

By using the volume-balancing ratio, as occurred with the conservation model, the queue length estimates improved significantly in nearly all cases, and in only a select few cases were

slightly more errors introduced. These errors were found to occur in the Kalman filter models because when the volume-balancing ratio is close to 1 (the detector volume entering and exiting the ramp are nearly equal), the Kalman filter coefficient K is also close to zero, but the equation still adds queue length to the estimate from the coefficient K , which would introduce additional error. In contrast, when the volume-balancing ratio is not close to 1, the Kalman filter equation yields more reliable results than the conservation model. Overall, both the Kalman filter and conservation model, especially when using the volume-balancing ratio, provide generally accurate estimates of the actual queue length, which can then be used to predict the expected wait time on the freeway entrance ramp.

2.6.2 Estimating Ramp Wait Time

With regard to estimating ramp wait time, significant data collection has been done to quantify wait time across the globe, as was explained in Section 2.5. In addition, estimation of delay or wait time at signalized intersections has been researched. However, little research has been done previously to predict wait time at on-ramps. Applying the same principles used in estimating wait time at signalized intersections is difficult, as the signal processes and timing at a metered on-ramp are dissimilar to those used at signalized intersections. Nevertheless, with the methods discussed with respect to ramp queue length estimation, it is expected that the queue length can be converted into wait time by using the ramp meter discharge rate. Further discussion and analysis of this procedure will be discussed in Chapter 3.0.

2.7 Chapter Summary

The purpose of this literature review was to analyze ramp meters and discuss the existing methods UDOT has used to analyze freeway and ramp performance. Many metering approaches have been used to manage freeway flow by limiting entry onto the freeway. Although specific approaches to ramp metering in individual areas differ to optimize overall system performance, using metering generally results in improved freeway performance. Meters may be programmed to specific rates based on historical data or adjusted to specific conditions within the system. Though timed meters are convenient to implement, over an extended period of time they become inefficient as traffic patterns change. Furthermore, they cannot adapt to unusual traffic events,

which may result in excessive or inadequate metering rates. Traffic-responsive meters determine the metering rate based on either the conditions in the area immediately around the ramp or the conditions across the entire metering system. These meters must be carefully calibrated to manage traffic, but usually require less upkeep over an extended period of time. Many algorithms may be chosen and modified to suit the goals of a given transportation agency.

In addition to discussing specific metering algorithms, this literature review introduced performance measures used to evaluate ramp meters specifically and freeway systems generally. Ramp meters may be analyzed in isolation based on the length and consistency of wait times. Ramp meter influence on arterial roads can be measured by changes in travel time on arterials as well as by the percentage of time that on-ramps spill back onto arterials. Ramp meter influence on freeways may be measured by a host of different criteria, as in many cases it has proven to cause significant changes to traffic. Common evaluation measures include travel time, reliability, flow rate, and occupancy. The means of determining these measures tend to vary across organizations but are effective in helping decision makers choose how to operate the system.

UDOT currently utilizes a modified version of the Seattle Bottleneck metering algorithm to manage traffic flow onto I-15. The current performance measures for the metering system are the change in travel time based on estimated on-ramp delay times and the reliability of ramp service as calculated from historical data. UDOT also uses a range of other performance measures pertaining to freeway use, including freeway travel times and travel-time reliability, average speeds and speed reliability, mobility, and delay times. Ramp wait times are currently estimated based on sensor occupancy values that are compared to historical data. These estimates tend to be somewhat vague, as a very broad range of occupancy values may correspond to a given maximum wait time and they require significant calibration for each ramp.

Based on the results of this literature review, there is a need to further develop reliable means of estimating ramp meter wait time. It is expected that the queue length estimation algorithms presented in this literature review can be used to convert the queue length estimates into wait times on the ramp. Understanding the wait times experienced at on-ramps will help UDOT to understand the effectiveness of the current ramp metering system and determine its impact on the larger transportation network.

3.0 METHODOLOGY

3.1 Overview

This chapter presents a methodology to predict ramp meter wait times and compare the predictions to observed wait times. A discussion on several variations of a Kalman filtering algorithm (Equation 2.11) that were used to predict queue lengths is presented in Section 3.2. A discussion on the methods of data collection is provided and the chapter concludes with a summary of the different models used to estimate the queue length and an overview of each ramp.

3.2 Methods

This section will describe the various methods developed to predict queue length using the Kalman filter equation. The purpose of this research was to develop an algorithm that could accurately predict ramp meter wait time at metered on-ramps in Utah using existing loop detector design that could be applied across any metered on-ramp throughout the state. These methods were developed to compare ways that the Kalman filter equation could be used without relying on manual data collection and ongoing calibration. Each method described in this section uses the Kalman filter as its base and has different ways that the Kalman filter constant K is calculated:

- Conservation model, which assumes $K = 0$,
- Vigos model, which assumes $K = 0.22$, which is a theoretically determined value from Vigos et al. (2006),
- Optimized K baseline comparison, which minimizes the root mean square error (RMSE) between the predicted and observed queue lengths in 15-minute bins,
- Linear regression model, which uses the detector data measurements to create an equation for K at each ramp studied, and
- Heuristic clustering, which places the detector data into three clusters and outputs one K value for each of the three clusters.

3.2.1 Conservation Model

A conservation model for estimating queue length on a ramp assumes that the queue length during a given period is equal to the number of vehicles entering the ramp during that period minus the number of vehicles exiting the ramp during that same period. If there was a queue length on the ramp from the previous period, that queue length is added to the current period as well. If the detector data on the ramp were perfect, the conservation model would be the ideal method to use, as it is the simplest possible method to measure queue length. The conservation equation was shown previously in Equation 2.8, which includes the volume-balancing ratio. This equation forms the basis of the Kalman filter equation, though the Kalman filter equation contains additional terms. The conservation model is the Kalman filter equation where $K = 0$. The detector data provided by UDOT showed that the EQ detectors were more accurate than the PQ detectors at estimating volumes on the ramp, so the volume-balancing ratio C for the conservation model was placed on the V_{out} term instead of V_{in} , as shown in Equation 3.1:

$$Q_n = Q_{n-1} + T(V_{in} - CV_{out}) \quad (3.1)$$

3.2.2 Vigos Model

While a conservation model would be sufficient for estimating queue length on a ramp if the detectors on the ramp were error free, many difficulties are introduced when relying solely on the volumes obtained from the detector data. The Kalman filter constant K , is intended to improve the conservation model by removing undesired random noise that occurs on the ramp by including additional variables such as the detector occupancy, the length of the ramp, and the number of lanes.

The Vigos model (Vigos et al., 2006) is an additional method of calculating the queue length by modifying the value used for K . Similar to the conservation model, which uses a constant of 0 for K for all metering periods, the Vigos model also uses a constant value of K for all periods. This model assumes a value of 0.22 for K , which was originally proposed by Vigos et al. (2006) based on calibration of K through microscopic simulation. Although the simulations may not fully represent actual traffic conditions, the results provide crucial insight with respect

to the behavior of the Kalman filter model because the tests that were created assessed various ramp scenarios and traffic conditions in their simulations. The value of 0.22 for K was the optimum value of K produced for all scenarios analyzed in their simulations.

The Kalman filter equation provided by Wu et al. (2008) was modified to have the volume-balancing ratio C placed on the V_{out} term instead of V_{in} . Equation 3.2 shows the equation produced by the Vigos model:

$$Q_n = Q_{n-1} + T(V_{in} - CV_{out}) + 0.22(\hat{Q}_{n-1} - Q_{n-1}) \quad (3.2)$$

3.2.3 Optimized Kalman Filter Baseline Comparison

The optimized Kalman filter equation is calibrated based on observed queue length data and thus cannot be used as a model. Rather, it is a useful comparison mechanism to assess the ability of the other Kalman filter models to represent the observed queue lengths. The Kalman filter equation used to measure queue length was previously introduced in Equation 2.11, as shown in Equation 3.3:

$$Q_n = Q_{n-1} + T(V_{in} - CV_{out}) + K(\hat{Q}_{n-1} - Q_{n-1}) \quad (3.3)$$

To better analyze the data, rather than finding an optimum K for an entire metering period at each ramp (Wu et al., 2009), the data were grouped into 15-minute bins during each day. Doing so allows for more specific optimization of K and provides additional observations that can be used to compare each K with the traffic analysis parameters. The K for each period is found by minimizing the RMSE between the queue length from the field data and that estimated by the Kalman filter equation. The RMSE is calculated by computing the standard deviation of the residuals. A residual is a measure of how far from the regression line each data point is. In other words, the RMSE can depict how closely concentrated data points are around the best-fit line. Therefore, a more accurate model has an RMSE closer to 0. An equation to represent how RMSE is calculated is shown in Equation 3.4:

$$RMSE = \sum_{i=1}^N \sqrt{\frac{(x_{p,i} - x_{o,i})^2}{N}} \quad (3.4)$$

where:

$\sum_{i=1}^N$ = summation of all observations in N , beginning at $i = 1$

N = number of observations

$x_{p,i}$ = predicted value for observation i

$x_{o,i}$ = observed value for observation i .

Because the data were grouped into 15-minute bins, the volume-balancing ratio was also calculated and used for each 15-minute period. The result of Equation 3.3 is an estimated queue length for each minute based on the optimized K . As mentioned, this method relies on field data and therefore cannot be used in real time. The optimized K functions as the baseline for comparing the different models produced by variations of the K value used in the Kalman filter equation.

3.2.4 Linear Regression Model

A linear regression model was developed to create an equation that could be used to calculate K for any metering period based on the optimized K . Several different data sources were used, such as the EQ, IQ, and PQ occupancies, the average vehicle density on the ramp, and a variable to distinguish from which ramp the data originated. In many linear regression models, log transformations of the data sources are used, which is a method that transforms the data by replacing each variable “x” with a $\log(x)$ instead. This is a common method used in statistical analysis, particularly when continuous data does not follow a normal distribution. The log transformation helps to remove the skewness in a dataset and produces a more normalized dataset in its place.

3.2.5 Cluster Analysis and Heuristic Models

A cluster analysis was performed on the loop detector data. Cluster analysis groups data together into clusters based on how closely related the data are to each other. The data points used in the analysis are not directly assigned to be within specific ranges prior to its use. A cluster analysis helps prevent some biases that may exist, as no direct assumption is made about the data prior to the cluster analysis being completed. The benefit of cluster analysis is that it can take a large dataset where the data may exhibit similarities to each other in a certain range of

values, and it allows the clusters to form and then produce a simpler, more comprehensible output.

A clustering method called the k-means algorithm was used in this research, which finds a centroid point of each cluster—the average of all data points within that cluster—and each centroid becomes the output of the analysis (UC, 2016). The steps used in the k-means algorithm are as follows:

1. Specify the number of clusters (k) to be used.
2. Randomly select k objects from the dataset as the initial centroids.
3. Each data point is assigned to the closest centroid.
4. The centroid of each cluster is updated by calculating the new mean of the data points assigned to each cluster, and assign that mean as the cluster center.
5. Iterations are performed of steps 3 and 4 until the cluster assignment of data points is halted or the maximum number of iterations used in the analysis is reached.

3.3 Data Collection

Four on-ramps to I-15 in Davis, Salt Lake, and Utah counties in Utah were chosen for data collection and analysis. These ramps include the NB on-ramp at Layton Parkway in Davis County, the SB on-ramp at Bangerter Highway in Salt Lake County, the SB on-ramp at Pleasant Grove Boulevard in Utah County, and the SB on-ramp at University Avenue in Utah County, as shown in Figure 3.1. Data were collected during several periods in April and July 2021. Five weekdays of data were collected at the four on-ramps during the PM metering period. These ramps were metered between 4:00 – 6:30 PM at Layton Parkway, 3:30 – 5:45 PM at Bangerter Highway, 4:00 – 6:30 PM at Pleasant Grove Boulevard, and 4:30 – 6:15 PM at University Avenue. The manual data collection was performed by recording the on-ramps during these PM metering periods using UDOT cameras and then in 60-second increments, counting the number of vehicles entering and exiting the ramp in each lane, the total number of vehicles on the ramp, and the queue length.

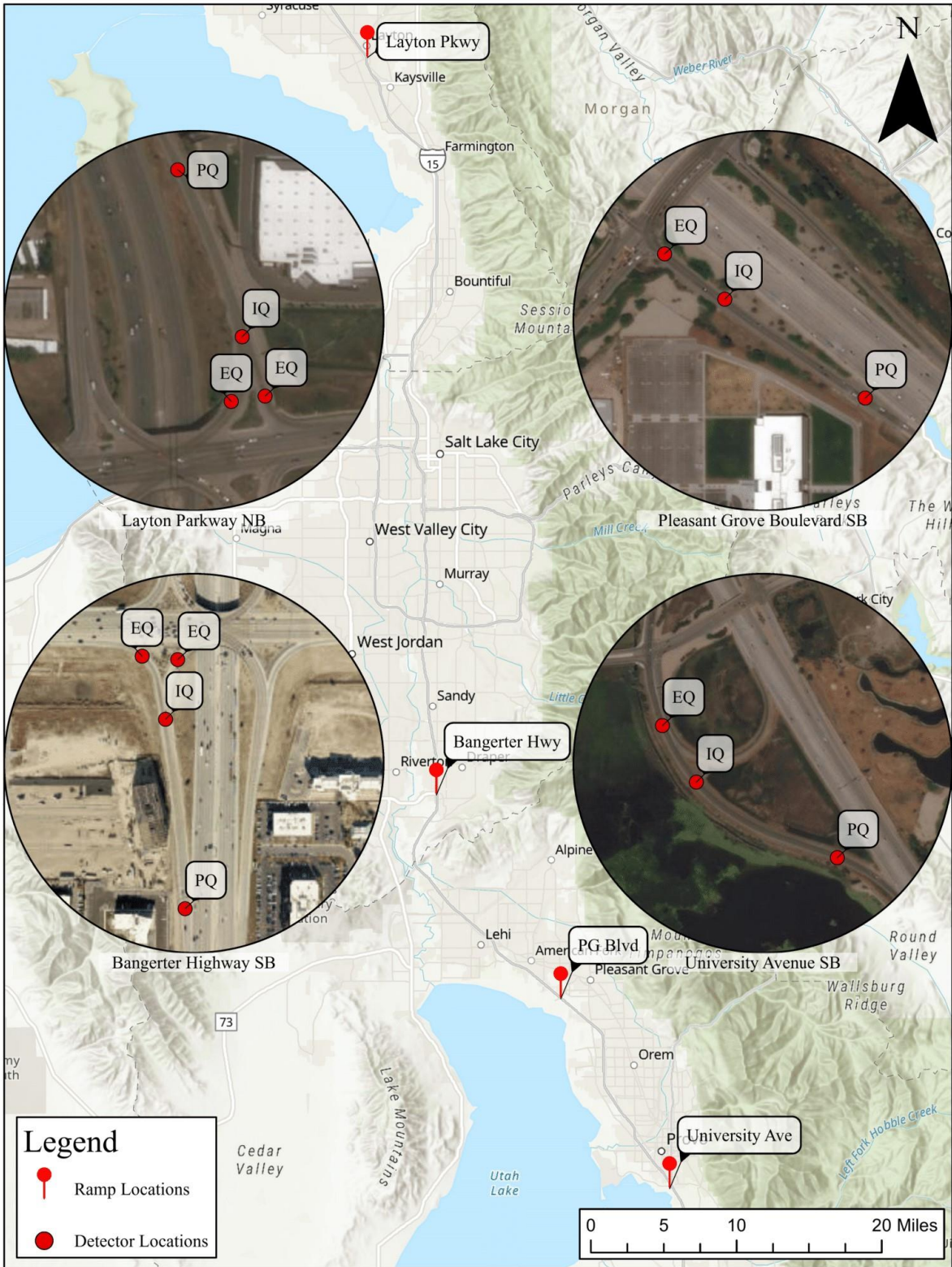


Figure 3.1 Selected ramp and detector locations.

On each ramp, there are loop detectors at three locations along the ramp, including the EQ detectors at the entrance of the ramp, the IQ detectors midway through the ramp, and the PQ detectors just beyond the ramp meter signal, as were introduced in Section 2.4. These loop detectors collect both volume and occupancy data in each lane and are recorded in 60-second increments. In addition, the variable ramp meter discharge rate (in units of veh/hr) for each minute is included with the detector data. The detector data used in this research were obtained from UDOT.

While beginning to analyze the data, it was discovered that the timestamps for the field and detector data were misaligned for each ramp. This significantly reduced the accuracy of the initial queue length estimates for the optimized Kalman filter model—the baseline for the other models. The adjustment of the timestamps between the field and detector data was required to be able to develop the optimized Kalman filter model, which relies on manually collected data and therefore cannot be done in real time. However, this was resolved by shifting the field data either backwards or forwards up to 3 minutes for each ramp to best match the detector data based on the minimum RMSE found for the number of vehicles entering the ramp. The process of adjusting timestamps would not be required in using the Kalman filter model to produce queue length and wait time estimates in real time because these estimates rely solely on detector data. The detector data is created in the UDOT TransSuite system in real time, therefore the queue length and wait time estimates predicted on each ramp would use the timestamp reported in the TransSuite system and would not need to be compared against other data sources.

3.4 Summary

This chapter presented a methodology to predict ramp meter wait times and compare the predictions to observed wait times. A discussion on several variations of a Kalman filtering algorithm that were used to model queue lengths and a discussion on the methods of data collection were provided in this chapter. The analysis of these queue length models and the conversion of queue length into wait times will be presented in Chapter 4.0.

4.0 DATA EVALUATION

4.1 Overview

This chapter begins with a discussion on the results of the optimized K analysis, the linear regression models, and the cluster analysis. The objective of each of the models discussed in this chapter is to be able to estimate queue lengths and wait times as closely as the optimized K values are able to achieve using observed data. The chapter will then explore the accuracy of each model presented in Section 3.2 against the observed data, including a discussion of the analysis performed on the queue length and wait time estimates, and will conclude with a summary of the results of the analysis.

4.2 Optimized K Comparison

As discussed in Section 3.2.3, the optimized K analysis was performed to provide a baseline for the other Kalman filter equation variations. The K produced for each 15-minute period was not restricted to the range of $0 < K < 1$, as was done previously by Wu et al. (2008). Rather, K was permitted to extend beyond this range of values based on the minimum RMSE found between the observed and modeled queue length estimates. The results of the optimized K variation is shown in Figure 4.1. The figure shows that although K does vary, the highest density of K values is between approximately $0 < K < 0.5$.

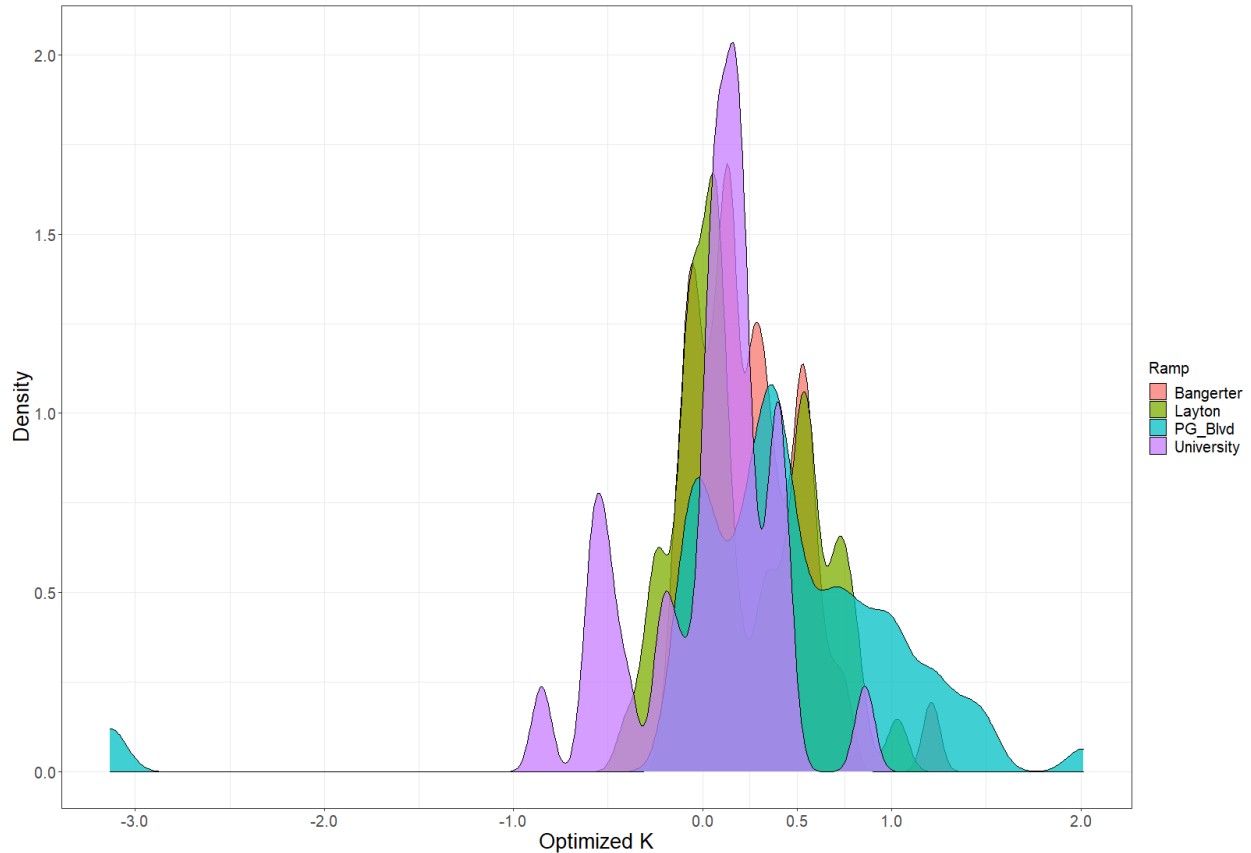


Figure 4.1 Variance of optimized K by ramp.

4.3 Linear Regression Models

Linear regression models were used to develop an equation to calculate K for any metering period. Four different linear regression models were tested, as shown in Table 4.1. In three of the four models, log transformations of the data were used. The variables that were log transformed included an additional factor of either 0.01 for the occupancy variables and 1 for the density variable to prevent these methods from producing errors if the occupancy or density were 0 at any point within the dataset, as a $\log(0)$ is undefined.

The four linear regression models developed are as follows:

1. Ramp Control [Density]: The inputs of this model include the IQ occupancy, a log transformation of the density, and a variable for ramp control.

2. Ramp Control [Occ.]: The inputs of this model focus primarily on the three detector locations and include the IQ, EQ, and PQ occupancy, in addition to a variable for ramp control.
3. Ramp Control [Log Occ.]: This model used the same inputs as “Ramp Control [Occ.]” but used a log transformation of each occupancy value instead.
4. Log Occ. [No Ramp]: This model used only a log transformation of each occupancy value, with no variable for ramp control, in other words, the output equation would result in the same K value for each ramp.

Table 4.1 Linear Regression Model Comparison Table

	Ramp Control [Density]	Ramp Control [Occ.]	Ramp Control [Log Occ.]	Log Occ. [No Ramp]
(Intercept)	-2.568 (-3.178)**	-0.211 (-0.802)	-0.402 (-0.620)	0.263 (0.557)
IQ Occ.	-0.052 (-3.828)***	-0.012 (-1.787)+		
Log(Density + 1)	1.168 (3.571)***			
Ramp = Layton	-0.219 (-2.026)*	0.123 (1.044)	0.086 (0.671)	
Ramp = PG Blvd	-0.624 (-2.489)*	0.011 (0.070)	-0.050 (-0.215)	
Ramp = University	-0.238 (-2.308)*	-0.241 (-2.271)*	-0.222 (-2.051)*	
EQ Occ.		0.005 (0.324)		
PQ Occ.		0.040 (1.938)+		
Log(IQ Occ + 0.01)			-0.079 (-0.894)	-0.086 (-1.314)
Log(EQ Occ + 0.01)			0.206 (0.813)	0.281 (2.325)*
Log(PQ Occ + 0.01)			0.184 (0.633)	-0.131 (-0.563)
# Observations	169	169	169	169
R ²	0.153	0.111	0.088	0.051
R ² Adj.	0.127	0.078	0.054	0.034
AIC	219.5	229.7	234.1	234.7
BIC	241.4	254.7	259.1	250.4
Log. Likelihood	-102.746	-106.833	-109.026	-112.362
F	5.89	3.373	2.595	2.952

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The Ramp Control [Density] model was selected for use in comparison against the optimized K model, as this model yielded the best results with respect to the R^2 value (closer to 1) and the log likelihood (closer to 0) versus the different linear regression models shown in Table 4.1. R^2 is a statistical measure that represents the proportion of the variation in the

dependent variable that can be predicted by the independent variable. A model that can explain 100 percent of the variation in the dependent variable that can be predicted by the independent variable would have an $R^2 = 1$. The log likelihood is also a measure of how well each linear regression model fits the data, but it is calculated as the natural log of the likelihood of observing a given sample. A perfect model with a probability of 1 (100 percent) would be equal to $\ln(1) = 0$; therefore a log likelihood equal to 0 would represent a perfect model and the closer the log likelihood is to 0, the more the model is preferred. The equation for K that would be produced by the Ramp Control [Density] model is shown in Equation 4.1(a-d), which has a unique final term in each equation dependent on which ramp is being used. Equation 4.1a is for Bangerter Highway, 4.1b for Layton Parkway, 4.1c for Pleasant Grove Boulevard, and 4.1d for University Avenue.

$$K = -2.568 - 0.052(IQ\ Occ) + 1.168(Density) \quad (4.1a)$$

$$K = -2.568 - 0.052(IQ\ Occ) + 1.168(Density) - 0.219(1) \quad (4.1b)$$

$$K = -2.568 - 0.052(IQ\ Occ) + 1.168(Density) - 0.624(1) \quad (4.1c)$$

$$K = -2.568 - 0.052(IQ\ Occ) + 1.168(Density) - 0.238(1) \quad (4.1d)$$

4.4 Cluster Analysis and Heuristic Models

For the cluster analysis performed in this research, the PQ occupancy was compared to the IQ occupancy for each 15-minute period. Each 15-minute period represented one data point and had its own K value. Three clusters were used in the analysis, as the use of fewer or additional clusters reduced its usefulness either in variability or prevented each cluster from having an adequate sample size to be reliable. From the cluster analysis, the average K of all data points within each cluster was calculated and then that K was applied across all data points for each respective cluster.

Table 4.2 shows the average K for each cluster, the number of observations (n) within the clusters, and the standard deviation (SD) of the data points within each cluster. Cluster 1 as it is designated in the table pertains to those time periods where there were both a low PQ and a low IQ occupancy. Cluster 2 represents data points with a high PQ occupancy with a similarly low IQ occupancy, while Cluster 3 captures data points that had a high IQ occupancy and either a

high or low PQ occupancy. Cluster 1 yielded an average K of 0.189, Cluster 2 had an average K of 0.337, while Cluster 3 was 0.170.

With this information, a heuristic model was developed to predict the queue length of vehicles at the metered on-ramp based on the traffic density, as shown in Table 4.3. This table shows the cutoff ranges that were used based on the cluster analysis that most approximately captured the data points within each of the three clusters, with the cutoff between Cluster 1 and Cluster 2 occurring at 13.5 percent PQ occupancy, while the cutoff between Clusters 1 and 2 versus Cluster 3 was set at 16.0 percent IQ occupancy. Therefore, any data point that fell within Cluster 1 would be given a uniform K of 0.189, while Cluster 2 would be assigned a K of 0.337, and Cluster 3 would have a K of 0.170.

Table 4.2 Cluster Analysis Results

Cluster	Mean K	n	SD
1	0.189	93	0.400
2	0.337	56	0.439
3	0.170	20	0.833

Table 4.3 Heuristic Model Boundaries

Cluster	Input 1	Sign	Value (%)	Input 2	Sign	Value (%)	K
1	IQ Occ	\leq	16	PQ Occ	\leq	13.5	0.159
2	IQ Occ	\leq	16	PQ Occ	$>$	13.5	0.337
3	IQ Occ	$>$	16	PQ Occ	$>$	0	0.170

Figure 4.2 shows a plot of the cluster analysis. The figure shows each of these clusters by color, while also having unique shapes to designate the ramp to which each data point belongs.

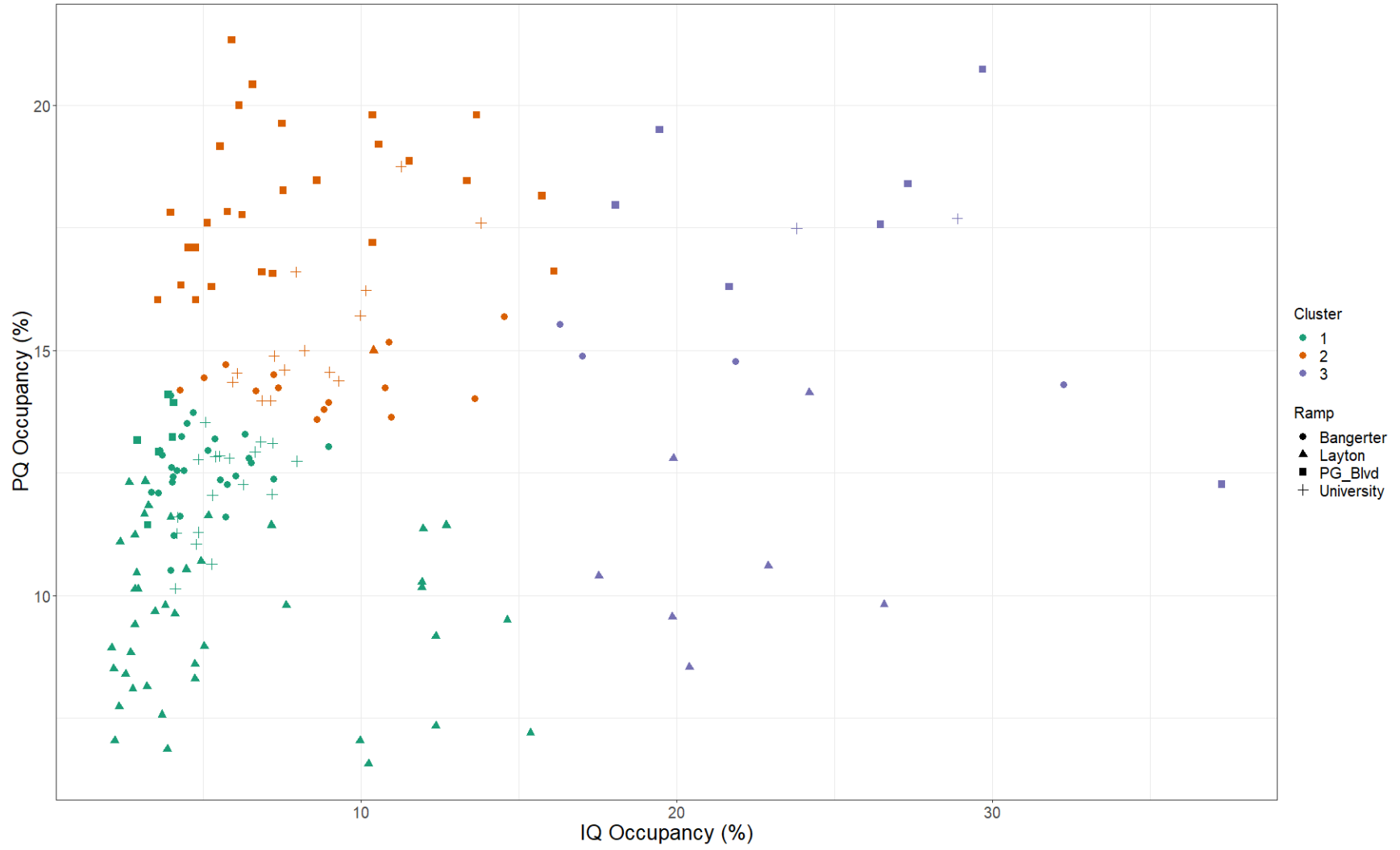


Figure 4.2 Cluster analysis plot of PQ occupancy versus IQ occupancy.

4.5 Queue Length Analysis

The queue length estimates were generated using several variations of the Kalman filter algorithm that were presented in Chapter 3.0, including an optimized K comparison, a conservation model, the Vigos model, a heuristic model, and a linear regression model. The optimized K comparison method was used as a baseline for the other models because it is the closest any Kalman filter model comes to the actual queue length. The K value was calibrated for each 15-minute period on each ramp and for each day by minimizing the RMSE between the field recorded queue length and the estimated queue length from the Kalman filter algorithm. Each of these models was then compared with the field recorded queue length to determine which model most closely resembled the actual queue length.

Each model was assigned a given K value based on the criteria that is met for each model as was discussed in Chapter 3.0. The optimized K would have varied K values per ramp every 15 minutes, dependent on which K value produced the minimum RMSE between the observed and modeled queue length. The conservation model used a constant value of 0 for K for all time periods on all ramps. The Vigos model used a constant value of 0.22 for K for all time periods on all ramps. The heuristic model used a cluster analysis that produced three possible K values that could be selected per ramp for each 15-minute period depending on where that period fit in the cluster analysis. Finally, the linear regression model produced an equation that calculated K for each 15-minute period.

The queue length estimates compared against each other are shown in Figure 4.3 through Figure 4.6 for Bangerter Highway SB, Layton Parkway NB, Pleasant Grove Boulevard SB, and University Avenue SB, respectively. The thicker line, called “Observed,” represents the field-recorded queue length, which is the target line that the modeled queue lengths seek to represent. Only one day of the five days that were collected for each ramp is shown for conciseness, but each ramp experienced similar patterns with respect to the accuracy of the models against the field-recorded queue length throughout each day. The results of the remaining four days at each ramp are presented in Appendix A.

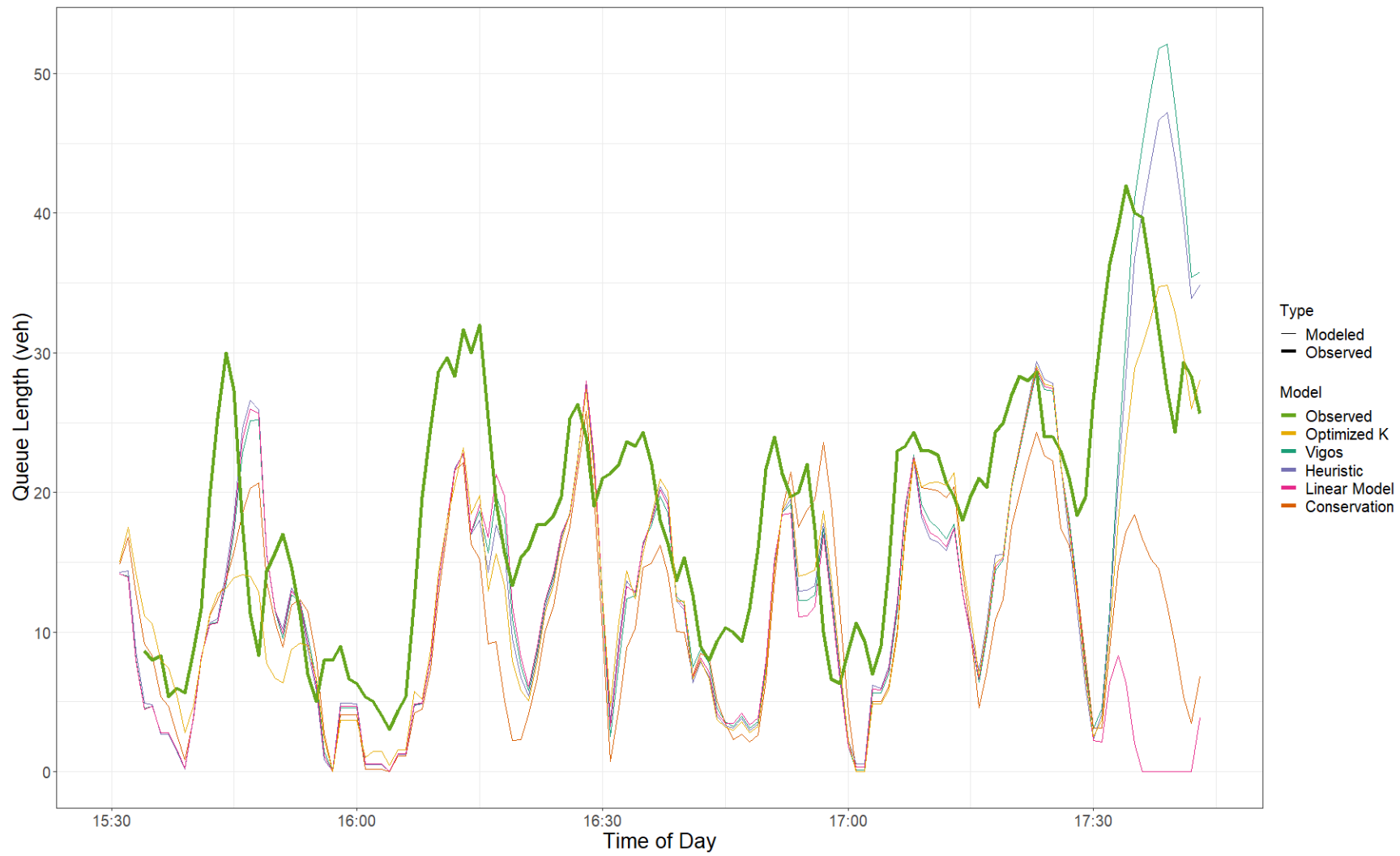


Figure 4.3 Queue length comparison: Bangerter Highway SB, April 15, 2021.

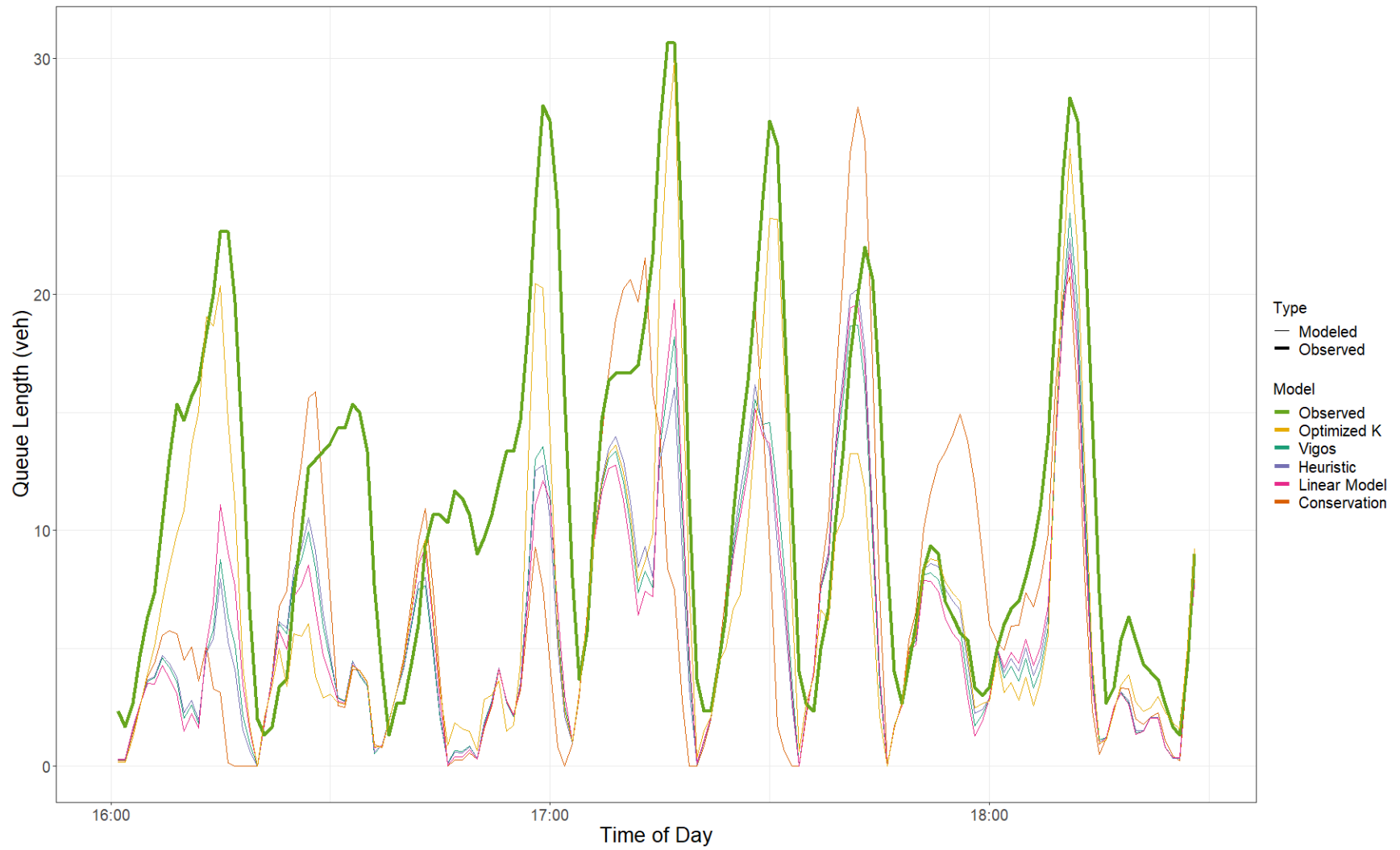


Figure 4.4 Queue length comparison: Layton Parkway NB, April 15, 2021.

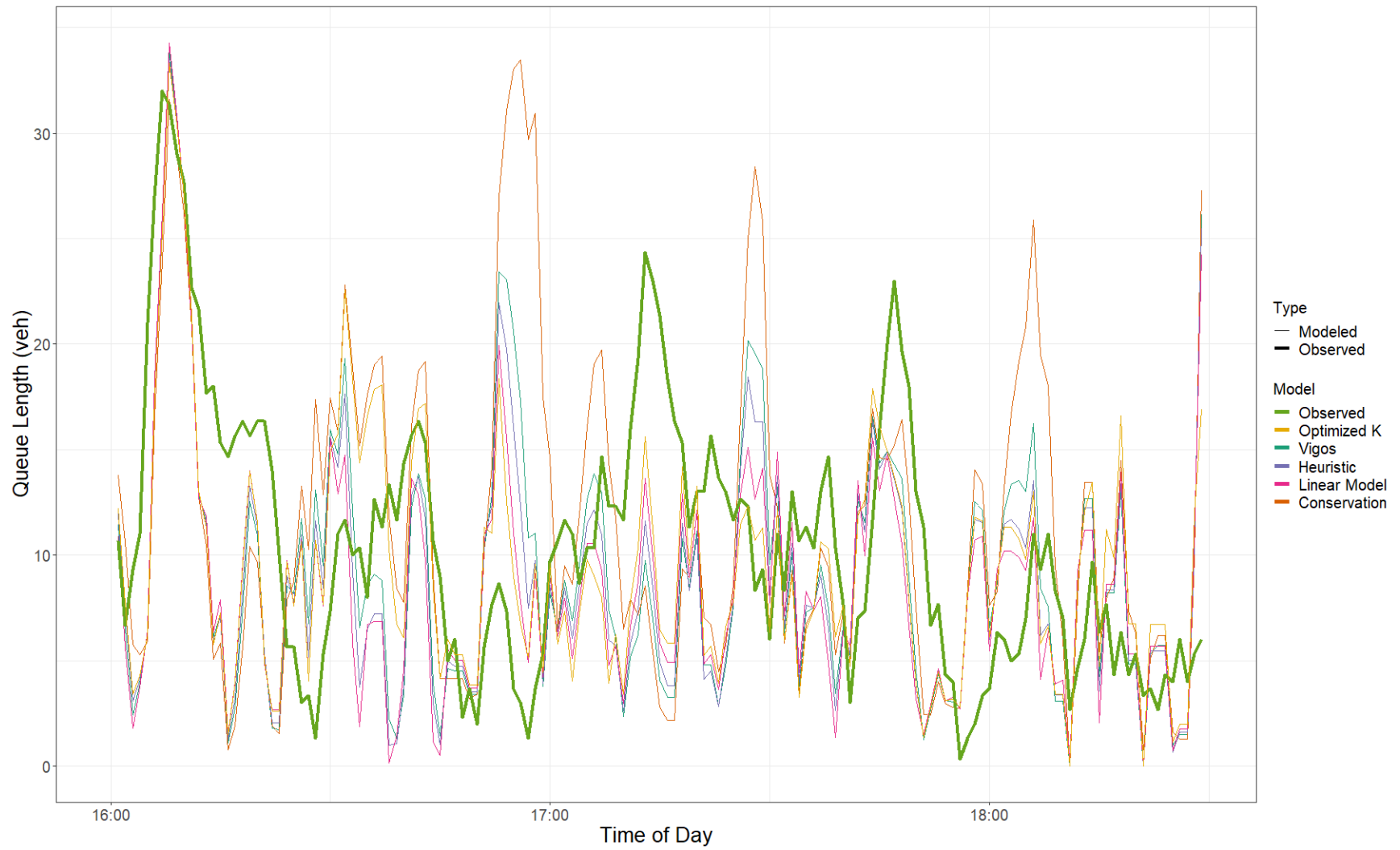


Figure 4.5 Queue length comparison: Pleasant Grove Boulevard SB, July 28, 2021.

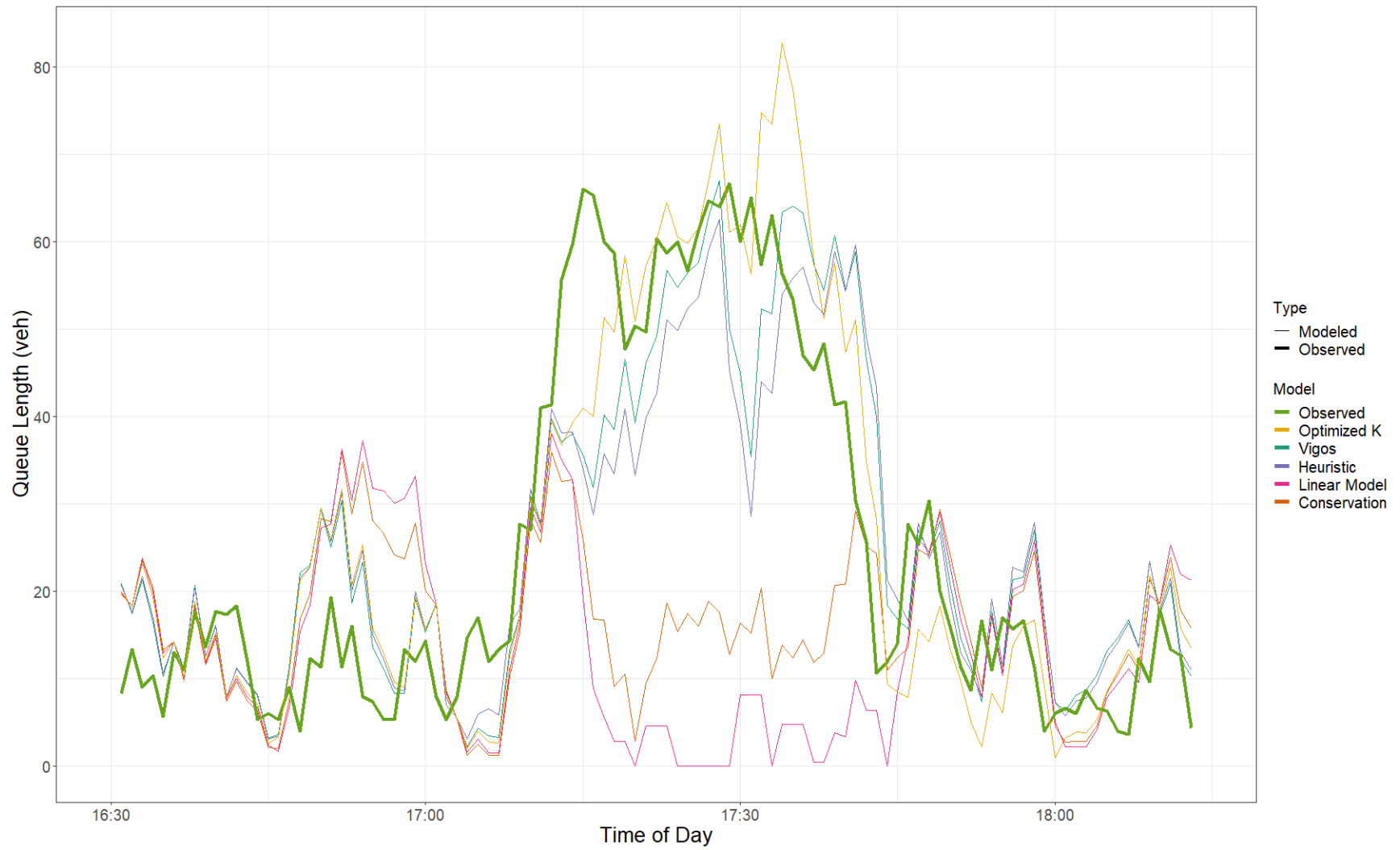


Figure 4.6 Queue length comparison: University Avenue SB, July 28, 2021.

Because each of the models analyzed are variations of the same Kalman filter equation, the models generally follow each other along a similar path, with some variation occurring in the queue length estimates throughout each day attributed to the variation in K . There is some variation in the quality of each model in reflecting the observed queue length. This is particularly evident in the linear regression and conservation models, while the Vigos and heuristic models generally follow the observed queue length more closely. In addition, not all ramps perform equally, as the modeled queue lengths for Layton Parkway appear to follow the observed queue length better than the other ramps. However, across the four ramps, the heuristic and Vigos models more closely follow the observed queue length and are within approximately 10 vehicles throughout each day. Table 4.4 provides greater clarification on which model most accurately resembles the observed queue length.

Table 4.4 shows the reported RMSE for each of the models that were analyzed. The RMSE values presented in Table 4.4 are reported for the entire dataset as well as the RMSE calculated for each ramp. The RMSE was calculated by comparing the modeled queue length against the observed queue length for each period. The optimized K method minimizes the RMSE between the field-recorded and the modeled queue lengths and is thus used as a baseline for comparison. The optimized K baseline cannot be used in practice without calibration through field data collection.

Table 4.4 Queue Length RMSE Results

Models	RMSE (vehicles)				
	Overall	Bangerter	Layton	PG Blvd	Univ Ave
Optimized K Baseline	7.16	6.84	5.90	6.76	9.42
Heuristic	8.28	7.31	7.02	9.14	10.00
Vigos	8.34	7.46	6.95	9.40	9.95
Linear Regression	10.10	8.24	7.03	8.12	16.30
Conservation	10.80	8.90	7.42	12.60	14.50

While the order of RMSE varies slightly by ramp, the heuristic model generally performs best when using the RMSE as the comparison mechanism. The heuristic model is based on a cluster analysis that yielded three possible values for K . However, the Vigos model, which uses a constant value of 0.22, performs nearly as well—if not sometimes better than—the heuristic

model. The Vigos model was most closely aligned with the average K that was calculated for the ramps used in this research, which was computed to be 0.22, matching the value found in the Vigos model.

Based on the results presented in this section, the heuristic model and Vigos model have both proven to come close to the observed queue length at each ramp. These models are also able to capture the peaks and valleys of the queue that occur throughout the metering period by using the Kalman filter equation. This has proven to be the case at each of the four ramps and from queue lengths ranging from as little as no queue to as many as approximately 70 vehicles. The following section presents the results of having converted the queue lengths to wait times.

4.6 Wait Time Analysis

This section will describe the results of converting the queue length into wait time and a comparison of the wait time results of each model.

4.6.1 Wait Time Conversion Method

To perform the wait time analysis at each ramp, the modeled and observed queue lengths (veh) were divided by the metering rate (veh/min). The output of this is the wait time in units of minutes as shown in Equation 4.2. This method was used because of its simplicity in using existing data that is provided by the detectors during each minute.

$$W_n = \frac{Q_n}{R_n} \quad (4.2)$$

where:

W_n = wait time (min)

Q_n = queue length (veh)

R_n = metering rate (veh/min).

A field verification was completed at Layton Parkway to ensure that this method was reliable. This was done by manually measuring the wait time in one-minute increments, measuring the time elapsed from when a vehicle entered the ramp until it passed the ramp meter signal. The field-recorded queue length was divided by the metering rate provided by the

detector data to compute the calculated wait time. The field recorded wait times were then compared to the calculated wait times, as shown in Figure 4.7.

Figure 4.7 shows that the calculated wait times follow the actual wait times quite well, as nearly every peak and valley throughout the day is captured, and the calculated wait times are generally never more than 30 seconds above or below the actual wait times during any given minute for this specific application. Therefore, it was concluded that using the metering rate to convert from queue length into wait time is appropriate.

4.6.2 Wait Time Models

Figure 4.8 through Figure 4.11 show the wait time comparison on one day for each model for Bangerter Highway SB, Layton Parkway NB, Pleasant Grove Boulevard SB, and University Avenue SB, respectively. These figures show that there is variation in terms of the accuracy of the wait time estimates depending on which ramp is considered. The models on both Bangerter Highway and Layton Parkway followed the observed wait time quite well. University Avenue performed better than Pleasant Grove Boulevard, but it did not follow the observed wait times as well as Bangerter Highway and Layton Parkway. Pleasant Grove Boulevard experienced much more variation than any other ramp analyzed. There may be many reasons for this such as difficulty in collecting accurate data because of camera angles and resolution, ramp density and vehicle speed, inaccuracy in the loop detector data, and other ramp characteristics. Most models used in this research across all ramps and periods tend to slightly underestimate the observed wait times as well. However, across all ramps, the heuristic and Vigos models generally fall within 45 seconds of the observed wait times throughout each day. The wait time results of the remaining four days at each ramp not included in the body of this report are presented in Appendix B.

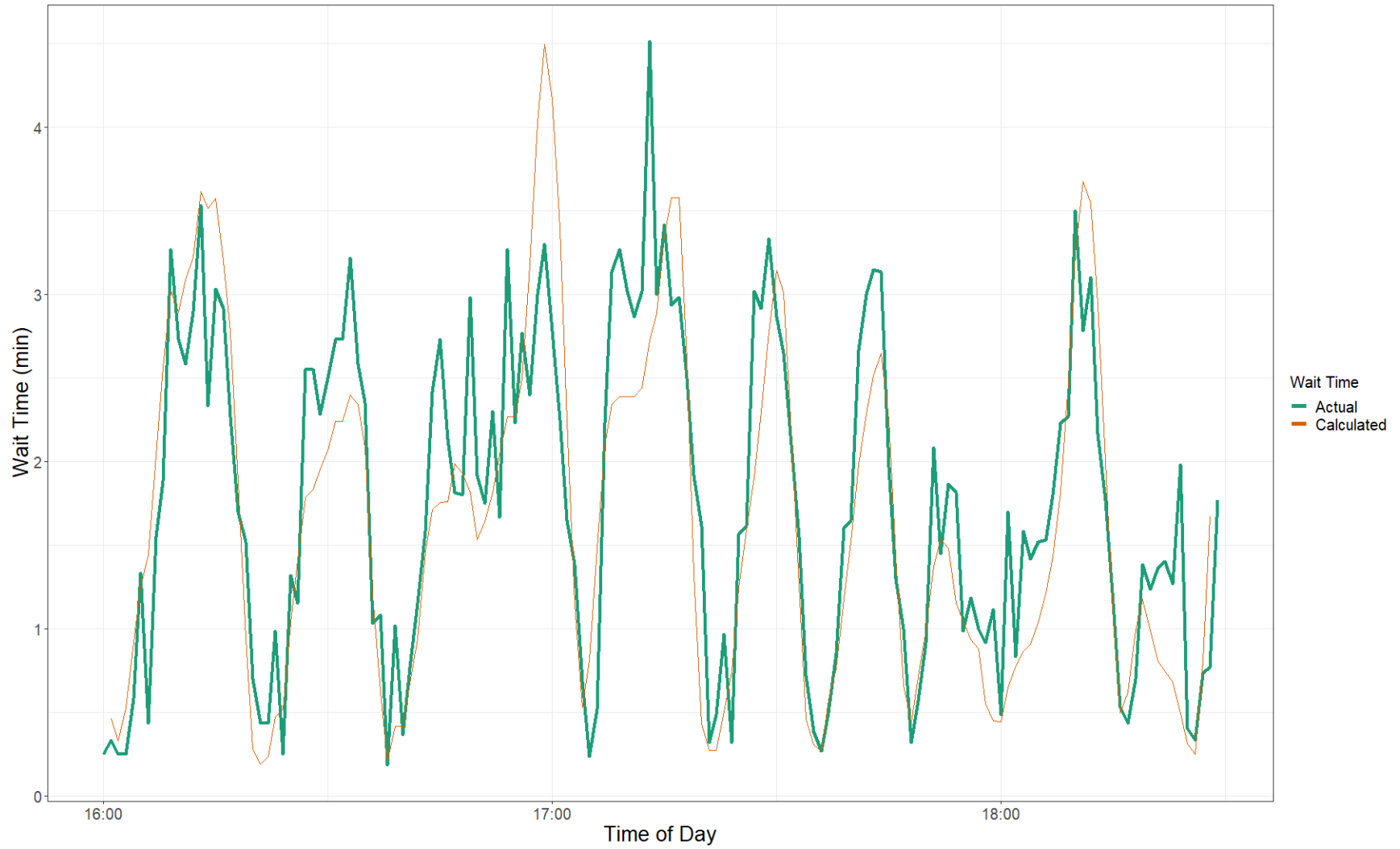


Figure 4.7 Wait time vs. metering rate comparison: Layton Parkway NB, April 15, 2021.

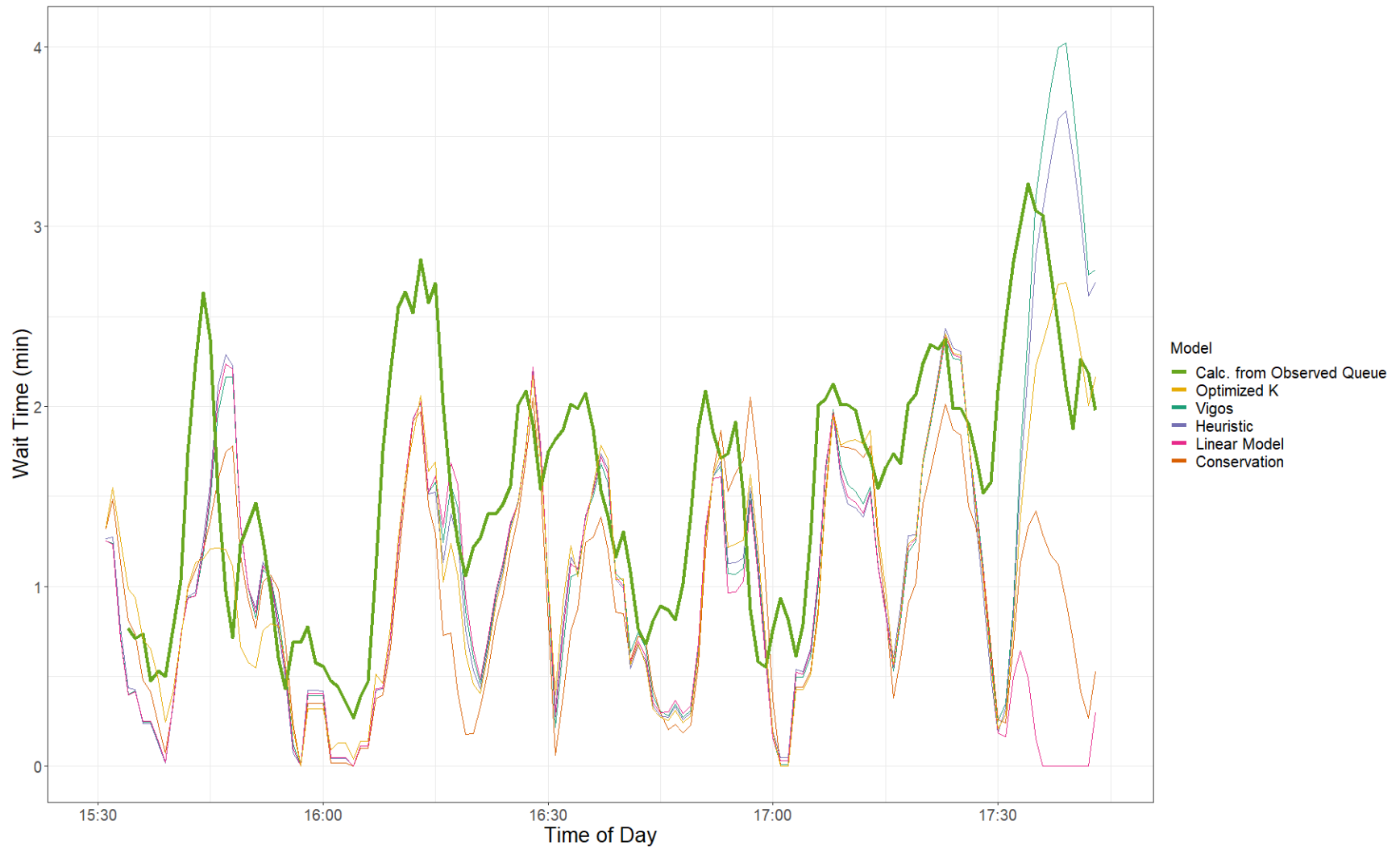


Figure 4.8 Wait time comparison: Bangerter Highway SB, April 15, 2021.

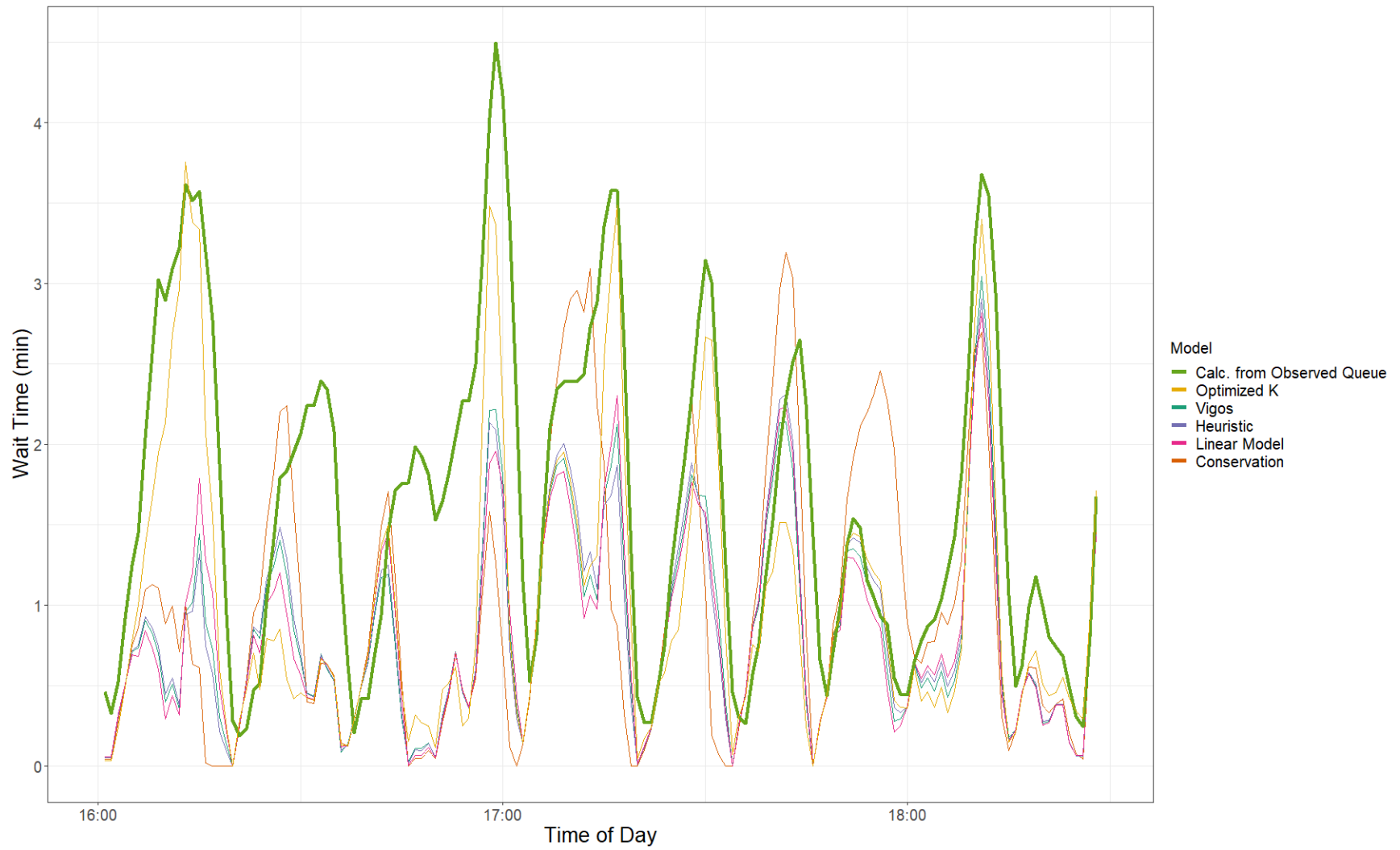


Figure 4.9 Wait time comparison: Layton Parkway NB, April 15, 2021.

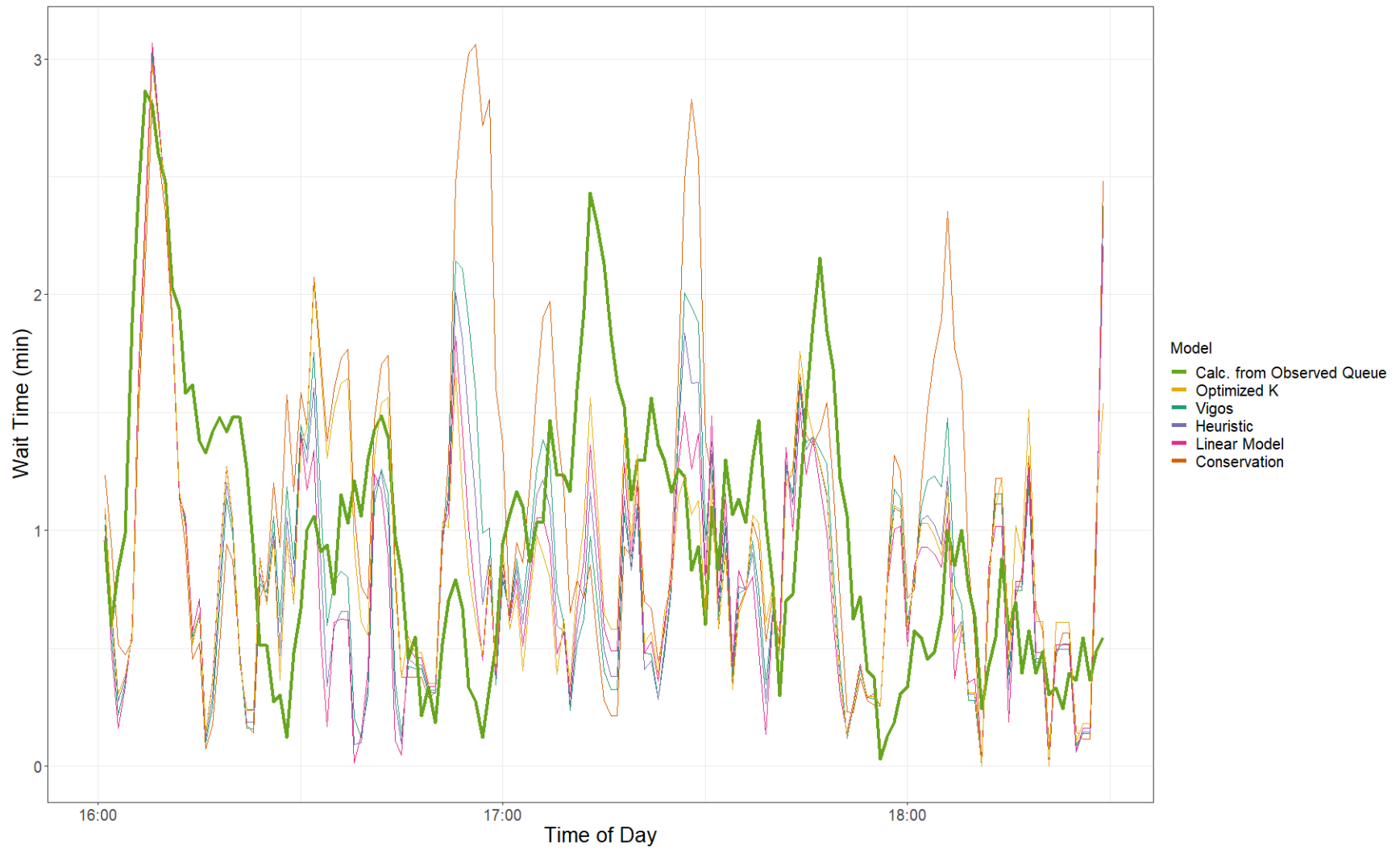


Figure 4.10 Wait time comparison: Pleasant Grove Boulevard SB, July 28, 2021.



Figure 4.11 Wait time comparison: University Avenue SB, July 28, 2021.

Table 4.5 shows the wait time RMSE results for each of the models that were analyzed. The RMSE is reported for the entire dataset as well as the RMSE calculated for each ramp, which was calculated by comparing the modeled wait time against the calculated wait time for each period. The order of RMSE, as occurred in the queue length analysis, varies slightly by ramp, but this table shows that generally the heuristic model performs best when the RMSE is used as the comparison mechanism. The Vigos model exhibits nearly the same RMSE both overall and by ramp. This again indicates that although the heuristic model is based on a cluster analysis that yielded three possible values for K , using a constant value of 0.22 performs nearly as well—if not sometimes better than—the heuristic model for representing wait times on a ramp.

Because the wait times are computed in units of minutes, the RMSE values provided in Table 4.5 are in units of minutes as well. The overall results of the heuristic and Vigos models, then, have an RMSE of 0.837 and 0.843 minutes, respectively, which come out to be approximately 50 to 51 seconds. RMSE is the square root of the average of the squared differences between the prediction and actual observations, so these results provide additional insight as to how closely the data points align with the line of best fit. As was described in Section 3.3, the optimized K is used solely as a baseline for the other models and cannot be used in real time as it relies on a comparison to field data during the same time period.

Table 4.5 Wait Time RMSE Results

Models	RMSE (minutes)				
	Overall	Bangerter	Layton	PG Blvd	Univ Ave
Optimized K Baseline	0.708	0.583	0.974	0.631	0.402
Heuristic	0.837	0.623	1.14	0.849	0.425
Vigos	0.843	0.635	1.14	0.875	0.422
Linear Regression	0.864	0.688	1.15	0.756	0.674
Conservation	0.981	0.755	1.18	1.17	0.603

4.7 Summary

This chapter presented the results of the data analysis of the queue length and wait times at each of the four ramps on which data were collected. The ramps were analyzed using several

variations of the Kalman filter equation, including an optimized K , a heuristic model, the Vigos model ($K = 0.22$), a linear regression model, and a conservation model ($K = 0$).

Queue length estimates provided mixed results across the models analyzed. Although the conservation model and linear regression models performed poorly, the heuristic model and the Vigos model produced queue length estimates that much more closely matched the observed queue length at each of the four ramps. The four ramps performed differently for each model as well, with the Layton Parkway and Bangerter Highway ramps having the best results, while the Pleasant Grove Boulevard and University Avenue ramps, although they performed reasonably well, were not as accurate overall.

To provide for full automation of estimating queue length solely from the detector data at the on-ramp, wait times were calculated by dividing the modeled queue lengths by the metering rate provided by the detector data. This method was tested on Layton Parkway by comparing field-recorded wait times to the calculated wait times, which were calculated by dividing the field-recorded queue length by the metering rate. It was found that the calculated wait times were generally within 30 seconds or less of the observed wait times as seen in Figure 4.7, thus it was deemed appropriate to calculate wait times by dividing the modeled queue length by the metering rate. As was found with the queue length analysis, the wait times presented in Figure 4.8 through Figure 4.11 were found to be most accurate with the heuristic and Vigos models, which were within approximately 45 seconds of the observed wait times.

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

The purpose of this research was to develop an algorithm that accurately predicts wait time at metered on-ramps in Utah using existing loop detector design that can be applied across any metered on-ramp throughout the state. Four ramps were studied during the PM peak period throughout Davis, Salt Lake, and Utah counties, including the NB ramp at Layton Parkway in Davis County, the SB ramp at Bangerter Highway in Salt Lake County, the SB ramp at Pleasant Grove Boulevard in Utah County, and the SB ramp at University Avenue in Utah County. This chapter details the findings from the analysis performed at each of these ramps, the limitations and challenges that occurred throughout the project, recommendations, future research topics, and concluding remarks.

5.2 Findings

Analyses were conducted on ramp meter queue lengths and wait times. Throughout the research process, there were several findings that will be presented in this section. This section will describe the conclusions made by prior research, the findings of the loop detector accuracy at on-ramps, and the findings of both queue length and wait time estimates.

5.2.1 Prior Research

Typical queue and delay estimation algorithms used at signalized intersections are difficult to apply to ramp metering. Although there is some past research that analyzed methods to predict queue lengths on metered on-ramps to freeways, there is relatively little that has been done. The main methods of research that have been done include using a conservation model and a Kalman filter model to predict queue lengths, however, no research appears to have been able to definitively recommend a reliable method to predict ramp queue length, much less produce wait time estimates. The Vigos model also relied solely on microscopic simulation to predict K and had never been verified through field data collection.

5.2.2 Detector Accuracy

The loop detectors on the ramps analyzed provided mixed results when compared against field-collected data, suggesting that the detectors are not entirely accurate in their reporting of volume and occupancy data. This can likely be attributed to several factors, such as vehicles passing over two detectors simultaneously, avoiding passing over a detector altogether, and other potential errors that can occur as the loop detection system ages. If the detectors reported volumes perfectly, the conservation model would have been the most accurate model, however, it was the model that performed most poorly. For this reason, it was imperative that a Kalman filter model be used, as it is able to use other detector and ramp data to help account for what the volumes counted by the detectors cannot do.

5.2.3 Queue Length Estimates

Various methods were used to estimate queue length at each of the four ramps analyzed, including a conservation model and several variations of a Kalman filter model, such as the Vigos model, a heuristic model, and a linear regression model. The queue length estimates' accuracy varied by ramp, but it was found that generally the heuristic and Vigos model represented the observed queue lengths fairly well, while the linear regression and conservation models did not. While there is some variation, it was seen that the queue lengths estimated by the heuristic and Vigos models were generally within approximately 10 vehicles of the observed queue length. These models were also able to capture the fluctuation in queue length at each ramp throughout the metering period.

5.2.4 Wait Time Estimates

The desire of UDOT was that through this project, accurate wait times would be able to be predicted for metered freeway on-ramps throughout the state. Wait time estimates were calculated by dividing the modeled queue lengths by the metering rate; this was verified to be an accurate method of establishing wait time estimates. Through the use of the loop detector data on the on-ramps, the queue length estimates were established. The loop detector data also provides the assigned metering rate for each 60-second period on any given ramp. The heuristic and Vigos models were nearly always within approximately 45 seconds of the observed wait times.

5.3 Limitations and Challenges

Throughout the duration of this project, there were some limitations and challenges that were encountered. The COVID-19 pandemic caused traffic to decline significantly, delaying the data collection period and overall project schedule. During the data collection, it was found that the timestamp of the video, the loop detectors, and the atomic clock time were misaligned, causing the queue length and wait time estimates to be shifted from what the detector data had given as an output. The misalignment in timestamps across these systems was simply because each uses its own configuration. This was resolved by writing code that would shift the data up to 3 minutes either forwards or backwards, based on the minimum RMSE between the total number of vehicles observed to be entering the ramp from the field-recorded data and the detector data. However, this adjustment was only required during the data analysis period and would not need to be done in practice moving forward.

In addition, once this issue was resolved, there were ongoing inaccuracies seen with the detector data, in that the volumes entering and exiting the ramp were often several vehicles off from what the field-collected data showed. This proved that the loop detectors are imperfect; using imperfect data provided by the loop detectors prevents the queue length and wait time algorithms from performing as well as they could have done with more reliable detector data. There were also periods where the loop detectors, or the TransSuite system that UDOT uses for the detectors, appears to have been malfunctioning, as there were times when the loop detector data was either unrealistic or unavailable entirely.

As mentioned in Sections 5.2.3 and 5.2.4, the best queue length and wait time estimation algorithms were generally within about 10 vehicles for the queue length and approximately 45 seconds for the wait time, although there were isolated periods where neither of these thresholds were reached. This can likely be attributed to several causes, most notably the inherent errors in the loop detector data. The wait times were found to rarely exceed 4.5 minutes, which restricts the ability of this project to assess whether the Vigos model remains effective at ramps that experience wait times longer than 4.5 minutes.

5.4 Recommendations

The heuristic and Vigos models most accurately represent both the observed queue length and wait times at each ramp analyzed. Although the heuristic model performed slightly better than the Vigos model overall, the heuristic model is more complex, as it relies on the cluster analysis performed on the occupancy data from the detectors. Because of its reliance on the occupancy data to provide a recommended K value to use in the Kalman filter equation, there is a possibility that the three provided K values may not be suitable for other ramps.

The Vigos model, on the other hand, uses one K value of 0.22, which allows for significantly simpler implementation by UDOT onto other ramps. The results of analysis performed in this research showed that the average K for the four ramps analyzed is also 0.22, further validating the Vigos model. The Vigos model allows for UDOT to require little ongoing effort once the algorithm is implemented. This model has shown to be within approximately 45 seconds of the observed wait times throughout the metering period at any of the four ramps analyzed and provides an automated method by which UDOT can estimate wait times at any metered on-ramp throughout the state. The implementation of this method will substantially reduce the effort and time required by UDOT to observe conditions on a ramp-by-ramp basis to calibrate arbitrary occupancy values to typical wait times at an individual ramp, and instead use one method that can be applied across the state.

5.5 Future Research

There is little publicized research available that analyzes queue lengths and wait times on metered freeway on-ramps. In addition, with the potential inaccuracies of the loop detector data, it is difficult to provide highly accurate wait time estimates. The following topics may be considered for further research:

1. Apply methodology on additional metered ramps throughout Utah to expand the data available and determine whether the Vigos Kalman filter model remains a viable wait time estimation algorithm.

2. Perform further research on the UDOT system of loop detectors, including quantifying detector inaccuracy and periods where no data is collected on the ramps, and determine whether there are feasible, more accurate methods to gather volume and occupancy data.
3. Assess incorporating queue detector occupancy—dependent on detector accuracy—results in real time to realign the Kalman filter algorithm.

5.6 Concluding Remarks

The ability to accurately assess wait times on metered freeway on-ramps throughout Utah is of high importance to UDOT, especially with the interest in implementing elements of a managed motorways system in the future. The methods proposed in this study have been developed to provide UDOT with a method to predict ramp meter queue length and wait time at these metered on-ramps with little calibration required. The implementation of the Vigos model is anticipated to help UDOT have a better idea of what ramp wait times are at metered on-ramps. Prior to this research, the Vigos model had only been used to estimate queue lengths through microscopic simulation. This research assessed various models of both ramp meter queue length and wait time through extensive field data collection. The result of this analysis shows that the Vigos model performs well with field data and that the metering rate provided by the detector data can be reliably used to convert queue lengths into wait times.

This method will significantly reduce the effort required by UDOT to calibrate wait times on a ramp-by-ramp basis and will allow for one straightforward method to be used that can be applied across any metered on-ramp throughout the state. It is recommended that further research be done to determine methods to improve detection on ramps if a more precise wait time algorithm is desired so UDOT may achieve its goal of establishing a robust managed motorways system throughout the state.

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APPENDIX A: QUEUE LENGTH ESTIMATION RESULTS

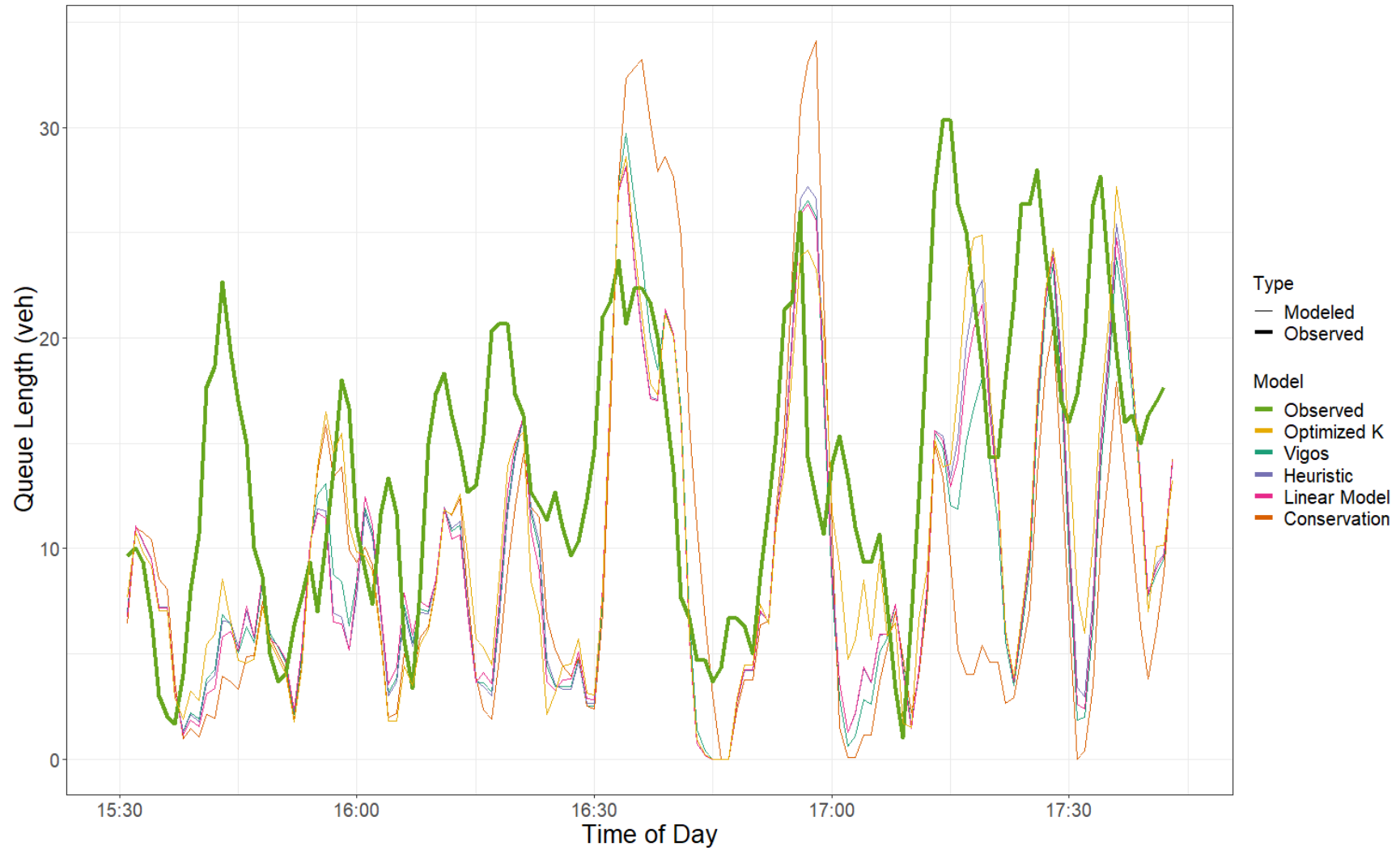


Figure A.1 Queue length comparison: Bangerter Highway SB, April 9, 2021.

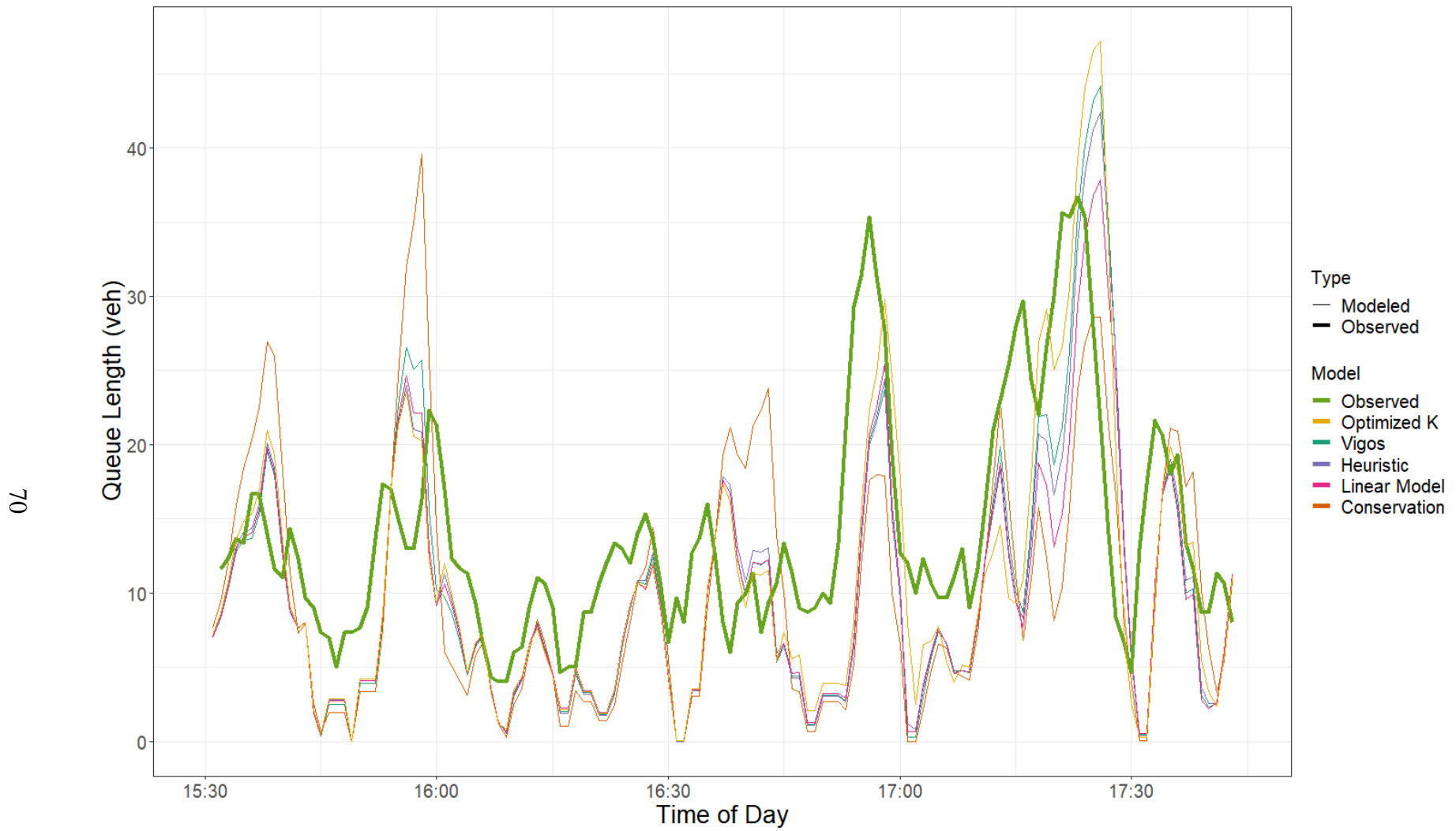


Figure A.2 Queue length comparison: Bangerter Highway SB, April 12, 2021.

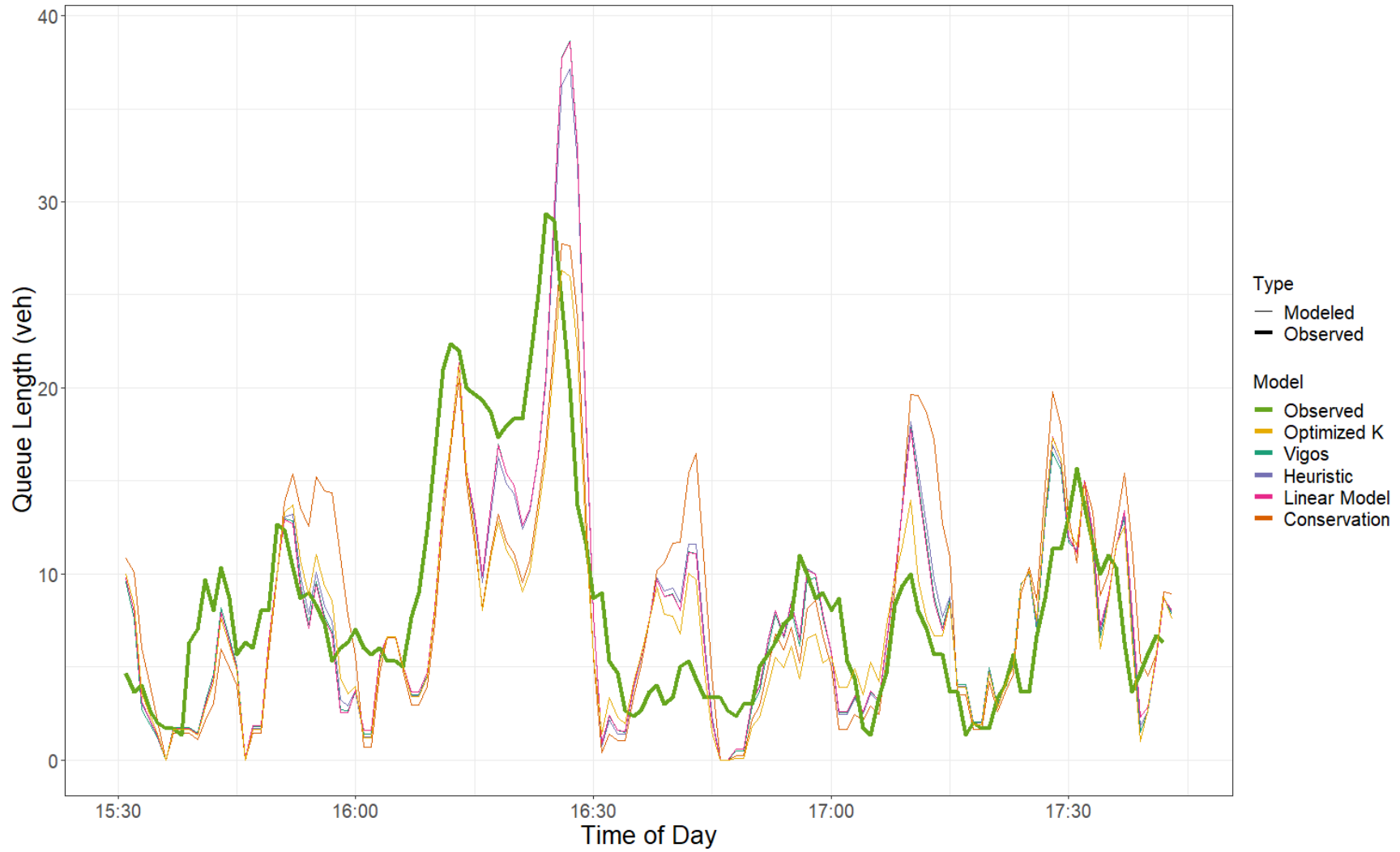


Figure A.3 Queue length comparison: Bangerter Highway SB, April 14, 2021.

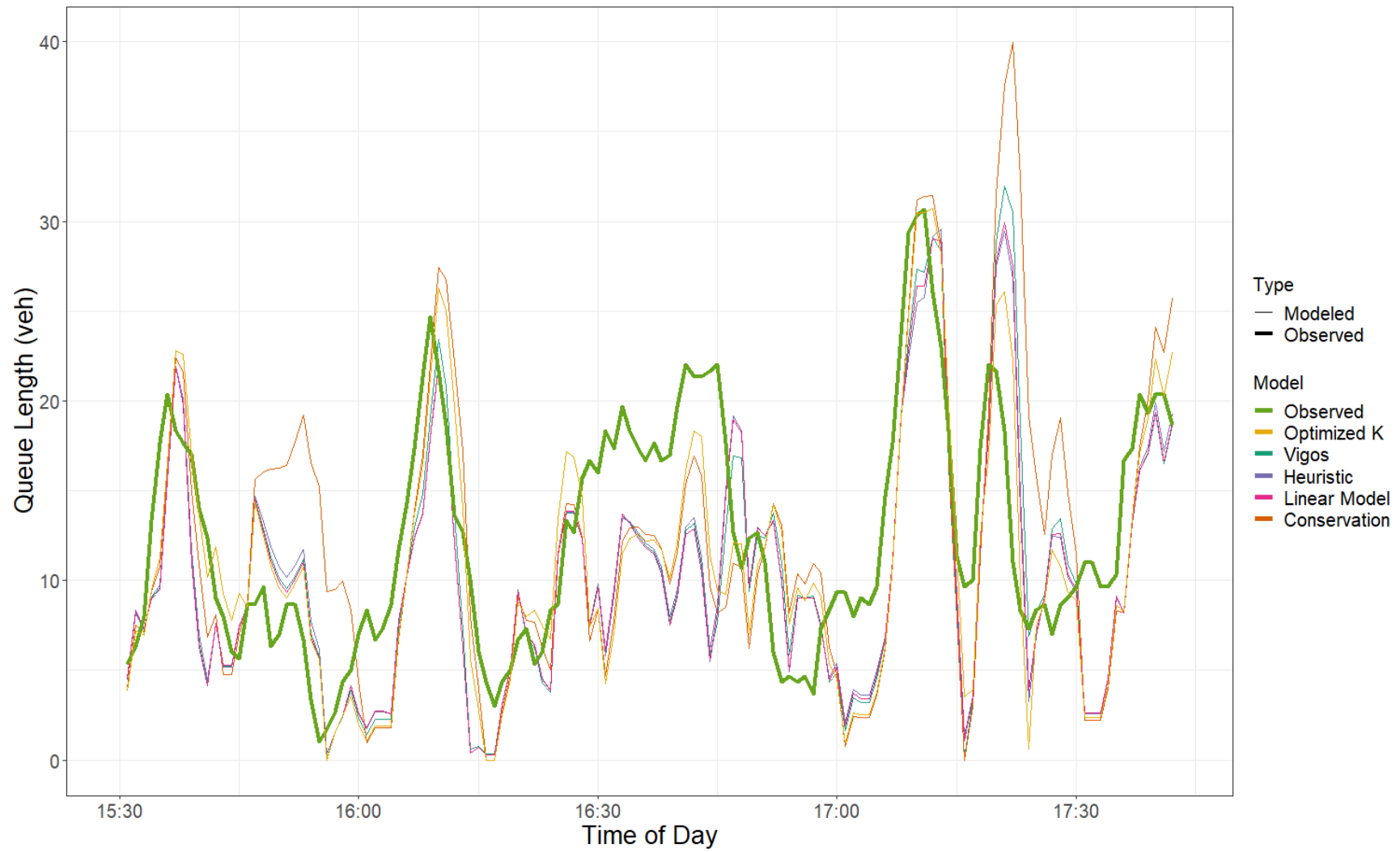


Figure A.4 Queue length comparison: Bangerter Highway SB, April 20, 2021.

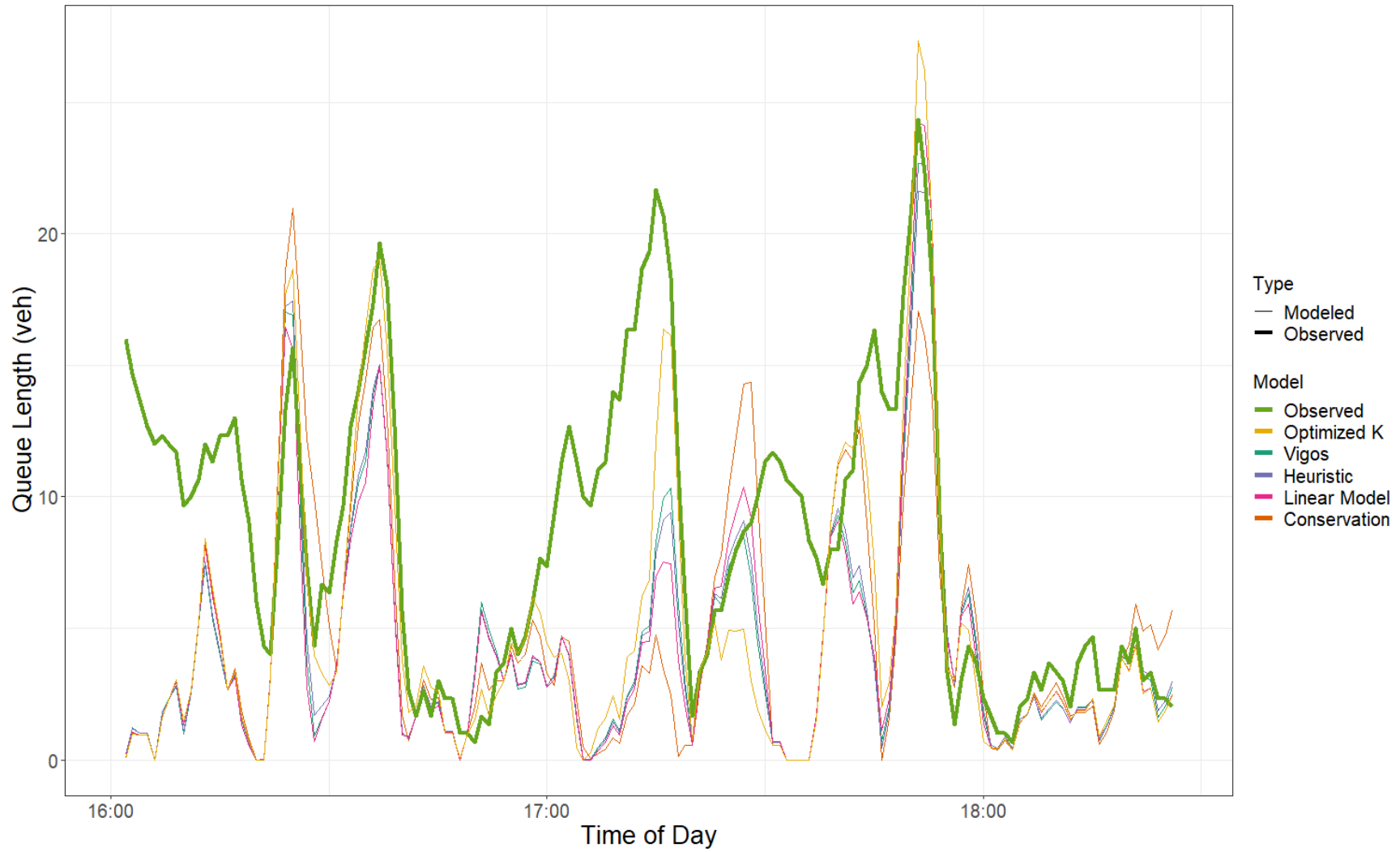


Figure A.5 Queue length comparison: Layton Parkway NB, April 9, 2021.

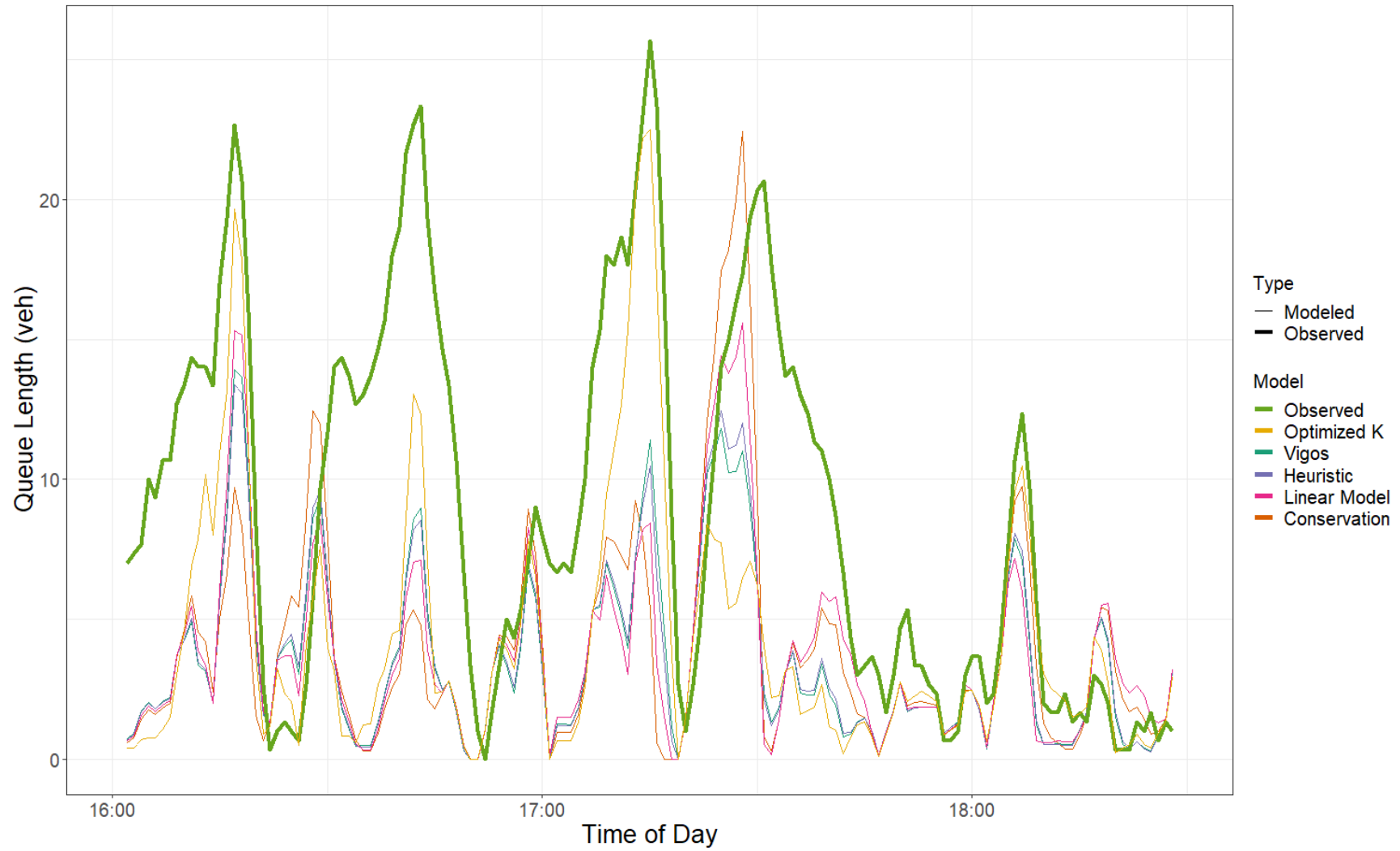


Figure A.6 Queue length comparison: Layton Parkway NB, April 12, 2021.

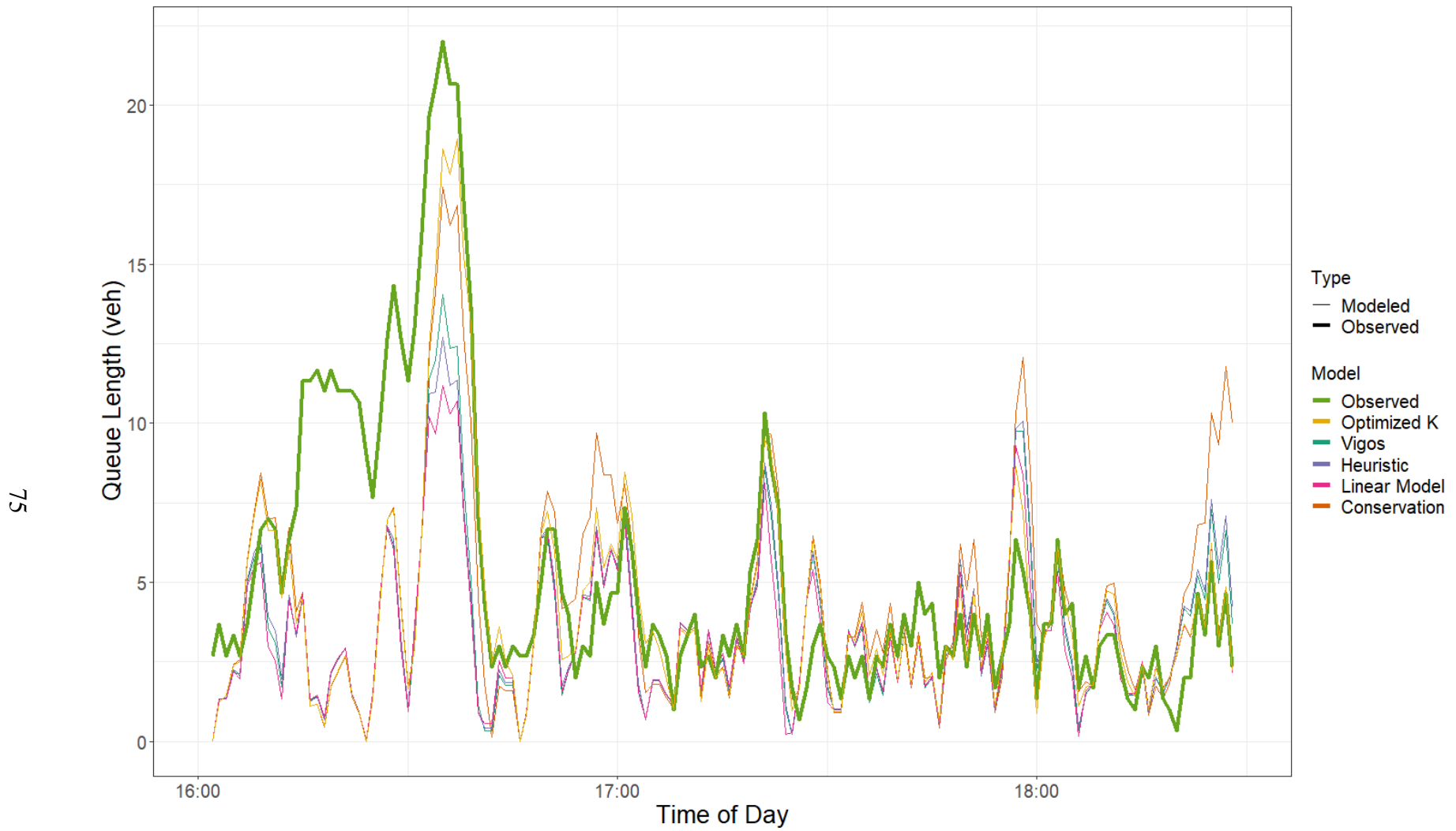


Figure A.7 Queue length comparison: Layton Parkway NB, April 14, 2021.

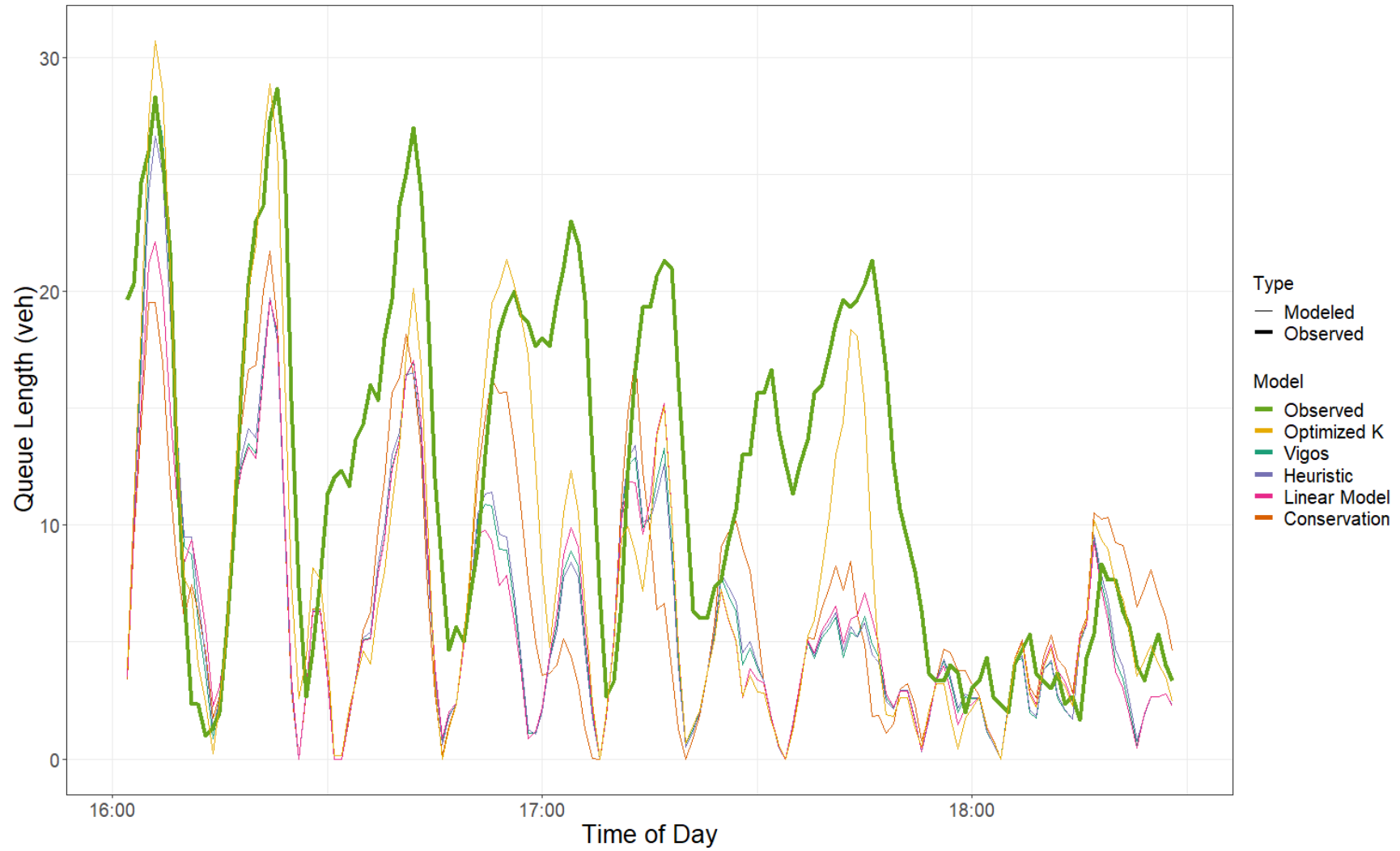


Figure A.8 Queue length comparison: Layton Parkway NB, April 20, 2021.

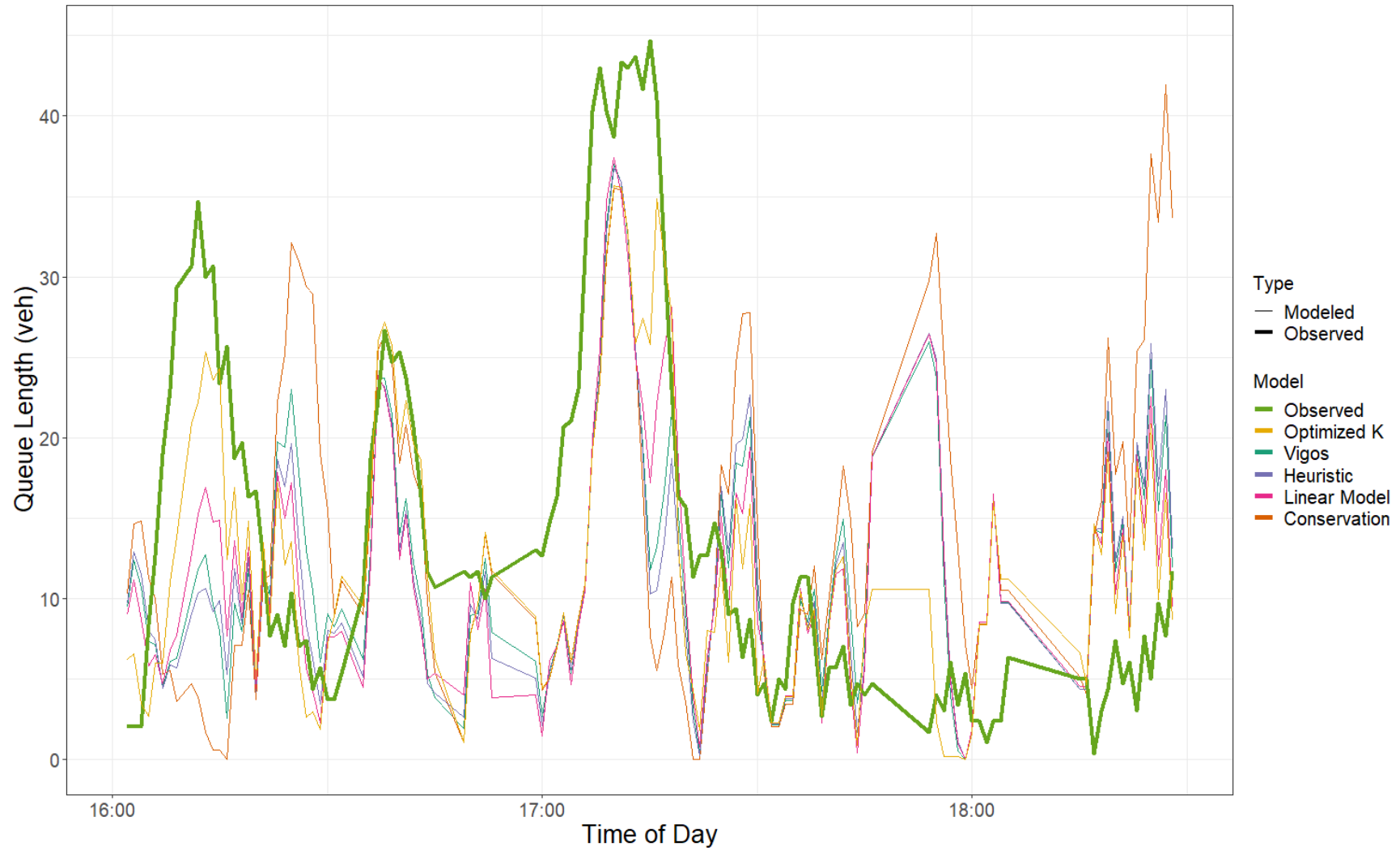


Figure A.9 Queue length comparison: Pleasant Grove Boulevard SB, July 13, 2021.

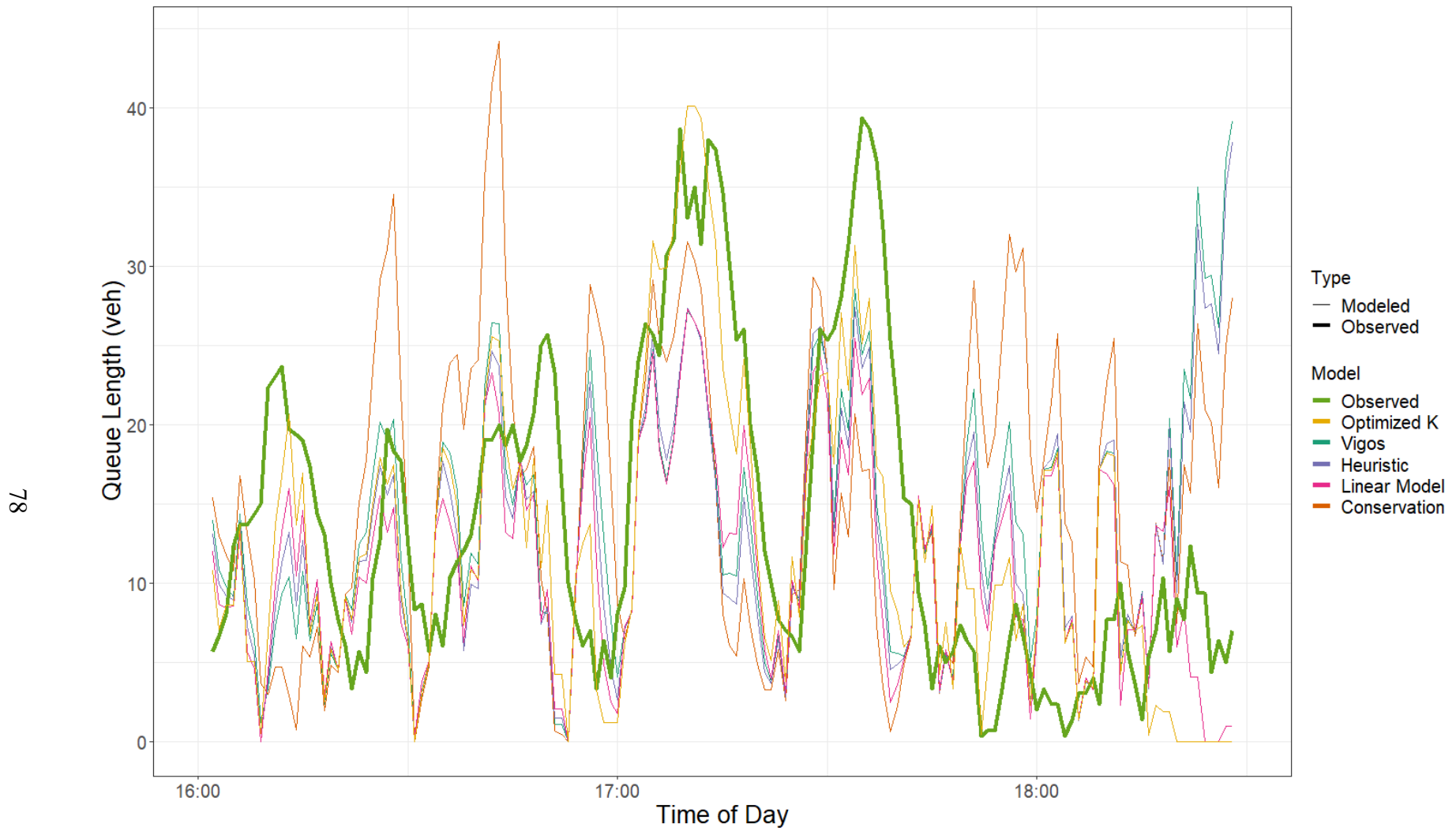


Figure A.10 Queue length comparison: Pleasant Grove Boulevard SB, July 29, 2021.

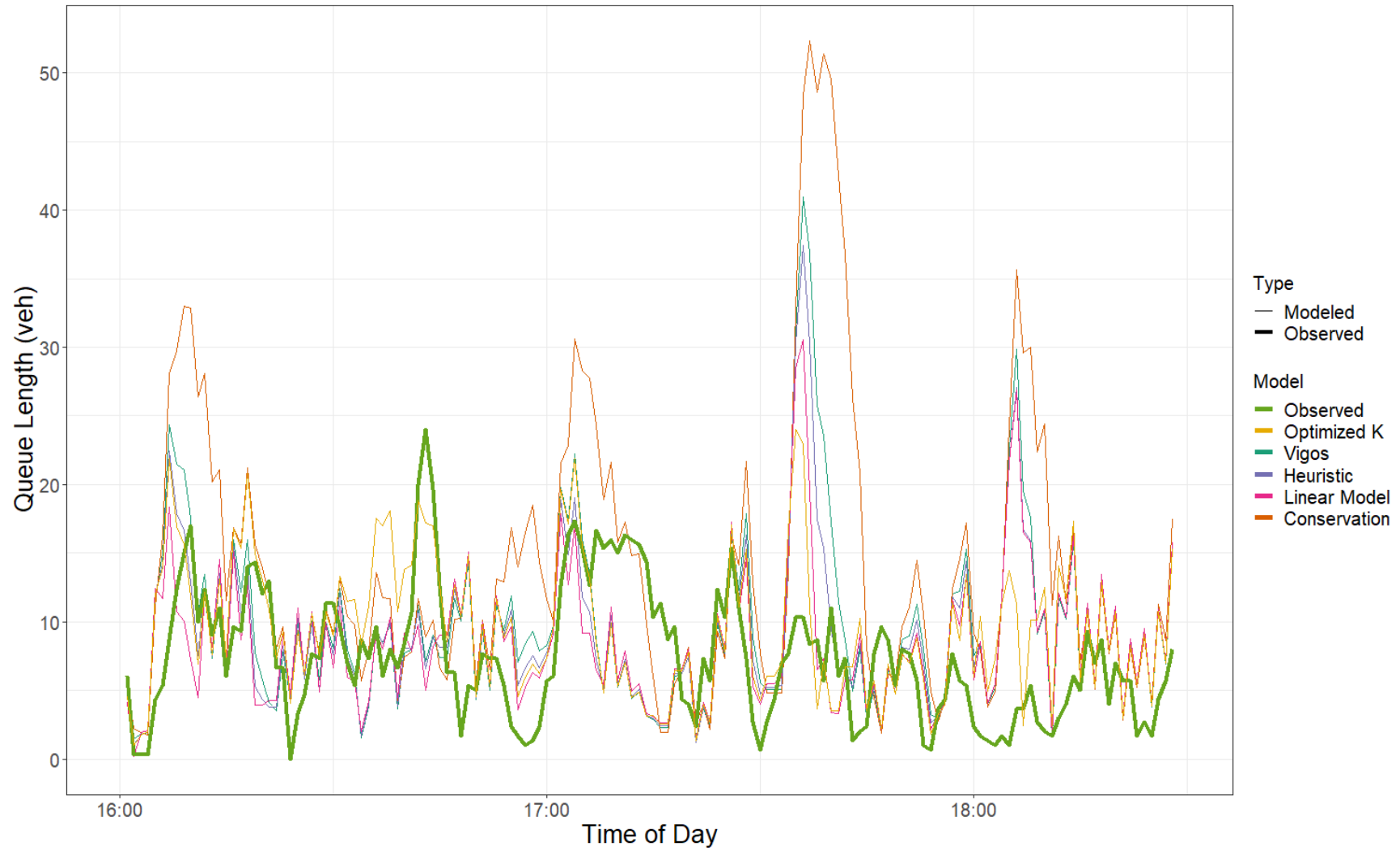


Figure A.11 Queue length comparison: Pleasant Grove Boulevard SB, August 6, 2021.

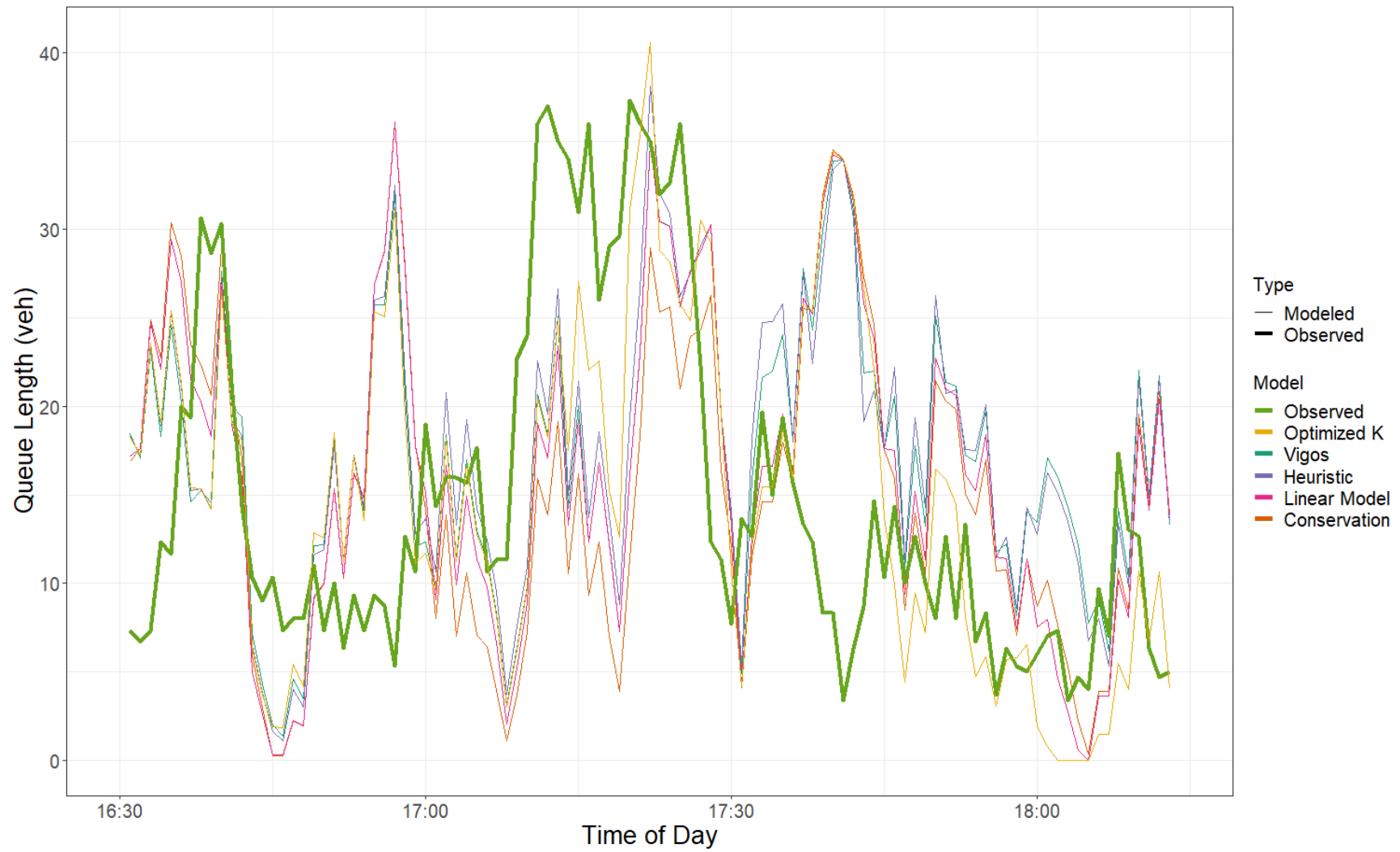


Figure A.12 Queue length comparison: University Avenue SB, July 12, 2021.

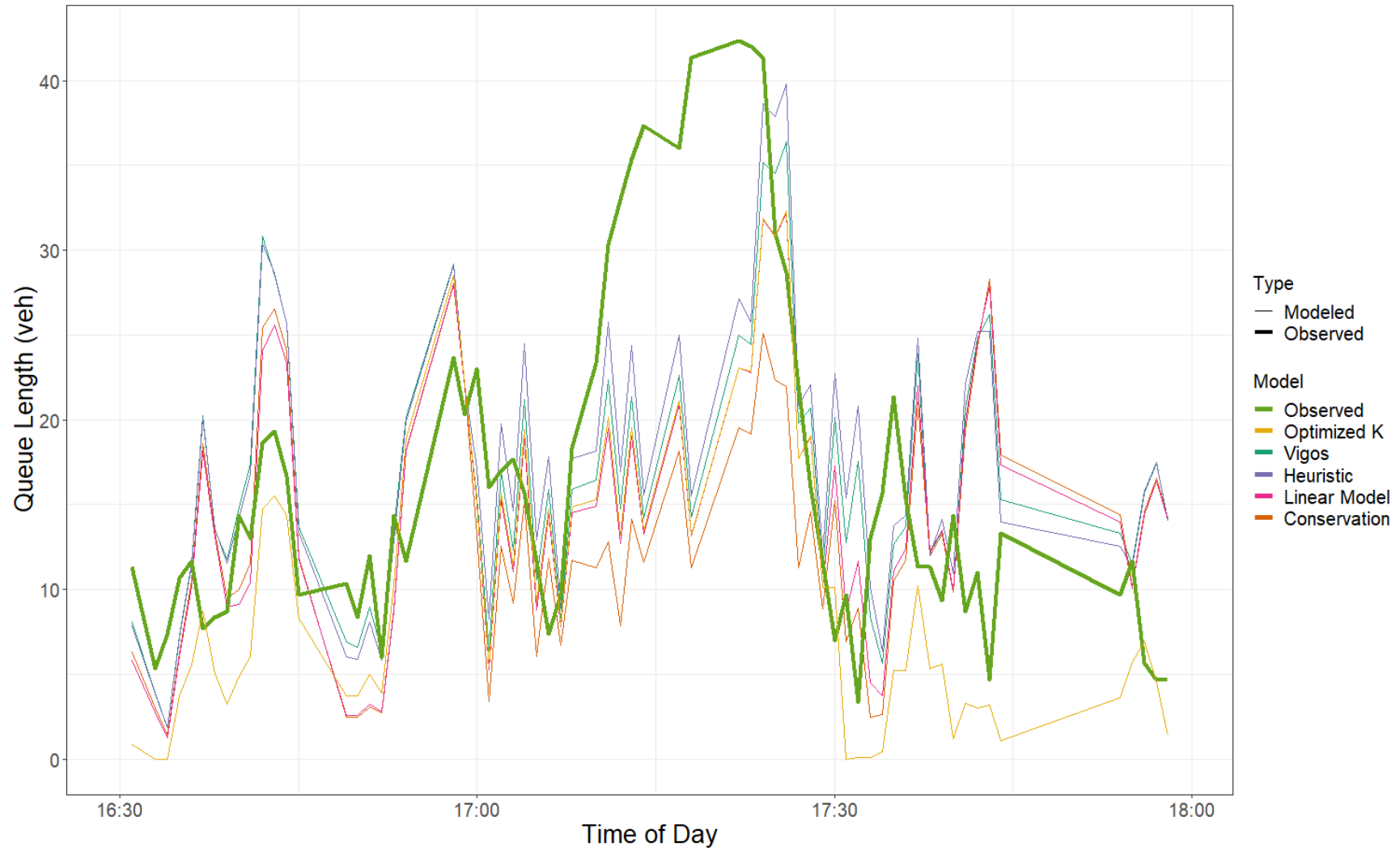


Figure A.13 Queue length comparison: University Avenue SB, July 13, 2021.

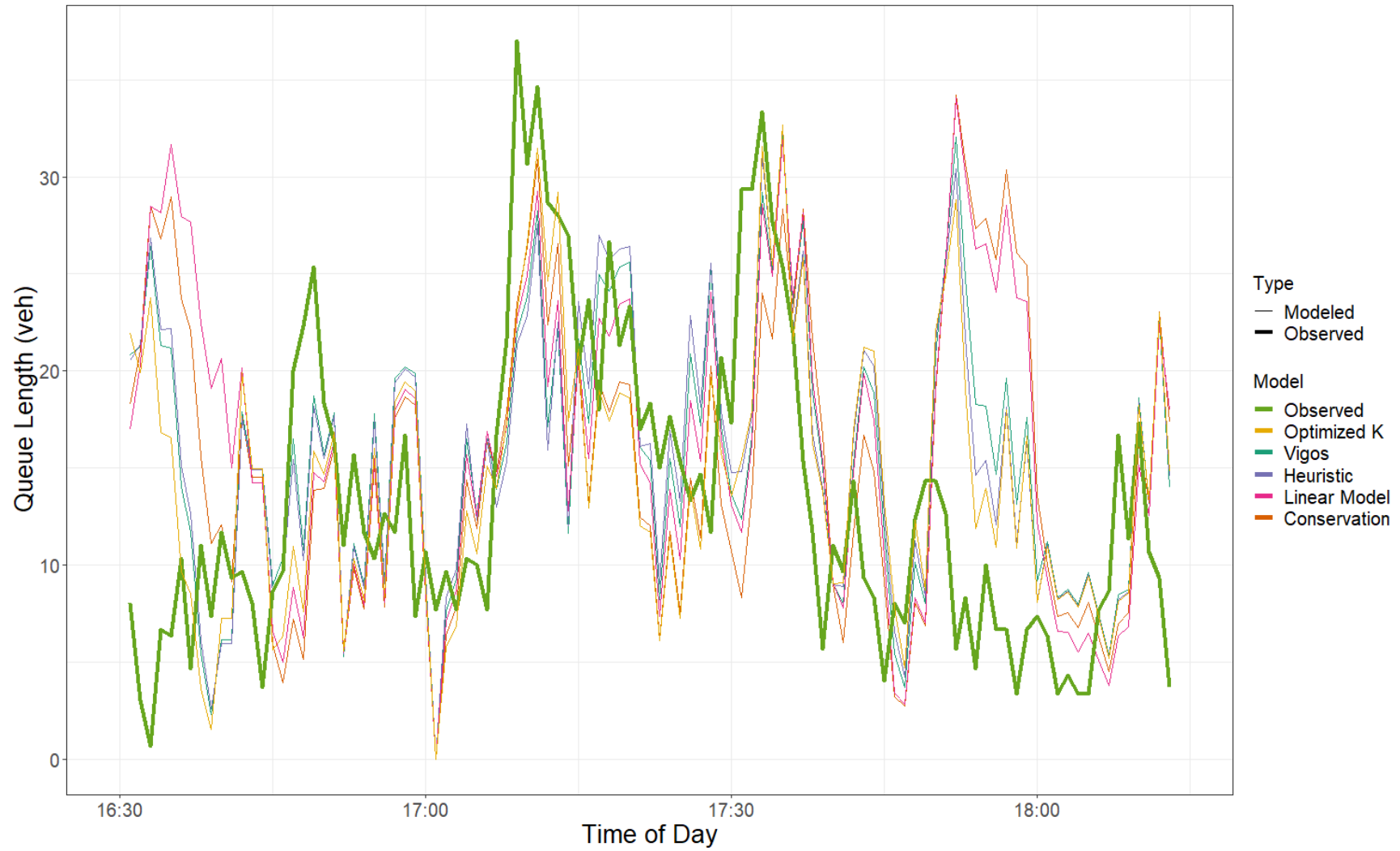


Figure A.14 Queue length comparison: University Avenue SB, July 29, 2021.

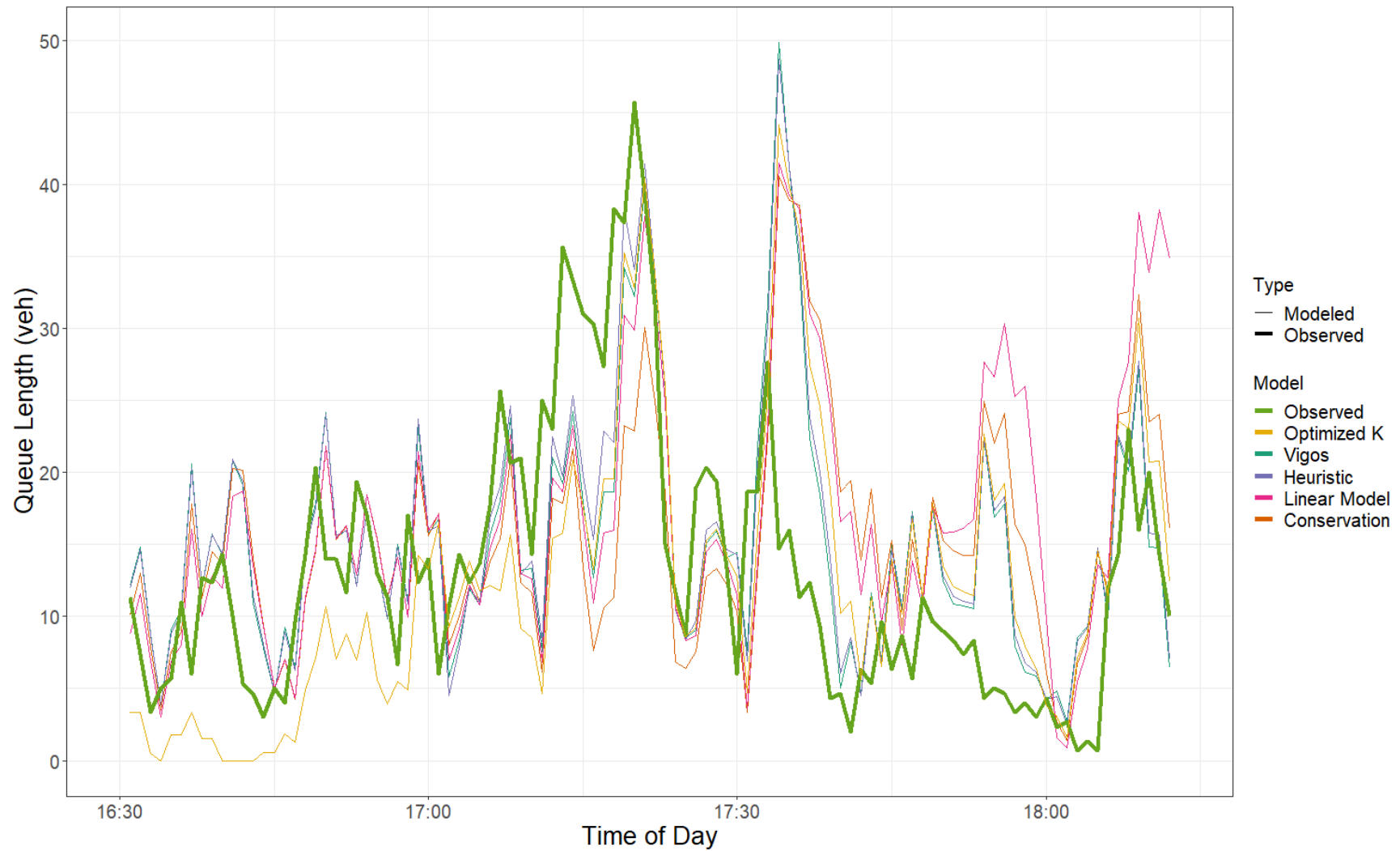


Figure A.15 Queue length comparison: University Avenue SB, August 6, 2021.

APPENDIX B: WAIT TIME ESTIMATION RESULTS

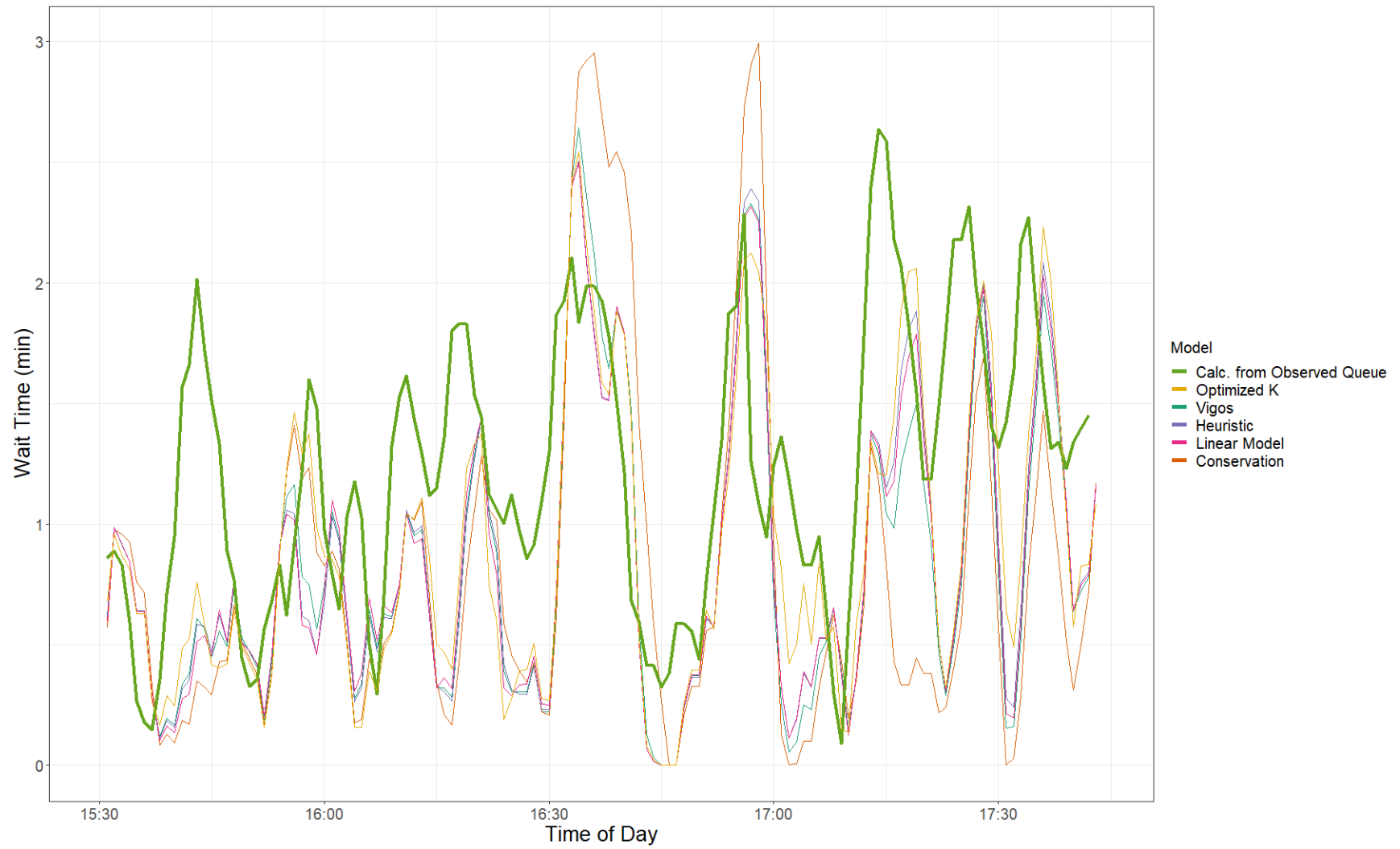


Figure B.1 Wait time comparison: Bangerter Highway SB, April 9, 2021.

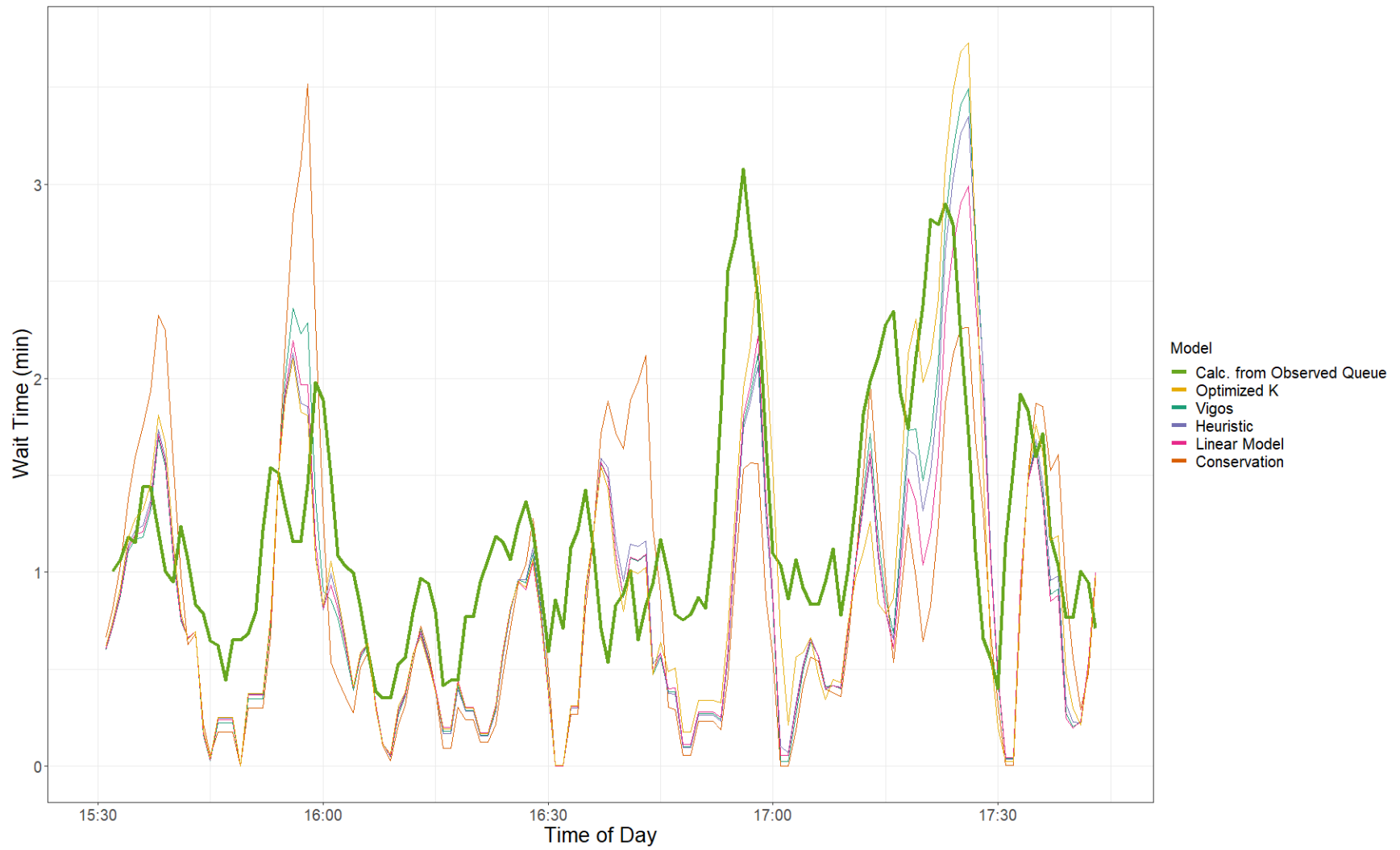


Figure B.2 Wait time comparison: Bangerter Highway SB, April 12, 2021.

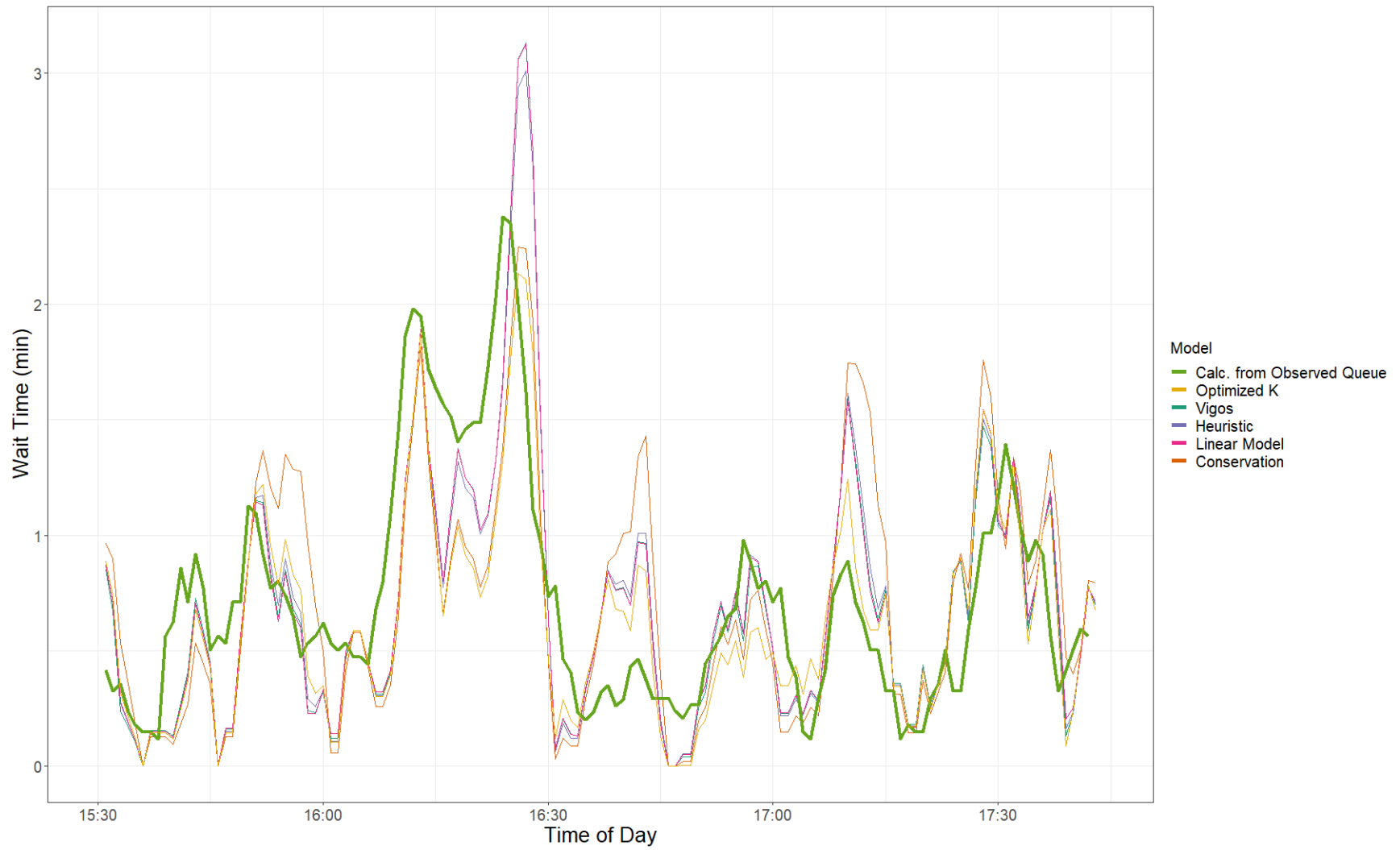


Figure B.3 Wait time comparison: Bangerter Highway SB, April 14, 2021.

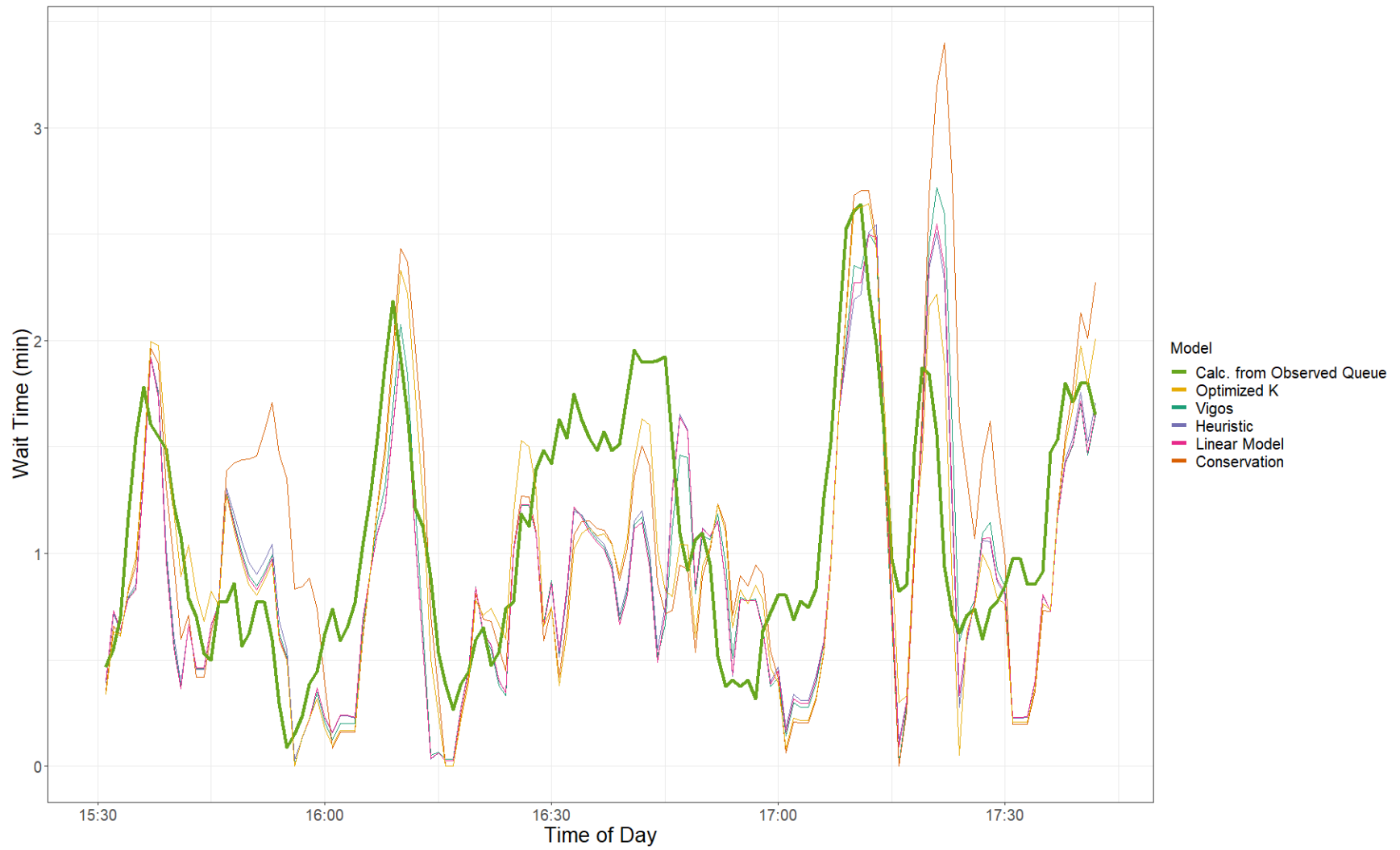


Figure B.4 Wait time comparison: Bangerter Highway SB, April 20, 2021.

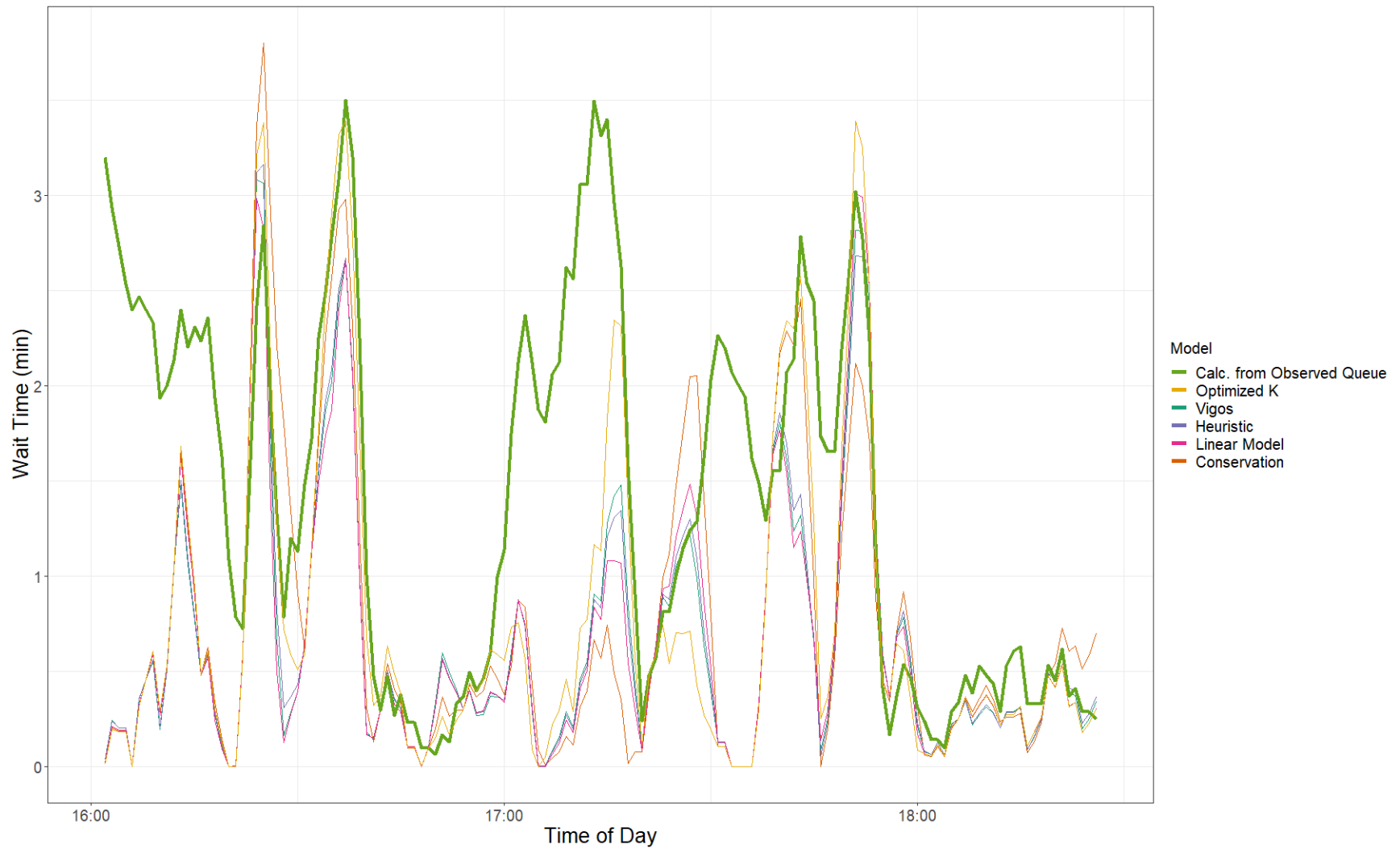


Figure B.5 Wait time comparison: Layton Parkway NB, April 9, 2021.

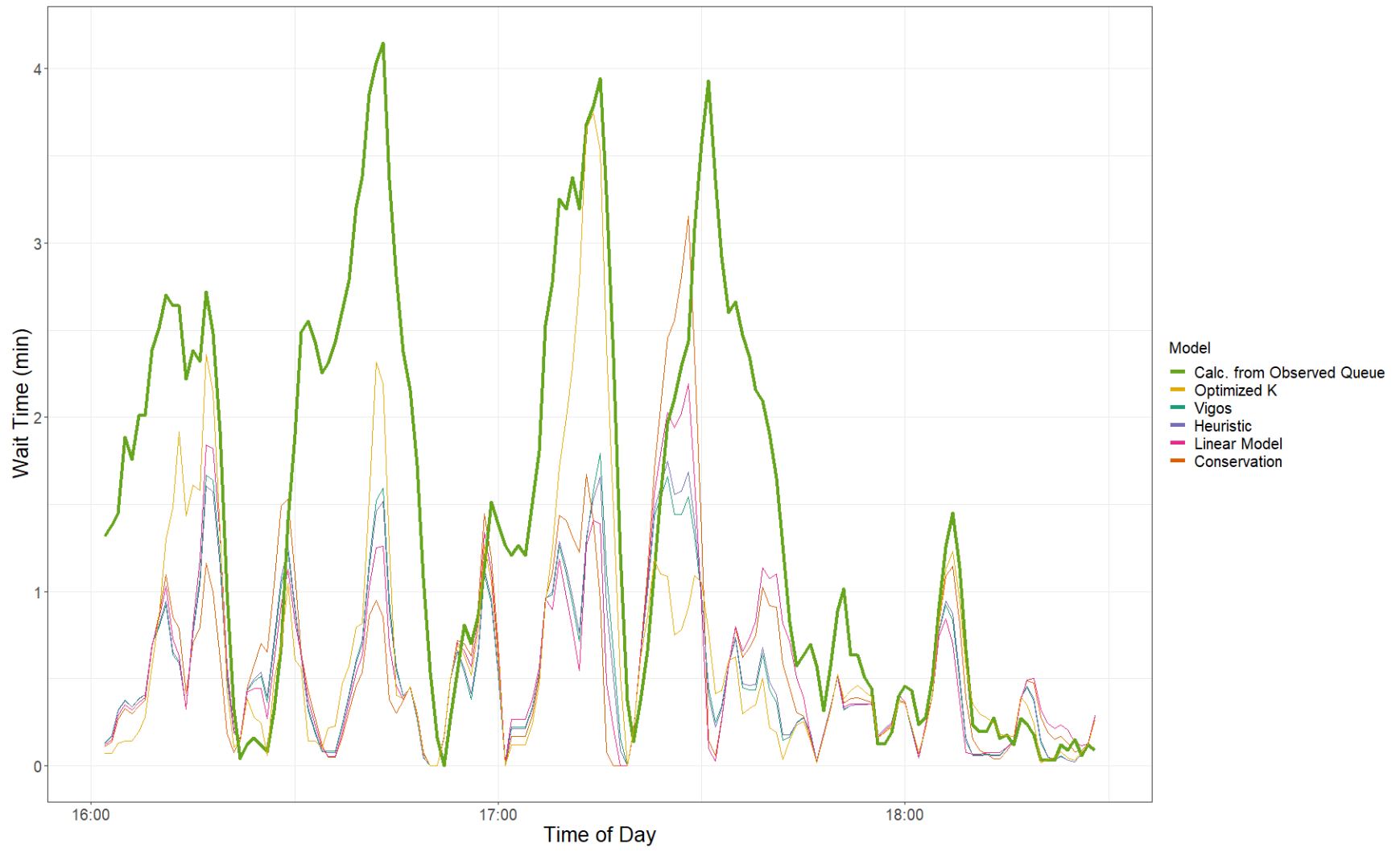


Figure B.6 Wait time comparison: Layton Parkway NB, April 12, 2021.

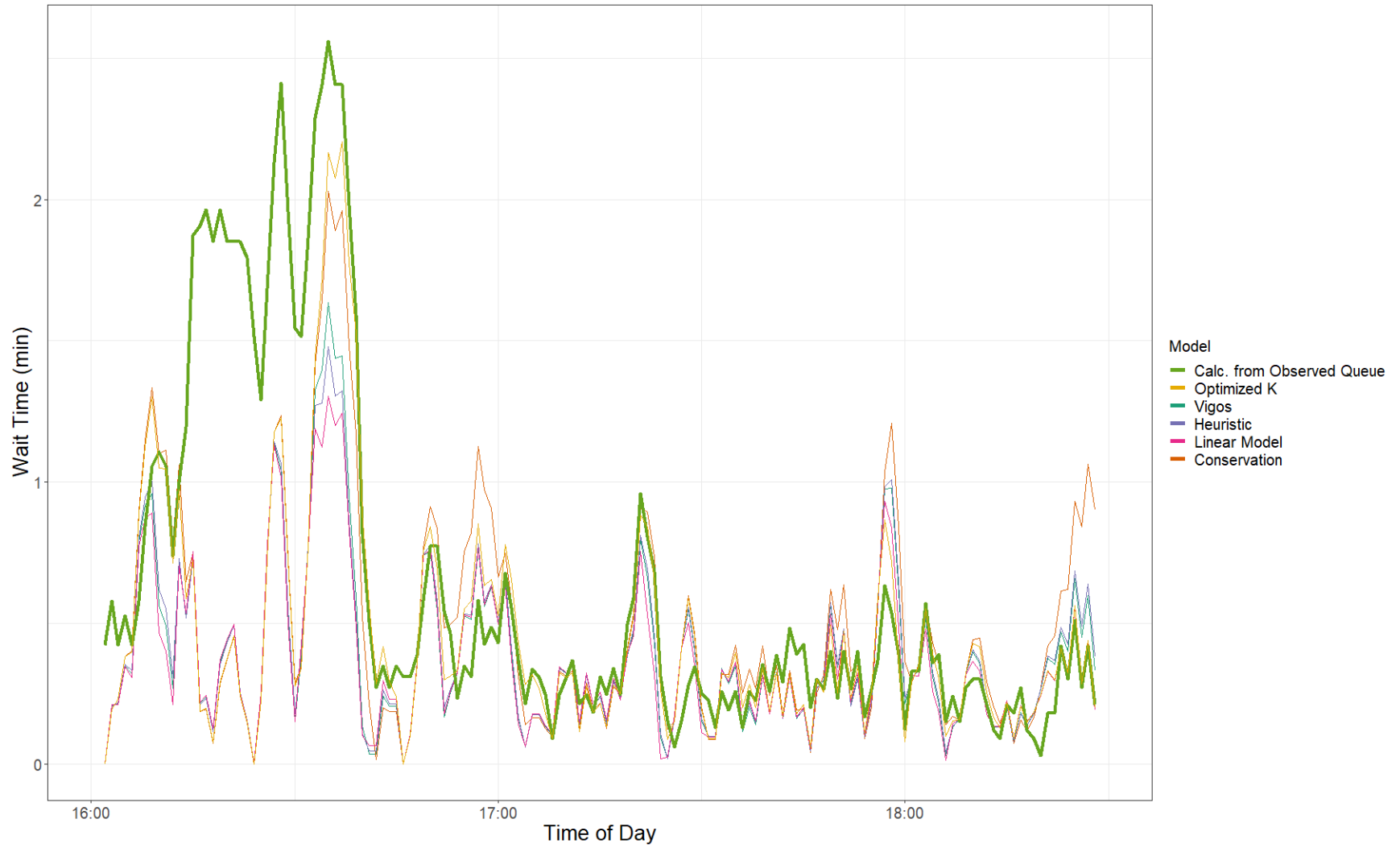


Figure B.7 Wait time comparison: Layton Parkway NB, April 14, 2021.

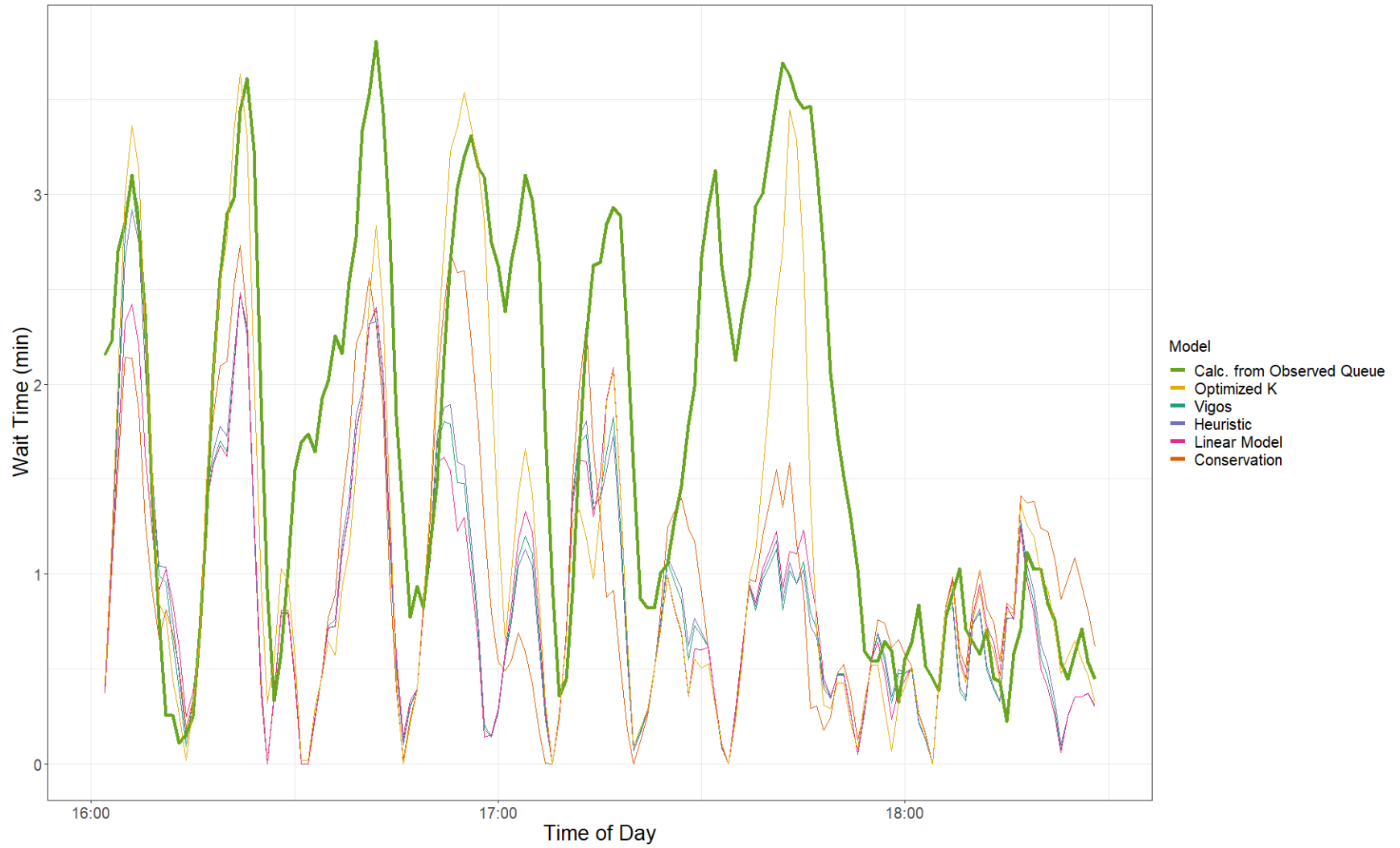


Figure B.8 Wait time comparison: Layton Parkway NB, April 20, 2021.

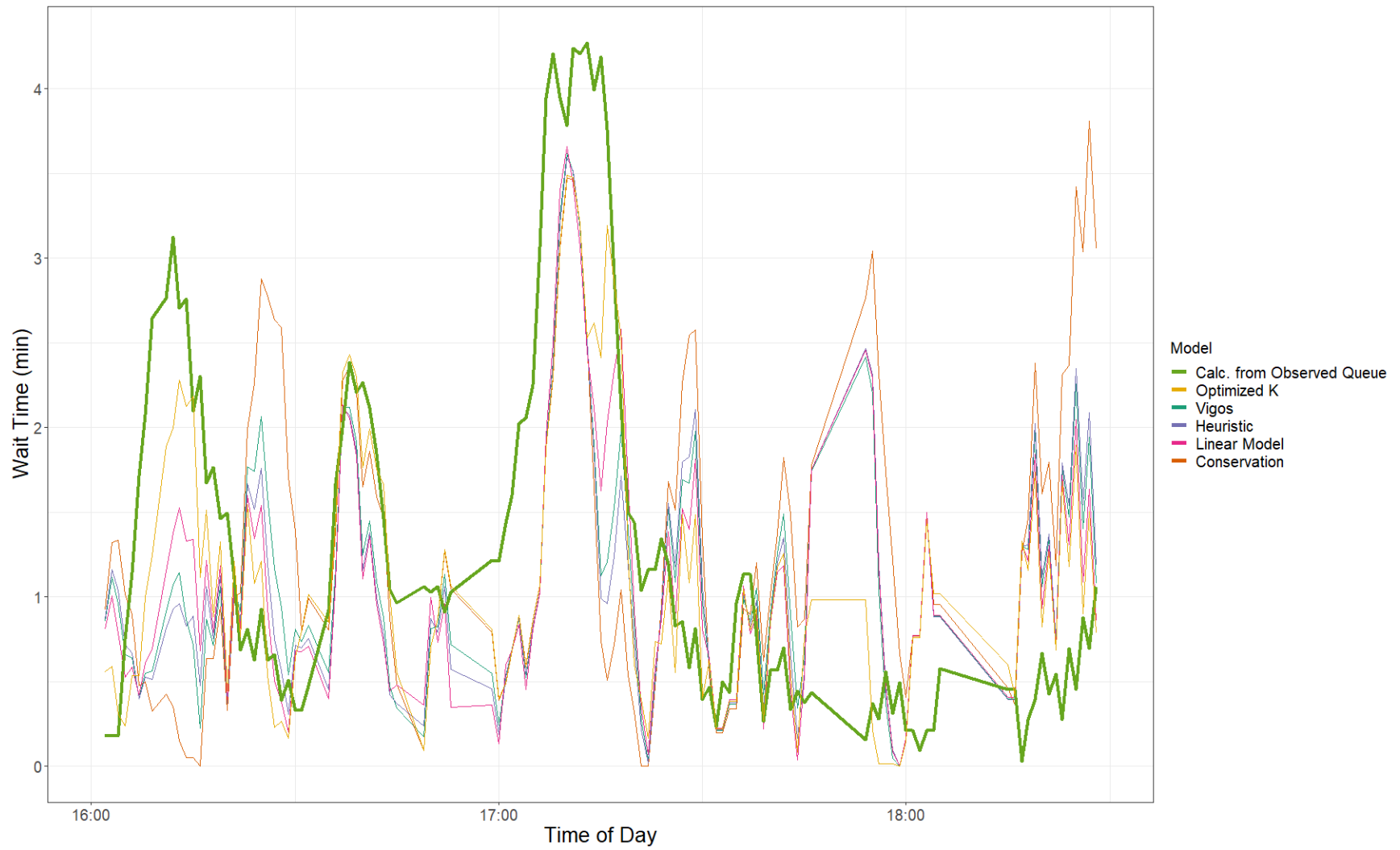


Figure B.9 Wait time comparison: Pleasant Grove Boulevard SB, July 13, 2021.



Figure B.10 Wait time comparison: Pleasant Grove Boulevard SB, July 29, 2021.

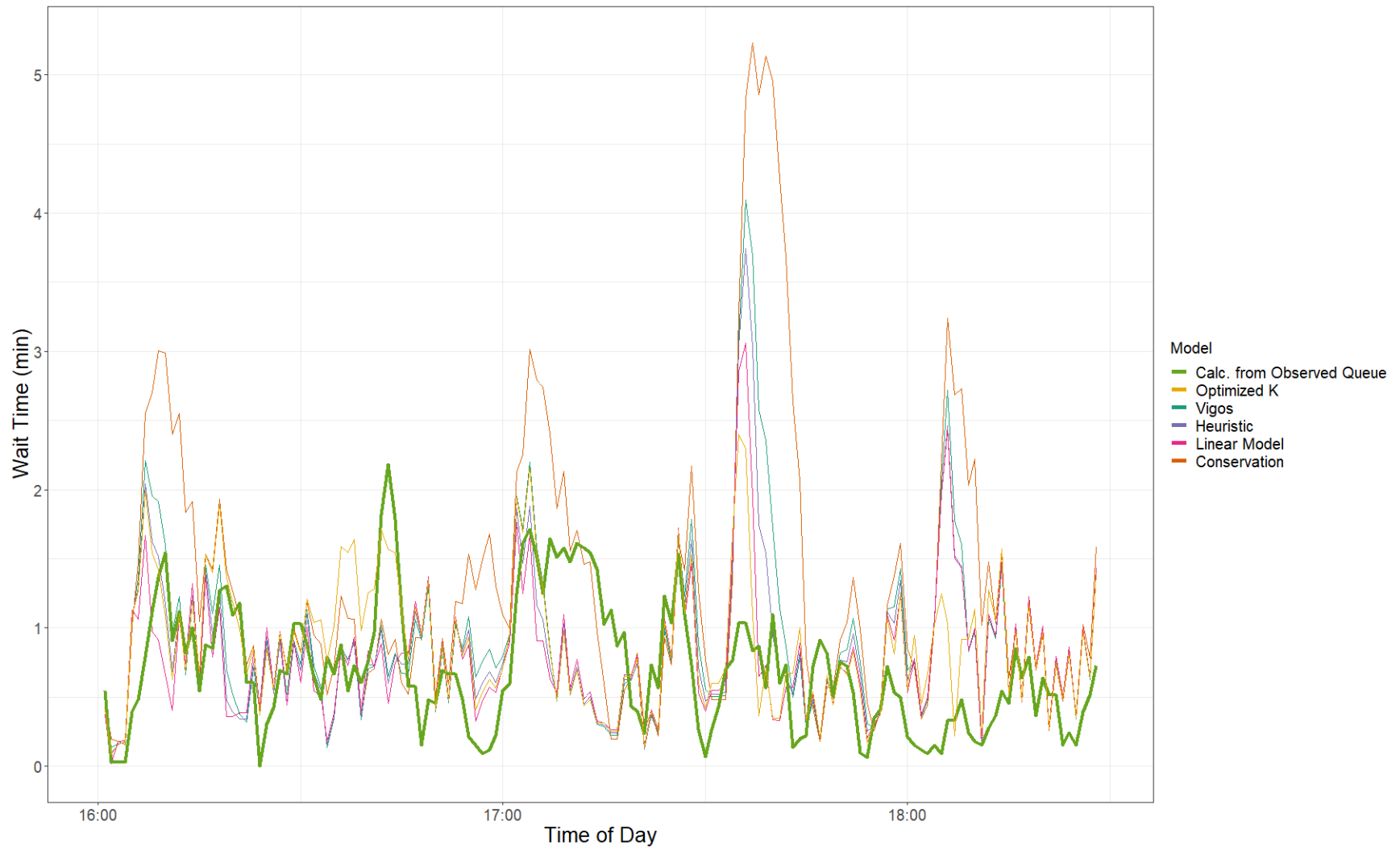


Figure B.11 Wait time comparison: Pleasant Grove Boulevard SB, August 6, 2021.

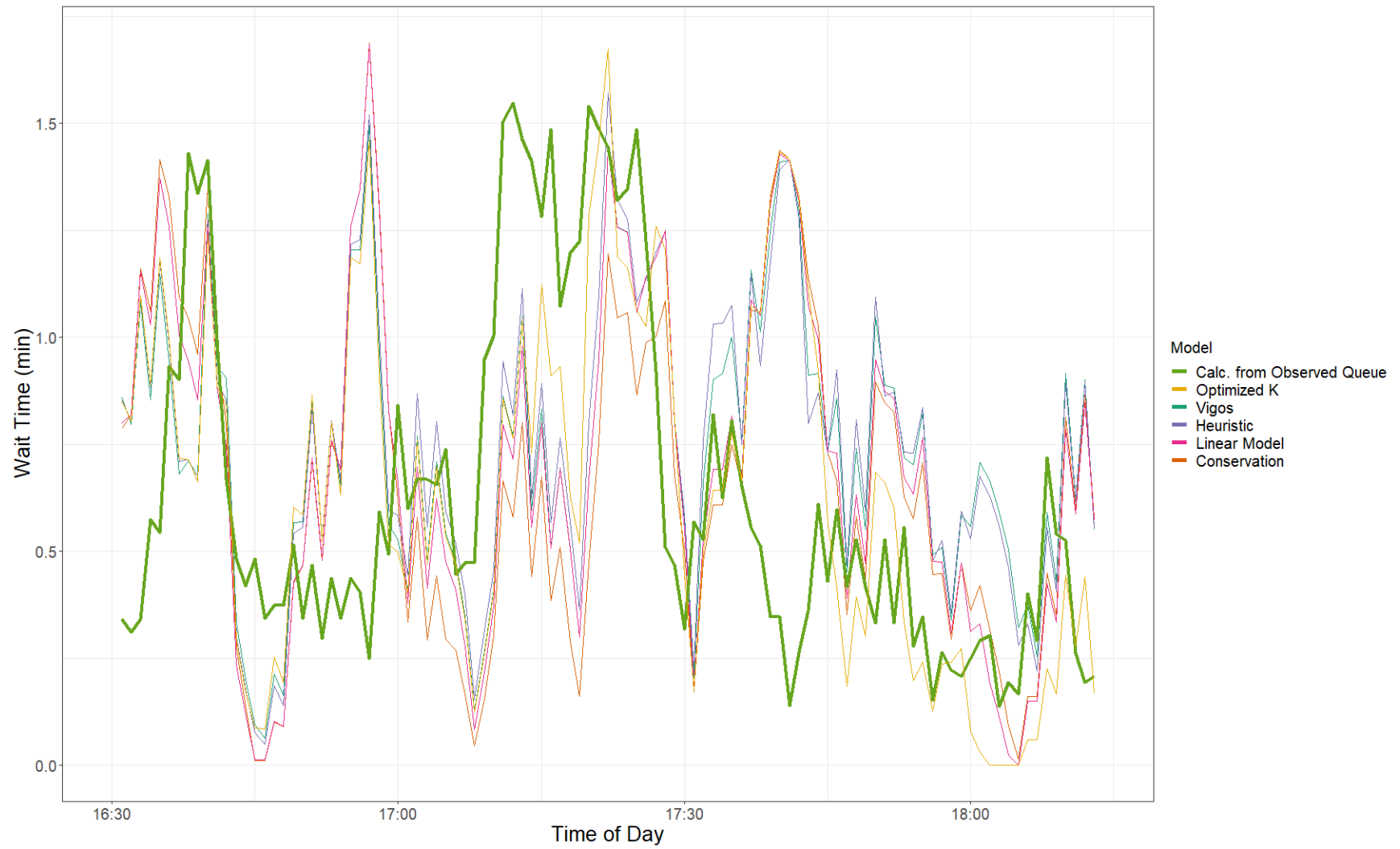


Figure B.12 Wait time comparison: University Avenue SB, July 12, 2021.

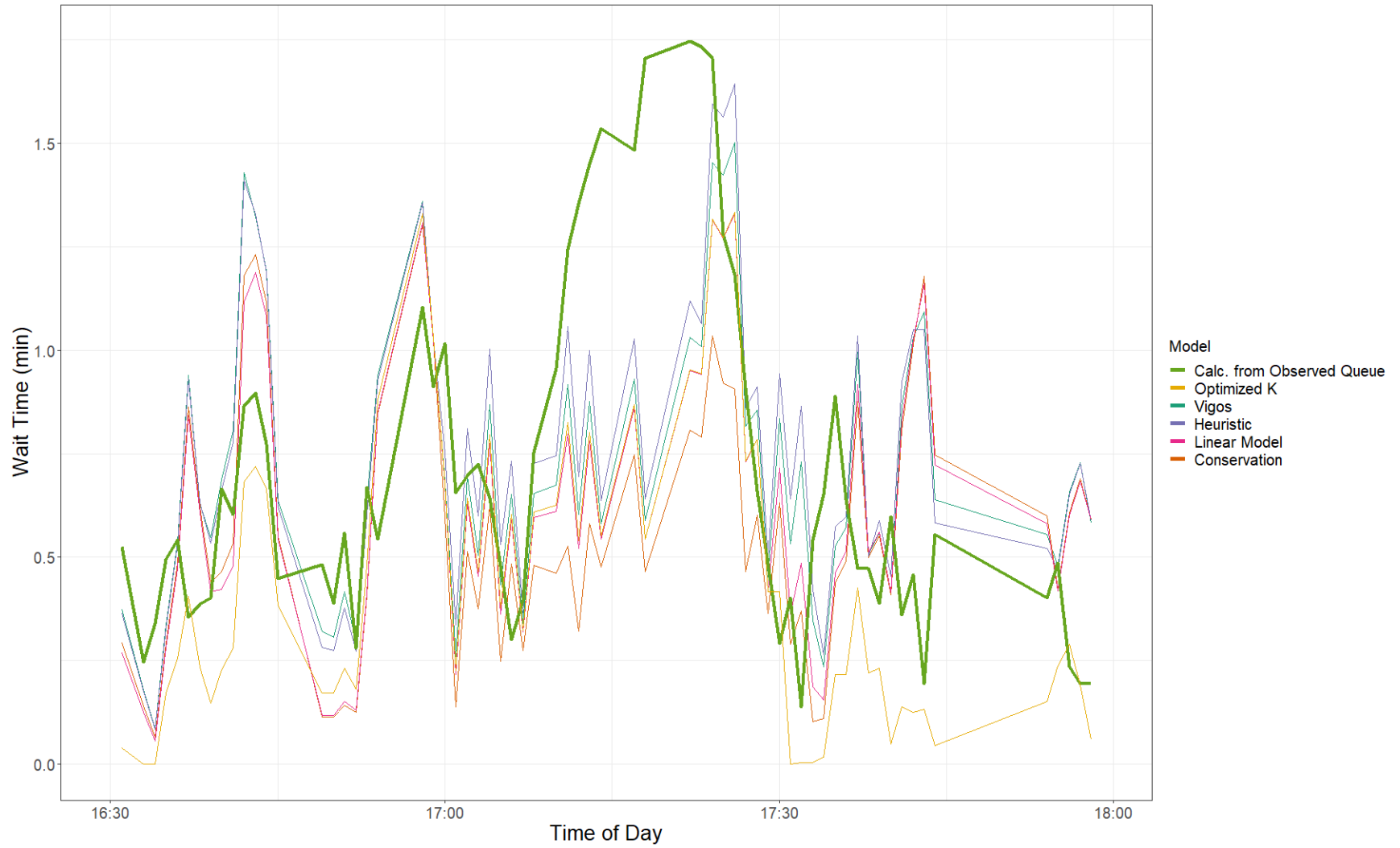


Figure B.13 Wait time comparison: University Avenue SB, July 13, 2021.



Figure B.14 Wait time comparison: University Avenue SB, July 29, 2021.

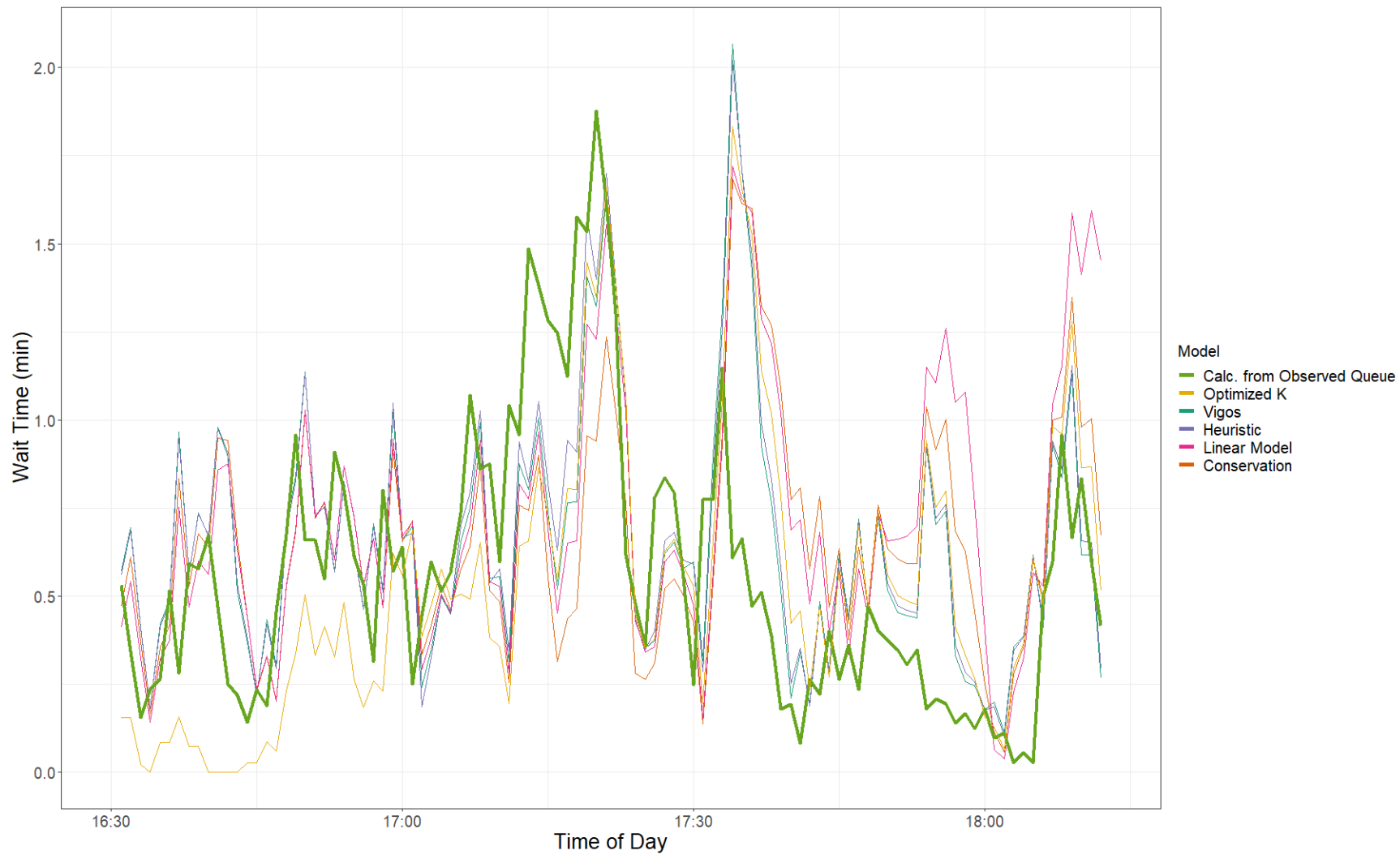


Figure B.15 Wait time comparison: University Avenue SB, August 6, 2021.