Quantifying the Resilience of Logistics Operations with Disaggregate Spatiotemporal Data for Transportation and Land Use Planning

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Author Signature: ____________________

This Dissertation has been read and approved by the examining committee:

Advisor: James H. Lambert

Committee Member: Michael D. Porter

Committee Member: Michael D. Fontaine

Committee Member: Andrew S. Mondschein

Committee Member: Julianne D. Quinn

Committee Member: ____________________

Accepted for the School of Engineering and Applied Science:

Craig H. Benson, School of Engineering and Applied Science

May 2020

ABSTRACT

There is worldwide interest to address the vulnerabilities of infrastructure systems that serve operations logistics. Risk to logistics operations from economic downturns, technologies, natural disasters, regulations, global pandemics, and other emergent and future conditions is a concern. Methods of assessing disruptions on various time scales are needed to inform planning and prioritization of improvements to infrastructure systems. In particular, the disruptions of transportation networks are often obfuscated by daily aggregation of performance data; however, recent advances in methods of data collection, dissemination and processing provide the disaggregated data to understand disruptions to operating conditions on the scale of minutes and hours. This dissertation develops methods of quantifying and monitoring disruptions of transportation systems from perceptions of scheduled operations logistics, which requires layers of disaggregate spatiotemporal data to assess sub-daily variations in system performance. Five methods are developed and demonstrated as follows: (i) new measures of quantifying disruption are introduced by methods of disaggregate data analysis for an arterial highway network system; (ii) perspectives of disruptions are extended with methods of kernel density estimation (KDE) to consider deviations from the most frequently observed conditions; (iii) changepoint detection is applied to identify performance thresholds occurring by system demand; (iv) a temporal corridor trace analysis (t-CTA) method is provided to assess regional performance by valuation across disparate time periods; and (v) the methods are demonstrated in a spatiotemporal agent simulation for evaluating site-specific land use initiatives. The methods will improve adaptation and resilience of the transportation systems to performance variability in topics including freight logistics, workforce commuters, public transit, emergency transports, event management, et al.

Acknowledgements

The work provided in this dissertation has been supported by the guidance, validation, critiques and support from numerous individuals and organizations. The Commonwealth Center of Advanced Logistics Systems (CCALS) facilitated collaboration across public and private stakeholders with interest in operations logistics. Partners include Virginia Transportation Research Council (VTRC), Virginia Department of Transportation (VDOT), Virginia Economic Development Partnership (VEDP), Port of Virginia (PoV) and other academic, public and private institutions.

As Director of the University of Virginia Center for Risk Management of Engineering Systems (CRMES), Prof. James H. Lambert provided the leadership and resources necessary to acquire data and model development for this dissertation. Prof. Michael Porter provided technical knowledge in data sciences and statistical programming. Michael D. Fontane (VDOT, VTRC) contributed to multiple works within this dissertation by providing technical support, reviews, and professional insights. Prof. Andrew S. Mondschein offered novel perspectives of land use and transportation planning with contributions to content review, application, and validation. Prof. Julianne D. Quinn provided expert evaluations of mathematical methods and topics of risk and uncertainty. Daniel Hendrickson (PoV), Jungwook Jun (VDOT), and Geraldine Jones (VDOT) provided professional validation and analysis.

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1. Motivation & Scope

1.1. Motivation

Traditional methods of assessing and prioritizing infrastructure improvements may erroneously influence development initiatives by measuring transportation disruptions from ideal operating conditions. These methods neglect the proven concepts of anthropological invariants, where travelers and enterprise operators have demonstrated an ability to adapt to changes in transportation conditions and technologies by modifying origins, destinations, routes, departure times, and travel modes as they pursue reliable transportation accessibility [1], [2]. Current metrics report the cost of highway congestion (around 300 billion USD each year in the U.S.) based on delays compared to an ideal free flow speed [3]. These metrics are used by planning agencies in the prioritization of infrastructure improvements, evaluations on the benefits of an improvement project, land use planning, identification of improvement needs, funding allocation, and project selection [4]–[6]. Figure 1-1 depicts the delay of commuters as reported in the 2019 Mobility Report across several decades, where delay is measured as deviations form ideal speeds [7].

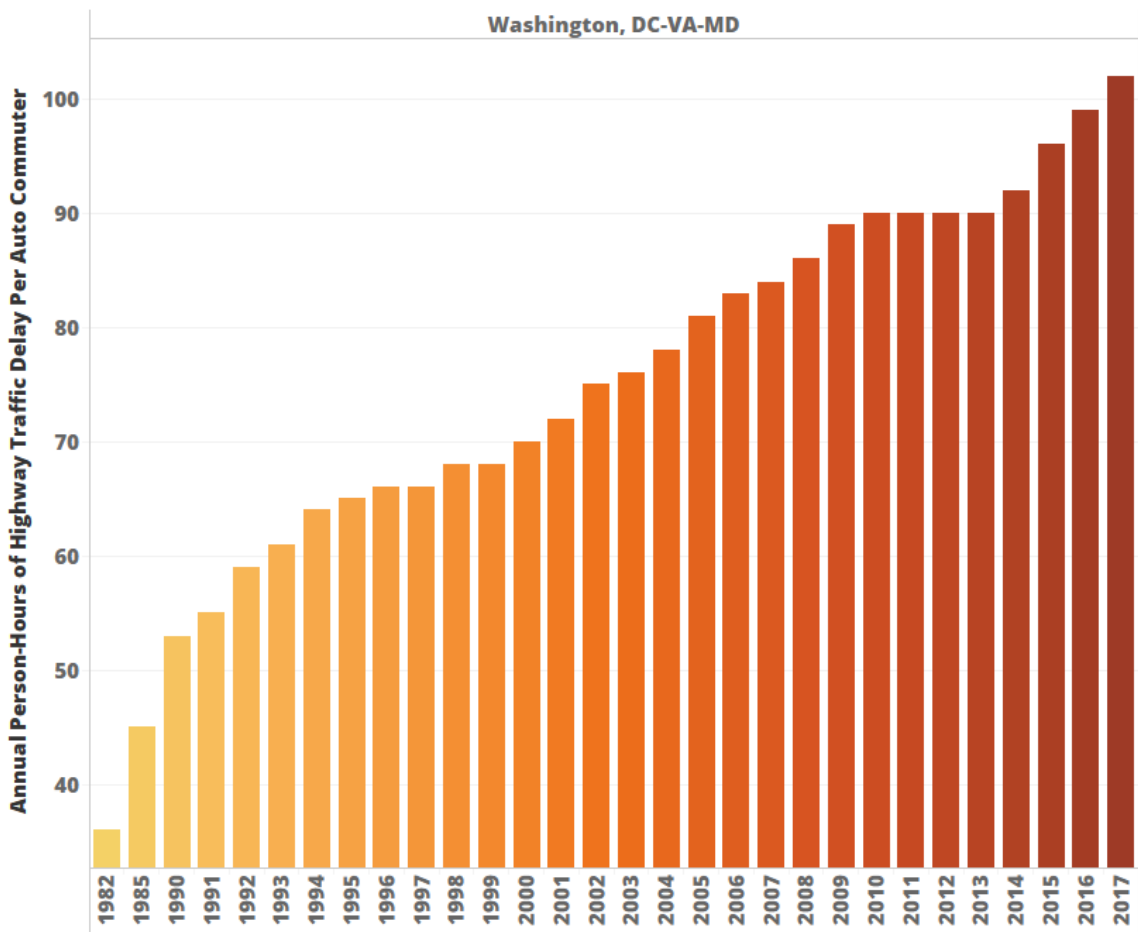

Figure 1-1: Growth of annual hours of delay per commuter, where traditional performance metrics reference delay as a deviation from free flow speed. Data from 2019 Mobility Report for a major population region (Washington, DC, USA) [7].

Instead of an emphasis on vehicle speed, the recent metrics of transportation performance focus on accessibility and system reliability [8]–[11]. Kelobonye et. al [8] defines accessibility as "the ease with which important destinations can be reached from [origins], subject to spatial separation, travel mode and time (e.g. morning or afternoon) of travel." One threat against accessibility comes in the form of variability and volatility of travel times, which is apparent from the recent emergence of transportation network reliability metrics. From perspectives of accessibility and reliability, there is an acknowledgement that travelers and enterprise operators can anticipate recurrent congestion (with an undesirable but predictable increase in travel time) but are most disrupted by the frequency and magnitude of deviations from the anticipated operations. An assessment of anticipated operations requires an evaluation of disaggregate data across disparate time periods and locations to consider the variability of transportation systems in hours, days, and months.

Logistics operations associated with civil infrastructure assets are important in real estate, humanitarian, and market contexts, with specific areas of concern varying between different stakeholders depending on locality-specific factors. Generally, a critical perspective lies in assessing vulnerable systems to ensure the overall sustainability of the built and natural environment. The focus of contemporary planning programs related to real estate and infrastructure systems often includes a connection to the Sustainable Development Goals of the UN's 2030 Agenda. The focus includes themes related to ensuring security of community and enterprise operations, including the provision of equitable accessibility in transportation systems and eliminating social inequalities propagated by traditional prioritization metrics and existing land use patterns [12], [13].

Land and infrastructure development projects are challenged by limitations in resources and the uncertainty of future conditions. The work is further bounded by political and physical environments that must consider the long-term operational requirements and the continuous shift of social, environmental, technological, and economic conditions. Infrastructure and land use planning is challenged to serve current needs while being resilient and adaptable to future conditions. These challenges are especially prevalent in infrastructure design because (i) the planning, funding, design and construction of a project will span multiple years; (ii) the technology, policies, economics and other factors change during the years of planning, design and construction; (iii) each project is unique; and (iv) the scale of infrastructure projects prohibits testing, prototyping, and agile development [14], [15].

The planning, design, construction, operations and maintenance of the built environment is interconnected and interdependent within a community and the economy. Water, transportation, energy, and communication infrastructure are critical to the community, environment and economic system [16], [17]. Once developed, real estate and infrastructure projects are difficult to modify. In some cases, extensive retrofitting or rehabilitation is not possible due to design or site constraints. Unanticipated changes in space use, materials, design, technology, or other components can limit functionality, increasing operating costs, or impact demand, leading to costly operations. Thus, it behooves land use planners and developers to account for future disruptions that may impact their projects before each asset reaches its natural point of functional obsolescence. Decisions of land planning and enterprise operations are faced by challenges associated with systems with noncommensurate variables (e.g., financial investment costs versus risk of life) and multiple objectives and must consider the shifting base of the system across time [18]–[20]. The multitude of stakeholders and contending objectives are constantly negotiated between local, regional and global environments. This interconnected state is not restricted to the physical infrastructure of the built environment – the rapid and continuous emergence of disruptions from technology, economic markets, supply chain logistics, and communication channels adds to the complexity and risks of real estate development [19], [21]. This complexity requires processes that serve, plan, and adapt to economic, social, physical, philosophical and environmental objectives with methods to quantify community perceptions of land use planning and resilience, ascertaining how such perceptions can differ from objective performance by traditional metrics.

Advances in data collection provide the disaggregated data that can be used to identify when and where disruptions occur and the population exposure. The methods provided in this dissertation influence the prioritization of infrastructure improvements based on deviations from anticipated conditions and informs appropriate mitigation strategies based on the location, time, cause and magnitude of disruptions. Travelers and enterprise operators rely on systems that are resilient to disruptions, even when travel conditions are not ideal (by measures of free flow speed conditions), as evidenced by the continued population growth and thriving economies of major cities that are documented with the worst traffic congestion [2], [9], [22]. Historically, as transportation technology has advanced to increase travel speed there is geographic sprawl of communities and operations [1]. As excessive transportation congestion spreads (geographically and across hours of the day) and reduces travel speeds, there is a retraction of origin-destination distance, change in travel mode, or emergence of new origin and destination centers [2]. Indeed, these paradigm shifts in transportation systems will shape the built and natural environments of communities whilst influencing enterprise operations and traveler mobility. This necessitates new perspectives of transportation performance that consider accessibility and reliability when planning and prioritizing infrastructure improvements that benefit operations logistics and the community. The following heuristics are applied to the primary topics of this dissertation:

1. "Risk and success is defined by the beholder, not the system architect" [23]:

    a. Operations disruptions are measured by deviations from *anticipated operations*, in lieu of traditional metrics that measure from ideal or designed conditions.

2. "Performance, cost and schedule cannot be specified independently" [23]:

    a. The *anticipated operations* vary by hours, days, seasons and the performance metrics must consider a variety of temporal domains.

In modern transportation operations the real-time traffic data and vast amounts of historical transportation performance observations has potential to inform personal and enterprise logistics. Recent advances in methods of data collection, dissemination and processing provide the disaggregated data necessary to expose new perspectives of operations performance. These perspectives, described in detail throughout this dissertation, provide new insights of land use planning and infrastructure design which is at risk of imminent disruption and obsolescence by emerging technologies, environmental policies, and a shifting landscape of economics and social dependencies.

1.2. Organization of this Dissertation

This dissertation is comprised of published peer-reviewed papers and submitted manuscripts. The text of the paper has been formatted to establish a cohesive narrative in the progress and contributions of the relevant work. This process both informed and validated methods and contributions. The work included in this dissertation was completed with support from the Commonwealth Center for Advanced Logistics Systems (CCALS) and from the University of Virginia faculty and researchers in the Engineering Systems and Environment department, Center for Risk Management of Engineering Systems. Together, these groups enabled collaboration between private businesses, academic institutions, departments of transportation, economic development agencies, and maritime port operations. The research provided herein was informed by interviews, meetings, presentations, charettes, and formal presentations held across several years between public, private, academic and industry stakeholders.

1.2.1. Organization and Scope of this Dissertation

The remaining sections in this chapter provide a brief overview of topics in the subsequent chapters (Chapters 2-6) with reference to the progression of methods to quantify and monitor disruptions from perspectives of operations logistics, which informs infrastructure system improvements and land use planning. Figure 1-2 illustrates the organization of this disseratation by topic and scope.

OVERVIEW

Chapter 1: Introduction
- The motivation, an introduction of topics by chapter, and an outline of the dissertation

THEORY, METHODS & DEMONSTRATIONS

Chapter 2: Quantifying Operations Disruption
- Literature review of transportation performance metrics and methods to quantify disruptions as deviations from average operating conditions.

Chapter 3: Other Perspectives of Operations Disruption
- Extension of methods in Chapter 2 to quantify disruptions based on deviations from anticipated conditions, with methods of kernel density estimation.

Chapter 4: Changepoint Detection of Operations Disruptions
- Methods to identify and monitor thresholds of performance, defined in Chapter 3, of transportation systems.

Chapter 5: Regional Evaluation of Operations Disruptions
- Temporal corridor trace analysis (t-CTA) as a method to evaluate performance across temporal domains of regional transportation networks.

Chapter 6: Spatiotemporal Simulation
- Data-driven agent simulation model to evaluate site-specific accessibility based on departure times, days of the week, months of the year, and other relevant categorization.

CONCLUSIONS

Chapter 7: Conclusions and Contributions
- Summary of content, applications and contributions.

Chapter 8: Extended Applications
- Planned extensions of current work, identified by topic.

REFERENCES

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A: Author's Biographical Sketch

Figure 1-2: Organization of dissertation

1.2.2. Chapter 2: Quantifying Operations Disruption

Chapter 2 provides a review of current transportation performance metrics and introduces novel methods to address the limitations of current practices. As defined by Lomax [24], congestion is traditionally quantified by measures of reliability, intensity, duration and extent (RIDE). Reliability is a fundamental concept that has recently been examined as a measure of disruption based on deviations from a speed statistic (mean or median) in lieu of ideal operations (e.g., traveling at free flow or posted speed limits) [25]–[27]. Measures of transportation network reliability provide new methods to consider the performance conditions associated with scheduled logistics, such as public transit, just-in-time delivery, and others.

In this chapter, a novel approach is developed to quantify operations disruption measured by deviations from the volume-weighted mean speed, the number of hours each year, and the volume of effected vehicles. The comprehensive method introduced in this chapter considers all foundational congestion metrics (RIDE). To address the variability in transportation performance across hours and days, disruptions are evaluated across disaggregate time periods (morning, midday, evening, nighttime and weekend). The quantification of operational disruption is demonstrated with a set of 6,747,400 speed and traffic volume observations across fifty-five locations throughout Virginia, USA collected over several years (2014-2017). Within the demonstration, the disparate time periods are identified to inform valuation, source of the disruption, and potential solutions to the observed disruption.

This chapter concludes with noted limitations of the metric and defines how future work (described in subsequent chapters) mitigates the limitations. The reference of a mean speed, for which disruption is measured in Chapter 2, was originally selected based on current methods of measuring transportation network reliability. Chapter 3 introduces methods of measuring disruption as deviations from the most frequently observed speeds, determined by methods of kernel density estimation (KDE). There are additional challenges in quantifying the extent of disruption based on limitations in current methods of traffic volume collection (sparse and static count stations). This is mitigated in Chapter 5, with concepts of temporal corridor trace analysis (t-CTA), in which performance criteria is weighted based on when a disruption occurs. Absent of disaggregate traffic volume data, this approach exploits institutional and operational knowledge of the transportation network to assign relative weights to performance conditions (e.g., delays during nighttime conditions could be weighted less because traffic volume is lower).

1.2.3. Chapter 3: Other Perspectives of Disruptive Conditions

Within Chapter 3, the methods of quantifying operational disruption are extended with applications of kernel density estimate (KDE), which serve to inform the most frequently observed transportation network operations as the reference condition for measuring disruptions. As identified in this chapter, the observation of vehicle speeds is nonparametric; therefore, the mean or median speed may be significantly less than the normal operating speed and a low frequency of occurrence. In this chapter, the speed and volume values with the highest KDE (mode statistic) are used to represent the operating conditions anticipated by travelers. The quantification of disruption is therefore modified with methods to measure deviations from the mode statistic.

Components of risk are referenced with measures of disruption, which extends analytical methods of categorizing disruption by traditional congestion metrics (from Chapter 2). The measured disruptions, as determined by deviations from speed values with the highest KDE, are evaluated based on the risk components of frequency, magnitude and exposure analogous to the congestion measures of duration, intensity, and extent. These attributes are evaluated in a table and chart to inform priorities of infrastructure investments that seek to mitigate disruption. As introduced in Chapter 2, time periods are evaluated independently to provide information on the source, valuation, and solutions for disruptive conditions.

1.2.4. Chapter 4: Changepoint Detection of Operations Disruption

There is significant interest in monitoring a transportation network with attention to conditions that promote rapid degradation of performance operations. Within Chapter 4, changepoint detection is implemented to investigate the presence of an abrupt change in the frequency of disruptive conditions (as defined in Chapter 3) based on the traffic volume of the corridor. Complexities of transportation networks, such as stochastic system capacity, necessitates the identification of operational thresholds. The traffic volume associated with an abrupt change is noted as the *reliability threshold*, which is notably less than traditional capacity values calculated by the Highway Capacity Manual [26]. Results from the demonstration dataset indicates an abrupt increase in the frequency of disruptive conditions when traffic volume approaches approximately half of the capacity defined by traditional traffic models. The threshold was determined with methods of changepoint detection and are variable across geographic locations and the years of observation, which conforms with concepts of stochastic system capacity based on inherent randomness of exogenous system factors.

1.2.5. Chapter 5: Benefits of Temporal Disaggregation

Chapter 5 addresses the limitations of data acquisition associated with the methods and results identified in Chapter 2 and Chapter 3. Specifically, the lack of traffic volume data at a regional scale introduces challenges in monitoring and prioritizing performance measures of a large-scale interconnected road network. There exists opportunity in evaluating disaggregate speed data in conjunction with institutional knowledge of system operations to inform priorities at a regional scale.

In this chapter, an extension of Corridor Trace Analysis is introduced to evaluate a set of performance metrics across geospatial and temporal domains. Corridor Trace Analysis (CTA) methods were introduced by Thekdi and Lambert [28] as an "evidence-based method" to evaluate corridor conditions at a regional scale. The CTA method has proven successful as evidenced by agency implementation, but has fundamentally used aggregate performance data (daily or yearly statistics) [29]. The temporal corridor trace analysis (t-CTA) introduced in Chapter 5 provides context and methods of valuation to observed performance conditions. For example, multiple corridors could report the same quantity of disruptive conditions but the timing of the disruption (morning rush hour, nighttime, weekend, or other) provides insights in the source of congestion and viable solutions. When traffic volume is unavailable at a regional scale, this method of t-CTA can be combined with agency and stakeholder knowledge to apply weights to disparate time periods based on operational conditions. For example, the disruptions that occur during the morning time period and in the direction of travel towards an urban city center would be weighted relatively higher by employment operations (when compared to low-volume nighttime disruptions or weekend travels).

1.2.6. Chapter 6: Spatiotemporal Logistics Simulation

This chapter provides methods to evaluate land use initiatives based on operations performance for freight logistics, which is informed by methods and perspectives of preceding chapters. Empirical data, acquired from vehicle probe speed sources (GPS), is evaluated with an agent-based simulation to calculate the number of trips between origins and destinations based on variations in departure time, day of the week, and month of the year. The simulation variables for handling times at the origin and destination. The results are presented in context to variable temporal domains (daily, weekly, monthly) to inform operations logistics for candidate development sites. The methods provide new insights to valuation of candidate sites and enterprise logistics based on success criteria (integer value of the number of completed trips). Variable success was noted across days and months, while an investigation of unique events (e.g. days with adverse weather) inform the vulnerabilities of operations faced with disruptions.

1.2.7. Contributions of Collaboration

Each chapter is representative of one published (or submitted) peer-reviewed paper that was primarily developed by the author. The citation and reference of contributions are listed herein. Chapter 2 [30] includes content from that was reviewed and discussed with Michael D. Fontaine of the Virginia Transportation Research Council (VTRC), with support from colleagues and the director of the Center for Risk Management of Engineering Systems (CRMES) at the University of Virginia.

An extension of this work, in Chapter 3 [31], uses methods of kernel density estimation, which was informed by collaborations with Prof. Michael D. Porter of the University of Virginia department of Engineering Systems and Environment as well as the CRMES. Prof. Michael D. Porter provided technical guidance on methods of changepoint detection for Chapter 4 [32], which included review and collaboration with technical staff of the Virginia Department of Transportation (VDOT). Chapter 5 [33] extends prior work of CRMES on topics of Corridor Trace Analysis (CTA) and included collaborations from the Port of Virginia and VDOT professionals. The topic of spatial association in the Conclusions [34] was developed with support from CRMES and VDOT, with use of the Pathway for Planning geospatial application. The discussion topic of emergent and future conditions [35] was informed by coordination with C. Kat Grimsely, Director of Real Estate Development at the George Mason University.

2. Quantifying Operations Disruption

2.1. Introduction

Transportation agencies, land planners and enterprise operators seek to measure and monitor the inherent uncertainty of transportation networks that serve as a critical component of logistics. Quantifying transportation system performance informs decisions of infrastructure design and prioritization. Traditional performance metrics may erroneously prioritize development initiatives based on transportation disruptions measured from ideal travel times; however, travelers have demonstrated an ability to accommodate recurrent congestion by adjusting departure times, transportation modes, origins, or destinations in commute planning. Recent performance metrics of transportation network reliability have demonstrated the importance of measuring disruptions from normal operating conditions, often referenced as the mean or median speed. In this chapter, we establish a quantitative multicriteria framework for measuring operational disruptions based on the intensity and duration of observed deviations from normal conditions. Advances in data collection provide the disaggregated data that can be used to identify when disruptions occur and the extent of affected volume. This approach influences the prioritization of infrastructure improvements based on deviations from typical conditions and informs appropriate mitigation strategies based on the category and time of disruption. A demonstration of the approach to a geographically diverse region is provided, with implications for several agency planning horizons.

2.2. Motivation

Recent reports have documented the global cost of traffic congestion as hundreds of billions (USD) per year, which is attributed to traveler delays associated with recurrent and non-recurrent traffic congestion [3], [19], [29], [36]–[38]. These cost measures serve to inform transportation planners that must prioritize infrastructure improvements to mitigate traffic congestion. There are demonstrated limitations of traditional highway performance metrics when evaluated in context with traveler logistics [39], [40]. Traditional performance metrics evaluate disruptions based on deviations from an ideal operating condition, such as a posted speed limit or free flow speed; however, travelers can anticipate recurrent congestion within logistics schedules and therefore place a greater interest in the variability from normal operating conditions [1], [22], [28], [40]–[44]. Monitoring and mitigating the variability of performance is a critical component of transportation performance as evident by the recent emphasis of transportation network reliability metrics [45], [46]. The multitude of transportation performance metrics is an indication of the challenge to comprehensively measure operational performance – in this chapter we refer to foundational measures of congestion: reliability, intensity, duration and extent (RIDE) [24]. Table 2-1 provides a summary of these terms.

Table 2-1: Summary of foundational congestion measures as defined by [24]

Congestion Measure	Summary
Reliability	Average speed +/- standard deviation; average delay +/- deviation
Intensity	Average speed delay
Duration	Hours facility operates below acceptable speed
Extent	Volume of vehicles, people, or goods affected

This chapter introduces methods to mitigate risks that are obfuscated by aggregate transportation metrics. We begin by identifying the challenges in assessing system performance based on limitations of current metrics that traditionally evaluate deviations from ideal operating speeds. We introduce methods of assessing operational disruption as measured by the reliability of system performance based on the intensity, duration and extent of observations that deviate from the mean speed. Disruptions are calculated at disaggregate time intervals to inform sources of disruptions and appropriate mitigation strategies. The methods identified in this chapter focus on performance of limited access highways as measured by vehicle speeds and traffic volume from continuous count station data sources.

2.3. Background

In this section, a review of transportation performance metrics is first provided to assess the variety of terminology and methods. The multitude of existing transportation performance metrics has been well inventoried by others and is an indication of challenges in establishing a comprehensive and accessible method of evaluating system performance [27], [43], [44], [47]–[49]. Decisions of infrastructure investments are influenced by performance measures and forecasts [39]; therefore, it is necessary to acknowledge limitations of current methods. Each component of congestion is subject to decisions in metrics and the appropriate disaggregation of data. Critically important, but often ignored, is the necessity to establish methods of measuring and monitoring performance that are accessible to transportation agencies and stakeholders. In this chapter, we have concentrated on the congestion components of reliability, intensity, duration and extent as reviewed in the following subsections. This review serves to inform the appropriate method of establishing a quantitative measure of operational disruption.

2.3.1. Reliability

Current metrics of transportation network reliability are based on measuring the variability of system performance, with several metrics comparing a percentile statistic to the mean or median speed. For example, if the calculated ratio of a the median and disrupted condition (e.g., 80^{th} percentile travel time) is above 1.50, the road network is deemed unreliable according to current U.S. performance measures [11]. The U.S. Federal Highway Administration (FHWA) has identified the importance of performance reliability based on economic, environmental, and social perspectives [50]–[52]. Transportation planners seek to measure, monitor and reduce the uncertainty and variability in travel times when considered in context to recurrent conditions across hours of the day and days of the week [27], [53], [54]. The emphasis on reliability acknowledges that vehicle operators can adapt logistics when faced with recurrent congestion, but are disrupted most by uncertainty and volatility in performance [22], [55].

From a systems perspective, reliability is defined as the "the probability of a system or system element performing its intended function under stated conditions without failure for a given period of time" [56]. By definition, a measure of reliability requires the identification of the (a) performance requirement, (b) time interval, and (c) operating conditions. The FHWA reliability metrics evaluate deviations from the mean and median conditions when assessing the variability [54]. The reference of a mean or median adds a new perspective when compared with other performance metrics, which otherwise measure congestion from discrete values such as the posted speed limit or free flow speeds [7], [26]. The analysis of system reliability considers different time periods (morning, midday, evening, night, and weekend) throughout the week to consider characteristics of disparate operating conditions when establishing the mean or median reference speed [54].

The reliability metrics can be applied to any road segment where travel time and speed data has been collected but can be misconstrued based on characteristics of percentiles, especially with nonparametric datasets that are observed in congested highway corridors [57]. Additionally, current metrics use percentiles based on speed observations at aggregate time intervals without accounting for the volume of vehicles that experience disruptions. Figure 2-1 depicts a speed distribution (from data used in the Demonstration in this chapter), which shows the distribution and labels the variability in vehicle volume associated with each observed speed condition. As a road network transitions between congested and uncongested modes (throughout the day), the distribution will vary.

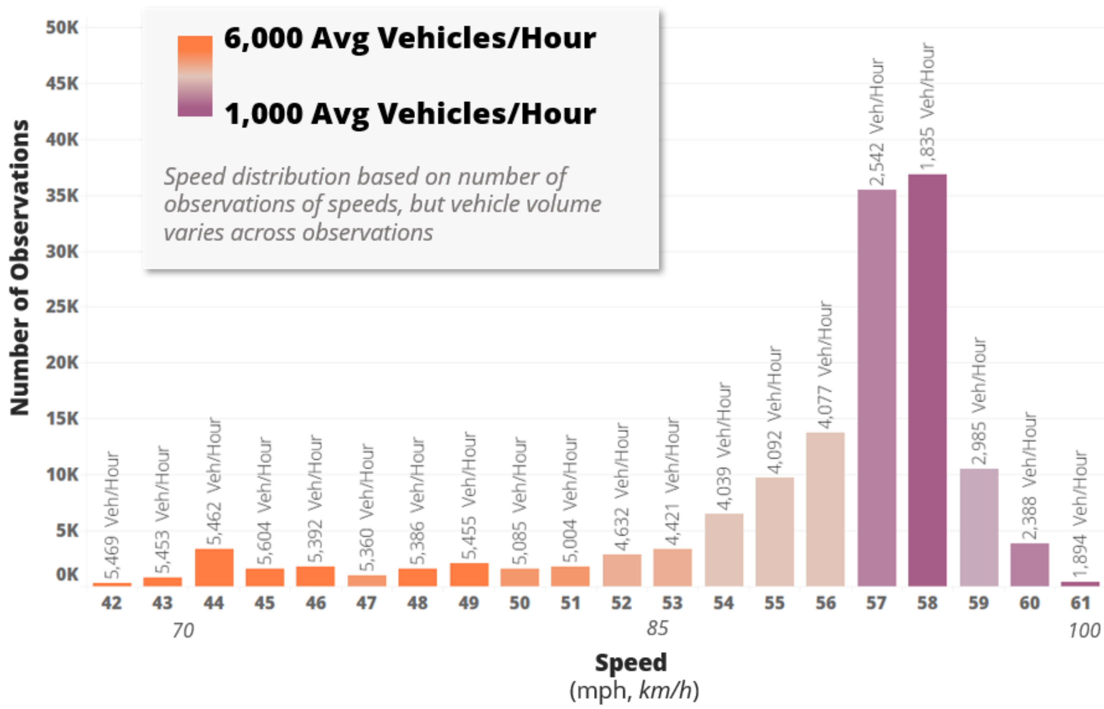

Figure 2-1: The distribution of speed observations (sample from demonstration dataset). The variability in traffic volume associated with speed observations is annotated for context.

When applied to a non-normal distribution, the percentile values do not adequately define the speed distribution of the road network. There is also no consideration for the magnitude of volume influenced by the unreliable conditions; therefore, most current reliability metrics deviate from the common description of reliability, which must consider the traffic volume as the (c) operating condition. Reliability measures are a critical perspective in defining the performance, which informs transportation agencies and vehicle operators of the volatility and uncertainty of deviations from normal operating conditions. Still, other information is required to provide a comprehensive evaluation of the network.

In this chapter (and throughout this dissertation), the foundation of measuring operational disruption follows the principles of reliability by measuring deviations from typical operating conditions at disparate time periods.

2.3.2. Intensity

The intensity of congestion is a measure of the severity of a delay condition, often represented by the magnitude of deviation from an established reference speed [24], [49]. The appropriate reference speed (for which a congestion condition is classified) varies across jurisdictions, but traditional metrics often use the posted speed limit, a discrete value, the free flow speed or a fraction of those values [47], [49], [58]. For example, the Travel Time Index (TTI) measures intensity as a ratio of the average travel time compared to the free flow travel time [54]. The free flow speed is an ideal operating condition of a corridor and calculated by variables of road geometry (lane width, shoulder width, ramp density) or measuring the upper percentile speeds during low flow conditions, such as an early weekend morning [26], [27].

Establishing the appropriate reference speed is critical when measuring congestion; however, there is inherent variability in operating conditions of the road network from endogenous and exogenous factors that limit the effectiveness of discrete reference speeds [48], [59]. For example, the TTI metric references intensity by measuring deviations from the free flow speed. While the free flow speed is an ideal condition, scheduled operations such as public transit, freight delivery, and personal commutes must plan for recurrent congestion. To consider the effects of recurrent congestion, transportation network reliability metrics have set a precedent for using a speed statistic (mean, median) as the reference speed [43], [44]. Some reliability metrics consider the variability by using speed statistics and disaggregate time periods; however, the appropriate disaggregation of time periods is often questioned [11], [27]. These factors create challenges in establishing the ideal reference speed from which a delay is measured. Adverse weather, road construction, roadway illumination, traffic volume, vehicle types, and other factors have an effect on transportation system operations [26], [47], [55]; this variability of operating conditions raises questions of the appropriate reference speed [26], [27]. In this chapter, we use the mean speed as the reference speed based on practices with current reliability metrics and discuss how the level of data disaggregation will influence performance measures.

2.3.3. Duration

The duration of congestion for limited access highways is generally defined as hours of operation below a reference speed within a set time period (e.g., hours of congestion observed in a single year) [26]. An accurate representation of duration relies on the level of disaggregate speed data, often constrained by data collection and processing limitations. Daily or even hourly aggregation of speed data can misrepresent the duration of delays. Recent advances in data collection technologies have improved the feasibility of monitoring operations with continuous observations at short time intervals [60], [61]. For example, probe speed data, from sources such as INRIX and the Regional Integrated Transportation Information System (RITIS), provide speed observations for intervals as short as five minutes [58]. Probe data uses spatial and temporal information from GPS receivers (personal or commercial) to report space mean speed and travel time associated with a corridor segment [57], [62]–[64]. In 2018, it was reported that INRIX data covered about 760,000 directional kilometers in the US, or about half the length of the traffic message channel (TMC) network [59].

Managing the big data associated with traffic performance monitoring should be acknowledged when considering the appropriate methods of analyzing and reporting disruptions. Even in a moderately sized region, each road segment (ranging from several meters to several kilometers in length) includes over 35,000 observations at a 15-minute interval in a single year. Several existing metrics consider an appropriate disaggregation between five and fifteen minutes, but time periods may be aggregated to several hours to represent a peak travel period [27], [44], [54], [55]. For example, recent metrics of travel time reliability evaluate disruptions based on deviations from disaggregate speed statistics across several hours of the week, such as weekday morning (6-10 AM), weekday midday (10AM-4PM), weekday evening (4-8PM), nighttime (8PM-6AM), and weekend (6AM-8PM) periods [54].

Data availability at a regional level provides opportunities in accurate measures of congestion duration and the potential to consider variability in speed conditions across hours and days of a week. Temporal disaggregation has demonstrated benefits in improving evaluation of highway performance, such as safety and capacity [55], [65]. A discrete reference speed (such as posted or free flow speed) does not represent the variability in operating conditions across hours and days. Recognizing that most systems will not operate at free flow speeds during certain time periods, such as conditions of poor visibility or hours of high traffic volume, there is interest in measuring the system disruptions based on normal operating conditions at disparate time periods.

2.3.4. Extent

Identifying the extent of congestion (measured by number of vehicles, vehicle type, occupants, or commodities) provides reference to the cost of congestion [43], [66].

For example, traffic delays that occur during nighttime periods likely has less traffic volume and is valued proportionately less than disruptions during peak operating hours [43], [67]. There are challenges inherent to current data collection methods for measuring the extent of congestion. Absent of disaggregated traffic volume data, the average daily traffic (ADT) of a highway segment is often used to reference the extent of congestion [26], [28], [40]. However, to ascertain the extent of disruption it is necessary to investigate when the disruptions occur with respect to the affected traffic volume at the time of the disruption.

The volume of vehicles (relative to system capacity) has a demonstrated influence on system performance. Transportation models shown in the Highway Capacity Manual, by the U.S. Transportation Research Board [26], have demonstrated that average operating speed decreases as the traffic volume increases. A measure of operations in a transportation system is represented by the traffic volume-to-capacity ratio (v/c) and often graded A-F as a level of service (LOS) to provide an accessible way of communicating the performance [26]. The v/c is a standard measure of system operation that evaluates the observed volume and available system capacity. The capacity is determined by the number of lanes, operational speeds, road geometry, and vehicle composition of the traffic stream as shown in (2.1), from the Highway Capacity Manual [26]. For reference, the capacity calculated for a limited-access highway is near 2,400 vehicles per hour, per lane at 112 km/h (70 mph) [26].

$$v/c_i = \frac{V_i}{\left(\frac{2{,}200 + \ 10 \times (\min(70, FFS_L) - 50)}{1 + HV_i}\right) \times Lanes_L}$$

(2.1)

where:

v/c_i = Volume-to-capacity condition of a given observation, i
V_i = Volume of a given observation
FFS_L = Free flow speed (mph) of a segment, L, for a given year
HV_i = Heavy vehicle (percentage) during the observation
$Lanes_L$ = Number of lanes for a given link, L, at observation location

There are challenges in monitoring system capacity because of the inherent randomness of crashes, visibility, and adverse weather that modify the operational capacity [26], [68]. The system capacity diminishes as a result of a crash or exogenous condition; for example, the blockage of one lane in a two-lane roadway is equivalent to a 65% capacity reduction [55], [68], [69]. Adverse weather, such as rain, fog, or snow will also reduce network capacity [55], [70]. These conditions have introduced recent concepts of stochastic capacity, which acknowledges the randomness in operating conditions [68], [71]. Stochastic capacity is explored further in Chapter 4 to identify a threshold traffic volume (changepoint) associated with abrupt changes in the frequency of disruptions. During system disruption, both the speed and observed volume have decreased, but the capacity adjustment is not represented in data collection equipment [71].

The v/c can have a range of values (0.0-1.0) across hours of the day based on normal operations or a disrupted condition. For road segments that have severe recurrent congestion, when the speed decreases it is often a sign of reduced (but undocumented) capacity conditions. The capacity reduction also reduces the flow of traffic. In this case, the data implies both low speed and low volume conditions, but the volume is deceptively low because of capacity constraints. For these reasons, there is practice in referencing demand volume by a statistic of observed volumes, such as the 90th percentile condition of a given hour the week, when referencing the extent of disruption [43]. The variability in traffic volumes across hours and days of the week requires disaggregate volume data to represent the affected volume during an incident.

2.3.5. Scope of Work

The volatility in conditions of transportation networks introduces deep uncertainties for traveler logistics and the decision-makers that seek to prioritize infrastructure investments in face of emergent policies, environmental conditions, and regional development [37], [72], [73]. In this chapter, we develop frameworks to inform the prioritization of infrastructure investments that seek to improve mobility and system operations [42], [74]–[77]. This chapter includes an investigation in the uncertainty of performance caused by challenges in traditional congestion metrics of reliability, intensity, duration and extent [24]. The methods developed in this chapter use the principles of transportation network reliability by emphasizing disruptions measured from space mean speed (in lieu of free flow speed), addressing challenges in the continuous unsteady state of transportation networks.

The next section provides methods of assessing system disruptions that consider the limitation and constraints of current reliability, intensity, duration and extent metrics. Specifically, we develop a quantitative framework for measuring operational disruptions in limited access highways based on observations of continuous data monitoring systems.

2.4. METHODS

This section describes how disaggregate speed and volume data can be analyzed to investigate the relationship between operating conditions and system performance while considering four components of congestion: reliability, intensity, duration, and extent. Prior work has established methods of multicriteria analysis for assessing project initiatives based on perceived benefits to mobility and safety [40], [42], [77], [78]. The quantitative framework has been successfully applied to various transportation systems, including highway corridor illumination, access management, and runway safety [28], [42], [79]. As with most transportation performance methods, aggregate data was used with prior work to represent the intensity and extent of adverse conditions. The framework is extended in this chapter to apply the benefits of utilizing disaggregate speed and volume data. Additionally, the framework introduced in this chapter acknowledges the constraints of traditional congestion metrics, noted in the preceding section, and focuses on disruptions as measured by deviations from typical operating conditions (referenced from mean speed).

Recognizing that transportation agencies have limited resources, the results from the multicriteria analysis are used to categorize project initiatives based on priority zones of multi-objective charts - as previously demonstrated by Xu et al. [42]. The categorization can be shown through data visualization based on criteria measures and candidate initiatives. With this approach, transportation planning agencies can screen large datasets to identify critical areas that warrant additional investigation. This approach is also seen in early works of quantifying congestion by Lomax [24], which categorized congestion by the intensity, duration and extent of delays as (1) broad general congestion, (2) critical system-wide problems, (3) limited problems and (4) critical links or corridors [24]. Figure 2-2 depicts the four categories based on duration and extent, as originally developed by Lomax [24].

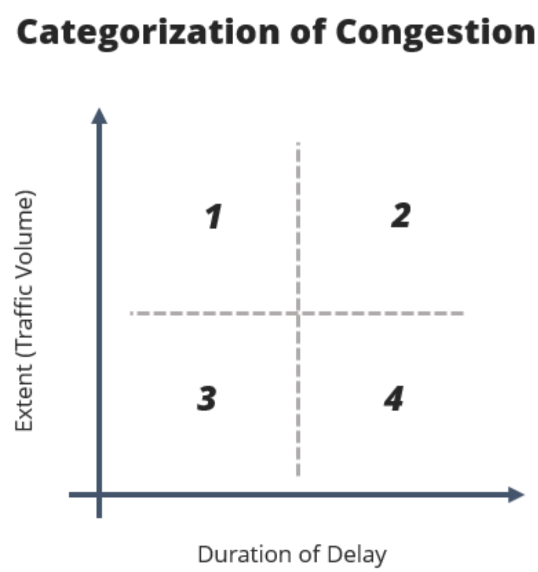

Figure 2-2: Categorization of the four types of congestion, as (1) broad general congestion, (2) critical system-wide problems, (3) limited problems and (4) critical links or corridors, as measured by duration and extent defined by Lomax [24].

The categorization of disruption is necessary to identify the nature of the problem, consider the appropriate solutions, plan for improvements, and establish methods to monitor the effectiveness of mitigation initiatives [24], [25], [80]. Solutions may include demand management strategies, operational improvements, public transit improvements, road capacity improvements and others [80], [81]. Temporal disaggregation refines how disruptive conditions are classified and informs planning agencies on the appropriate strategies. For example, public transit improvements would serve to benefit congestion during peak commute hours but would be less effective for freight-related disruptions that occur overnight. Similarly, projects that seek to improve driver visibility through roadway illumination should be prioritized based on disruptions during nighttime operations. This section provides details on the methods of classifying congestion and informing prioritization.

These methods are applicable to large datasets of continuous observations of traffic speed and volume across tiers of data aggregation, which may include a source time interval aggregated to a time period across a large temporal domain. For example, a 15-minute interval evaluated across several hours of a peak weekday morning period for a single year for each geographic location.

2.4.1. Quantification of Disruptions

Measuring deviations from normal operating conditions is the primary focus of this analysis. The normal operations are quantitatively described as a range of acceptable speeds around the mean speed condition – observations of speed values outside this range are classified as disruption events. This approach is based on measures of reliability, as established by referencing the mean or median speed conditions [54]. Intensity of the disruption is measured as the difference between an observed speed and the mean speed. Duration is measured by the accumulated time of disruptive conditions across an extended period (such as hours of a year). The extent is identified as the vehicular volume as a statistical measure (90^{th} percentile) of a time interval to consider demand volume during disrupted conditions. The emphasis on reliability and normal operating conditions requires evaluation of disaggregate speed and volume data to identify when disruptions occur, prioritize initiatives, and to identify appropriate mitigation strategies.

As indicated in the preceding section, the reference speed is critical when measuring delay conditions. Based on travel time reliability frameworks, we set the reference speed as the mean speed, which was chosen to represent the typical operating condition based on current practices of transportation reliability [54]. The mean speed will vary based on location and time, with values that could be above and below the posted speed limit (and likely below the free flow speed) [47], [58]. In this chapter, an observation is classified as a disruption event if the speed is not within the established range of values centered around the mean speed, where the range includes a buffer (e.g., +/- 5%) to consider minor deviations and acceptable conditions.

Calculating a mean speed requires an aggregation of data, which could focus on several hours of a day or a single time interval across a year of data (e.g. 8:00-8:15 on a weekday). We apply a volume-weight when calculating the mean speed to consider the number of travelers that experience the observed speed condition with aggregated data, which would otherwise weight each observation of a time interval equally. For example, if the data is aggregated to a morning weekday peak period (6:00 – 10:00 AM) the mean speed is weighted proportionate to the volume observed in the disaggregate time intervals within the time period (likely highest between 7:00-8:00 AM). As indicated in the proceeding section, the value used for traffic volume should be a statistic of the observed condition to represent demand volume and mitigate correlation errors between low speed and low volume data reported during a disrupted condition. This is shown as indicated in (2.2).

$$\bar{s}_p = \frac{\sum_{i=1}^{n} V_i \times s_i}{\sum_{i=1}^{n} V_i}$$

(2.2)

where:

$\bar{s}_p$ = volume-weighted mean speed for period p
V_i = upper percentile (e.g. 90th) volume of time interval i
s_i = observed speed during time interval i
n = number of time interval observations, i, in given time period, p (per year)

The intensity of observed disruptions is measured from the mean speed. The intensity is calculated as an average value for each time period (e.g., morning, evening, or other) of a given year for a single road segment, as shown in (2.3). Deviations above the mean speed (early arrivals) are not a common measure of congestion but can be reported separately to evaluate variability in operating conditions.

$$\delta = \{\alpha(\bar{s}) \ldots \beta(\bar{s})\} \rightarrow \frac{1}{n_d} \sum_{i=1}^{n_d} (|\bar{s} - s_i|)$$

(2.3)

where

δ = intensity of disruption
$\bar{s}$ = volume-weighted mean speed
α, β = buffer variables, defined by stakeholders (e.g. 95% and 105%)
s_i = observed speed
n_U = number of time intervals with a classified disruption condition

The piecewise function for an unreliable condition is shown in (2.4). As shown, this approach calculates the average deviations from the mean speed for all time intervals with a classified disruption condition (d). The perception of disruption should be considered when establishing speed buffer parameters (α, β) and evaluating geographic regions of the network to consider operator expectations. For instance, prior work has demonstrated that travelers on rural freeways are less tolerant of moderate congestion conditions than what is suggested by the *Highway Capacity Manual* criteria; therefore, a smaller range of speeds (e.g., +/- 3%) may be appropriate [82].

$$d_i = \begin{cases} 1, & \text{if } s_i \notin \{\alpha(\bar{s}) \ldots \beta(\bar{s})\} \\ 0, & \text{if } s_i \in \{\alpha(\bar{s}) \ldots \beta(\bar{s})\} \end{cases} \tag{2.4}$$

where

d_i = piecewise function associated with counting congestion condition
s_i = observed speed
$\{\alpha(\bar{s}) \ldots \beta(\bar{s})\}$ = range of acceptable speed conditions

The duration is calculated across a temporal domain (e.g., year) as the number of time intervals classified as disruptions, as shown in (2.5). This could be reported as the number of hours of congestion each year (or each month, season, etc.).

$$\tau = t_i \times \sum_{i=1}^{n} d_i \tag{2.5}$$

where

τ = duration of disruption (e.g. hours per year)
d_i = piecewise function associated with counting congestion condition
t_i = length of time interval (e.g. 15 minutes)
n = number of observations for a time interval across temporal domain (e.g., 15-minute interval, one year)

The extent of unreliable conditions is determined by a volume statistic, as referenced with the volume-weighted speed observation in this subsection. Prior work has suggested an upper percentile of volume (e.g. 90th percentile) to represent the demand volume of a given time interval [83]. Traffic volume values should consider independent reporting of heavy vehicles or a conversion to passenger car equivalent (PCE) as noted in the Highway Capacity Manual, which may range from 1.1 to 7.7 for each heavy vehicle based on geometric conditions [26].

Independently, each of these metrics provides some information on a measure of reliability, intensity, duration and extent of disruptions in a road network. As a multicriteria framework, the metrics serve to prioritize infrastructure investments and inform transportation planners of appropriate strategies. To quantify disruption, we consider the segment length associated with the space-mean speed observation and the ratio of normal conditions compared to the intensity of disruption. For example, with a mean speed of 100 km/h and an average disruption of 30 km/h along 2 km of roadway, there is approximately a 30 second difference from the planned operation for every 2 km traveled by each vehicle. This value is evaluated across the number of hours experienced per year and the affected volume. The quantitative measure of disruption is therefore shown in (2.6).

$$\varphi = \left[\left(\frac{\bar{s}}{(\bar{s}-\delta)} - 1\right) \times \frac{L}{\bar{s}}\right] \times \tau \times V$$

(2.6)

where:

φ =	system disruption from typical operating conditions (vehicle-hours, per corridor length per year)
$\bar{s}$ =	volume weighted mean speed (km/h, mph)
δ =	intensity of disruption (km/h, mph)
L =	unit length of space-mean speed observation (km, miles)
τ =	duration of disruption (hours)
V =	extent of disruption, traffic flow (90^{th} percentile PCE traffic volume, per hour)

The disruption is reported as vehicle-hours. For example, a given number of vehicles experienced a number of disrupted hours, based on the speed deviation from normal operations (km/h, mph), the duration of disruptions in a year (hour/year), and the extent of vehicles disrupted (vehicles or PCE). This disruption measure provides a quantitative value; however, this metric does not distinguish between the intensity, duration, and extent of disruption. Multi-objective charts and supporting tables provide insights of each measure, as shown in the Demonstration section of this chapter. Temporal disaggregation of the observed performance provides additional insights in methods of mitigating disruptions and improves the correlation between each criterion.

2.4.2. Data Processing

This subsection provides details in processing big datasets associated with transportation systems. A common source of speed and volume data is continuous count stations (CCS), which use loop detectors to document speed and volume conditions at set time intervals with continuous operation. The data collected from a CCS is documented as the average observed speed for a time interval and the total traffic volume (including percentage of heavy vehicles). Each interval includes a unique timestamp with the day and time of the observed data. For example, with a time interval of fifteen minutes, there are approximately 35,000 observations from a CCS each year (technical operating limitations and quality control may reduce the number of available observations). Sources of vehicle speed data and travel times can be acquired from probe vehicle speed sources, as collected from GPS received on personal or commercial devices. To process the data in a format conducive to the methods identified in this section, this subsection includes detailed steps in data processing. Statistical programming can be used to efficiently process the data as described:

1. **Quality Control:** Data errors or observations with low confidence (typically documented in data collection processes) should be noted and omitted if necessary. Each time interval should have a traffic volume and speed value.

2. **Time Period:** Time periods should be established based on time intervals of data and daily or seasonal characteristics (e.g., weekday and weekend)

across the temporal domain (year). For reference, time periods established by FHWA [11] are listed:

a. Morning: 06:00 – 10:00 (Monday – Friday)
b. Midday: 10:00 – 16:00 (Monday – Friday)
c. Evening: 16:00 – 20:00 (Monday – Friday)
d. Night: 20:00 – 06:00 (Overnight)
e. Weekend: 06:00 – 20:00 (Saturday – Sunday)

3. **Volume-Weighted Mean Speed:** The mean speed for each location and time period is computed to determine if a disruption condition is observed. This is calculated as shown in (2.2).

4. **Intensity:** If an observed speed is outside the range of normal conditions, established by mean speed with a given buffer condition, the difference between the observed speed and mean speed is reported.

5. **Duration:** Each observation of a time interval (e.g. 15 minutes) that is outside the range is documented as a system disruption. The duration is reported with respect to the temporal domain (year).

6. **Extent:** The extent of traffic volume affected by the disruption conditions is determined based on a percentile statistic of a time interval calculated across the temporal domain (e.g., 90th percentile volume for a given hour of the week for a given year) to represent demand volume during disrupted conditions.

Data analytics focus on the relationship of volume, speed, and observed time when reporting reliability, intensity, duration and extent of system operations. This information provides stakeholders with a method to measure unexpected operating conditions that are most disruptive to enterprise and personal logistics. The visualization of the processed data provides an accessible method of scanning the dataset to identify critical regions and time periods. The next section provides a demonstration of the methods introduced in this chapter.

2.5. Demonstration

This section follows the framework developed in the preceding section as applied to a big dataset across a diverse geography. Data was collected from 2014 to 2017 at fifteen-minute intervals from fifty-five (55) continuous count stations across Virginia, USA, which provides 6,747,400 speed and traffic volume observations (after filtering data based on quality methods and removing any incomplete observations). The count stations are geographically dispersed, and Virginia provides diverse topographic and climate conditions from the eastern coast to the western mountain regions with both rural and ultra-urban areas. An investigation of outliers revealed that five of the fifty-five locations were subject to construction activities (I-95 Express Lanes) during the data collection time periods which incurred variable and undocumented capacity and speed disruptions associated with traffic management plans; therefore, those stations were removed from the analysis. Probe speed data was collected from INRIX via RITIS [84] to assess the space-mean speed and associated segment length near each volume continuous count station. The data provider INRIX reports vehicle travel times from vehicles and smartphones equipped with GPS receivers and road sensors, which covers more than five million miles of road networks, primarily in the U.S. and Europe [3], [85]. Figure 2-3 provides a graphic depiction of each count station location used within the demonstration.

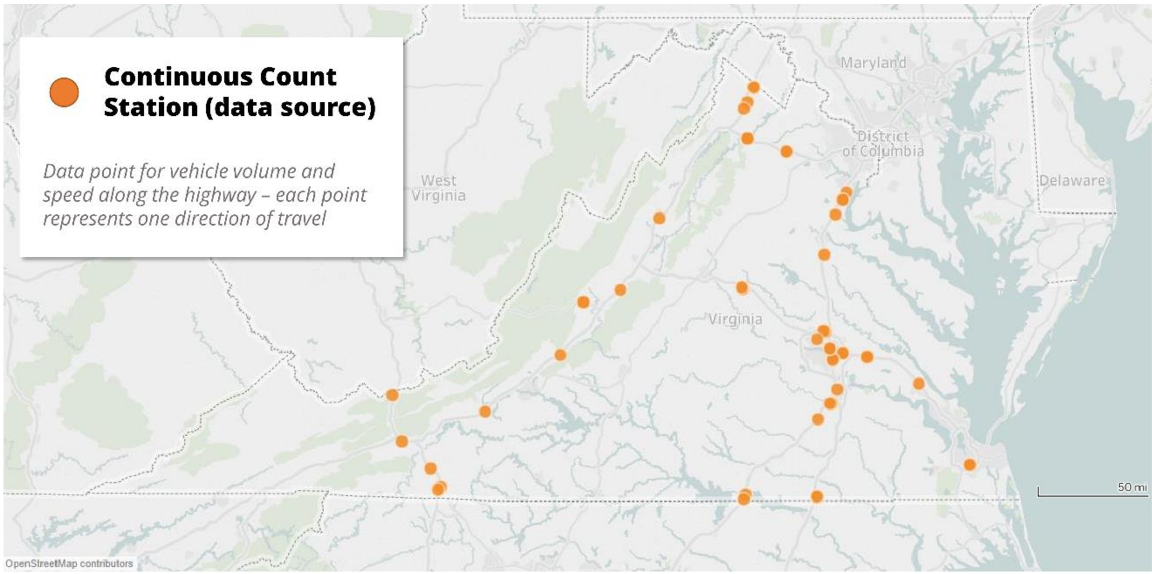

Figure 2-3: Map depicting the location of 55 count stations throughout Virginia, which recorded speed and volume data at 15-minute intervals.

The data was formatted as described in the preceding section. The continuous count station data is collected at time intervals of 15 minutes and was aggregated to time periods based on those established by FHWA [54] travel time reliability methods (morning, midday, evening, night, and weekend). Each performance metric of reliability, intensity, duration and extent was evaluated across a single year for each geographic location.

The statistical programming language, R, was used with the software package RStudio for efficient data processing [86]. Table 2-2 provides the descriptive statistics of the processed data. Each data point (n) represents one time period of one year for a count station, ranging from approximately 4,000 to 14,000 observations each year, depending on the time period and available data [86].

Table 2-2: Descriptive statistics of project data, provided for context.

	Hours of Delay per Year	Average Speed Delay mph (km/h)	Median V/C
n (data points)	1065	1065	1065
Minimum	45	0.7 (1.1)	0.02
Maximum	4,724	34 (54)	0.88
Median	415	5.2 (8.4)	0.28
Mean	592	7.4 (12)	0.30
Std Deviation	554	5.8 (9.3)	0.18

The demonstration described in this work is based on data collected from continuous count stations throughout Virginia – the data is subject to limitations of data collection technologies and the inherent errors associated with the technology. The collected data from the Virginia Department of Transportation (VDOT) is evaluated daily for quality assurance and the count station hardware (inductance loops) are regularly maintained to ensure accurate data collection, which generally results in high confidence levels of the data [60]. Noted challenges associated with the current technologies include issues of accurately collecting volume data during complete breakdown (no vehicle movement) conditions [60]. In this demonstration, we apply the 90th percentile of observed traffic volume when referring to the extent metrics.

2.5.1. Demonstration of Assessing Operational Disruptions

An evaluation of the system performance based on the intensity (deviation from mean speed), duration (hours of unreliable conditions per year, per period) and extent (90th percentile traffic volume) within each year. In this demonstration, the buffer values of α = 0.95 and β = 1.05 were used around the calculated mean speed to consider an acceptable range of normal operating conditions. Each time period is reported separately, and the intensity of disruption (average deviation from normal speeds) is portrayed by the size and color of the data point. Figure 2-4 depicts one year of data (2017) as a multi-objective chart and includes disruptions below the mean speed (delays) when showing the duration and intensity. The extent of disruption is shown as the v/c ratio (90^{th} percentile) to account for the presence of both two-lane and three-lane highway segments in the dataset. Critical system-wide problems, as categorized by Lomax [24], appear in the top right of each time period chart segment. The numeric identification number is listed for several points (referenced later in this section).

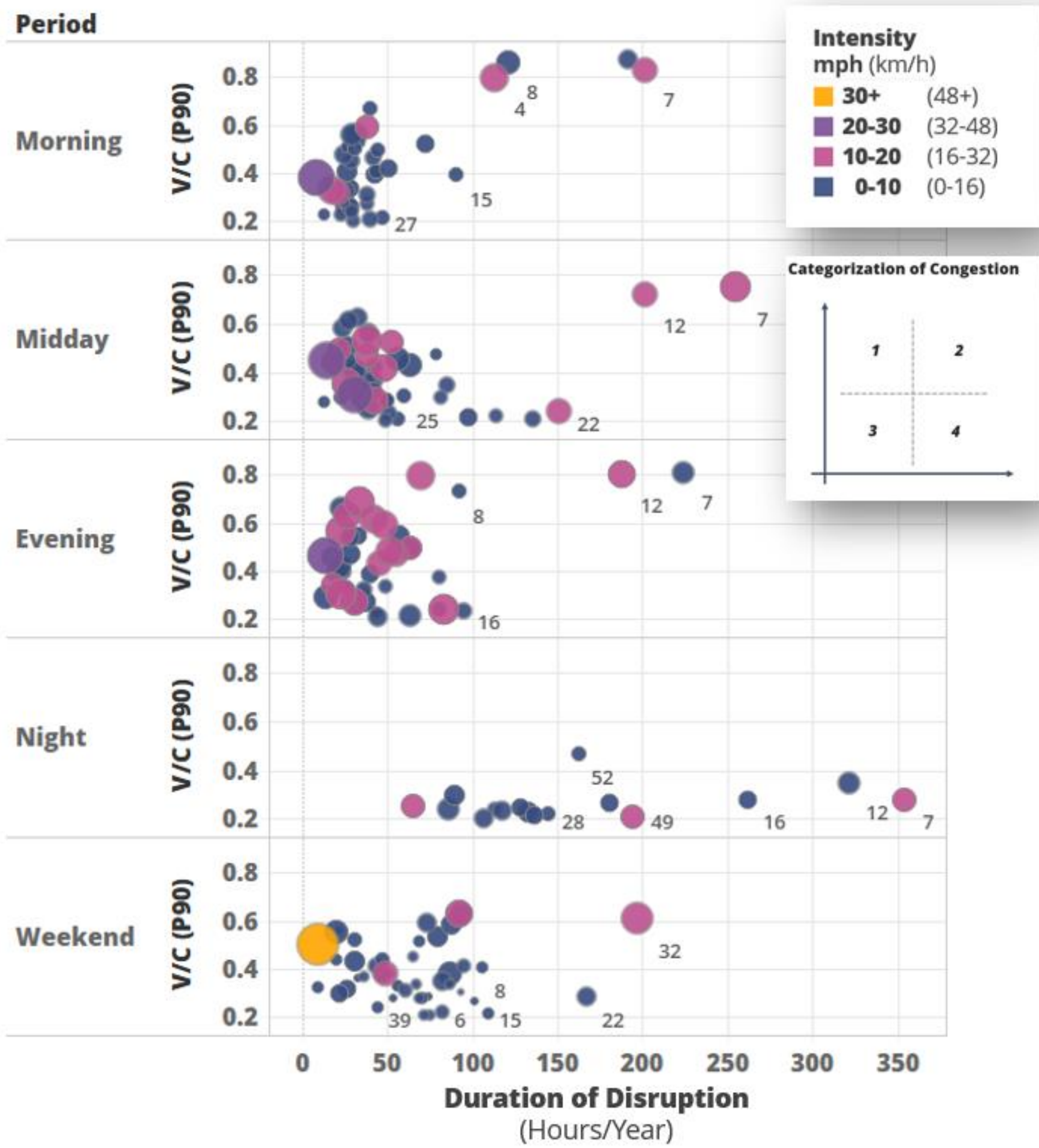

Figure 2-4: Multicriteria chart of intensity, duration and extent of disparate corridors across five time periods. This data visualization facilitates scanning of a large geography to assess performance and prioritization. Congestion is categorized as (1) broad general congestion, (2) critical system-wide problems, (3) limited problems and (4) critical links or corridors.

There are several considerations in the depicted data. The aggregation of time periods is based on FHWA standards that use different durations. For example, the nighttime period (8:00 PM – 6:00 AM, all days) represents 70 hours (41.67%) of the week, whereas the morning period (6:00-10:00 AM, weekdays) is only 20 hours (12%). It is intuitive then to see a longer duration (hours of delay) of disrupted conditions in the nighttime period. As anticipated, the disruptions occur when the volume (representing the extent) is low, and the intensity of disruption is relatively moderate. There are two locations (ID 07, 12) which demonstrate the greatest duration and extent of disruption across all time periods, except weekend conditions. These locations represent opposite directions of the same geographic location within an urban area (Richmond, VA). During the weekend time period, a separate location (ID 32) exhibits the highest duration and extent of disruption, which is in a suburban area east of the major city center.

The intensity of disruption provides new perspectives on categorization and mitigation of each observation. For example, some points with a moderate observation of v/c and a low duration value exhibit a high intensity of disruption. This indicates severe, but infrequent, events occurring when the road is unlikely to be constrained by capacity congestion. Specifically, one data point was calculated with average deviations greater than 30 mph (48 km/h) during the weekend time period when the v/c condition was near 0.5, with a duration of about 10 hours across the year. Such outliers warrant investigation by transportation operators.

Supporting tables provide detail to the data visualizations. Table 2-3 provides a sample of results ranked by the measured disruption and depicted across the five time periods applied to the demonstration. The disruption is as vehicle-hours per year per mile. The four locations (ID 7, 12, 32, 4) with the largest measured disruption are shown as well as the lowest ranked location (ID 53). For context, the calculated free flow speed was higher than the mean speed by 7 mph (11 km/h) for the highest ranked locations.

Table 2-3: Sample of quantitative results of one year (2017), in measuring disruptions, ranked by the disruption across all time periods (reported as vehicle-hours of deviations from normal operations, per mile, per year).

Rank	ID	Disruption Metric	Morning	Midday	Evening	Night	Weekend
1	7	Disruption (veh-hours)	2094	3218	2104	1002	402
		Volume (PCE)	5636	5044	5716	2224	4616
		V/C	0.83	0.75	0.81	0.28	0.63
		Mean Speed (mph)	54	55	52	57	59
		FFS (mph)	62	62	62	62	62
		Duration (delay hours)	201	255	224	354	93
		Intensity (delay, mph)	11	16	9	11	9
		Duration (early, hours)	454	890	436	821	192
		Intensity (early, mph)	3	2	3	2	1
2	12	Disruption (veh-hours)	1051	1221	2325	768	208
		Volume (PCE)	6072	5008	5716	2588	4312
		V/C	0.87	0.72	0.80	0.34	0.59
		Mean Speed (mph)	56	57	54	59	60
		FFS (mph)	63	63	63	63	63
		Duration (delay hours)	192	201	188	321	74
		Intensity (delay, mph)	7	11	13	9	7
		Duration (early, hours)	335	438	463	589	127
		Intensity (early, mph)	2	1	3	1	1
3	32	Disruption (veh-hours)	22	83	92	72	1076
		Volume (PCE)	2204	2516	2412	1064	3072
		V/C	0.50	0.45	0.47	0.16	0.61
		Mean Speed (mph)	71	70	70	68	67
		FFS (mph)	73	73	73	73	73
		Duration (delay hours)	45	57	56	157	197
		Intensity (delay, mph)	4	10	11	5	17
		Duration (early, hours)	11	38	57	339	578
		Intensity (early, mph)	0	0	0	1	3
4	4	Disruption (veh-hours)	878	96	196	77	50
		Volume (PCE)	5167	3140	3292	1536	3204
		V/C	0.79	0.47	0.48	0.20	0.44
		Mean Speed (mph)	63	66	65	64	67
		FFS (mph)	69	69	69	69	69
		Duration (delay hours)	113	38	51	139	47
		Intensity (delay, mph)	14	10	14	4	4
		Duration (early, hours)	274	70	100	204	88
		Intensity (early, mph)	2	1	1	1	1
5	8	Disruption (veh-hours)	761	60	155	145	74
		Volume (PCE)	5783	3328	4812	1712	2924
		V/C	0.86	0.48	0.73	0.27	0.40
		Mean Speed (mph)	61	64	63	63	65
		FFS (mph)	67	67	67	67	67
		Duration (delay hours)	261	91	104	187	121
		Intensity (delay, mph)	10	2	4	5	2
		Duration (early, hours)	121	79	91	181	106
		Intensity (early, mph)	2	1	1	2	1
	…						
51	53	Disruption (veh-hours)	2	4	3	3	3
		Volume (PCE)	236	384	364	136	480
		V/C	0.05	0.08	0.08	0.03	0.08
		Mean Speed (mph)	68	69	68	67	68
		FFS (mph)	71	71	71	71	71
		Duration (delay hours)	30	38	28	82	42
		Intensity (delay, mph)	5	3	4	4	1
		Duration (early, hours)	31	66	42	191	78
		Intensity (early, mph)	1	1	1	1	1

These samples of quantitative results demonstrate the variability of normal operating conditions and performance across disparate locations, hours of the day and days of the week. Based on the visual analysis and the summary tables of the dataset, there are several corridors that would be prioritized based on the intensity, duration and extent of observed disruptions. For a specific project initiative, such as roadway illumination, the corridors could be ranked after filtering to evaluate only the nighttime conditions (ID 18, 12, 8, 7, 48 become the highest ranked corridors).

Several locations in the dataset were exposed to major construction activities for an extended duration (several years), which were removed from the charts, table summary and prioritization process. These segments reported extreme variability in operating conditions (likely influence by temporary traffic control plans), with average speeds ranging from 65 km/h (40 mph) to 107 km/h (67 mph) based on the time period with a free flow speed of 116 km/h (72 mph). Average delay speeds included values as much as 50 km/h (31 mph) less than the mean speed). Total disruption of these segments was intuitively higher (at over 20,000 veh-hours, more than twice the value of the highest rank segment in the primary dataset). While these locations pose challenges in assessing performance conditions based on variable and undocumented operating conditions, the values reported serve to inform disruption caused by construction operations.

The timing and locations of disruptions inform transportation planners on potential strategies for performance improvements. Similarly, stakeholders such as commuters and enterprise operators may weigh each time period differently based on value associated with operations during a given time of day (commute to work, nighttime freight traffic, weekend operations, or others) in the prioritization of infrastructure improvements (this is explored further in Chapter 5).

2.6. SUMMARY

The quantitative method of evaluating disruptions, defined in this chapter, provides a new perspective for monitoring transportation systems. These methods are not intended as a comprehensive assessment of the system. Operators may emphasize the importance of a given time period, vehicle type (such as freight vehicles), or component of congestion based on operational objectives. If an operator seeks to assign a monetary (or other) value to the observed performance, then additional methods can be applied to address and monetize performance uncertainties and weight individual performance criteria [37], [40], [42], [66], [67], [87]. In this way, a monetary value for time can be applied to the number of vehicles, type of vehicle (passenger or heavy vehicle), cargo, vehicle occupancy and other factors. The time period (day versus night, weekday versus weekend) or vehicle type (passenger versus commercial) can be used to adjust the applied monetary rate. The valuation of the disruption is subject to each transportation operator, stakeholder, and planning agency.

Quantifying operational disruptions of transportation networks provides new insights into the system performance and informs prioritization of resource allocation. The temporal disaggregation of performance measures succeeds in reducing correlation errors between the intensity, duration and extent of system disruptions. Understanding when the disruptions occur, by utilizing disaggregate data, will influence the strategies and priorities of mitigation. Traditional delay metrics calculate the volume of affected traffic during a disruption, but generally focus on comparing speed observations to discrete and ideal speeds, which can misrepresent the scale of disruption from the perception of commuters and enterprise logistics that can adapt to recurrent congestion [7], [62], [81], [88]. Additionally, traditional performance metrics reference the system's annual daily traffic, which does not accurately reflect volume distribution across time periods of a day and week, and therefore does not represent the extent of each disruption event.

The work documented in this chapter serves as the foundation for investigating traveler-centric performance measures based on accessibility threats caused by unreliable travel conditions. These methods serve as new perspectives to identify and rank regional network disruptions. In the next chapter, Chapter 3, this framework is extended with additional methods to quantify disruption. As noted in this chapter, the nonparametric datasets of vehicle speed observations creates challenges when using metrics such as the mean speed as a reference condition for disruptions. While this approach follows current FHWA methods of measuring reliability, Chapter 3 explores benefits of calculating the most frequently observed speed as the reference speed.

3. Other Perspectives of Operations Disruption

3.1. Introduction

There is worldwide interest of transportation professionals to quantify traveler perceptions of system performance, ascertaining how such perceptions can differ from objective performance by traditional metrics. Such perceptions include the operational variability of vehicle travel times across hours and days of the week within highway transportation networks. Improvements to transportation infrastructure are informed by performance metrics; however, traditional methods evaluate delays based on deviations from a discrete or ideal condition. In this chapter, we measure traveler perception with a novel approach of evaluating delays as deviations from the speed value with the maximum kernel density estimate (KDE). This approach provides a foundation for a risk-based multicriteria framework to inform stakeholders of appropriate reliability and safety mitigation methods. Recent advances in vehicular volume and speed data collection provide the disaggregate traffic data that depicts the variability across disparate time periods. The framework demonstrated in this chapter informs enterprise operators and transportation agencies with new perspectives of relative congestion and infrastructure investment planning.

3.2. Motivation and Scope

Infrastructure improvements are constrained by available resources, which requires macroscopic evaluation of the system and prioritization of investments [55], [89]–[91]. Prioritizing infrastructure investments is often a function of performance evaluation with various metrics that can influence project selection [19], [39], [54], [92], [93]. As referenced in Chapter 2, there is a an emphasis to measure and monitor the reliability of transportation performance by investigating the variability of a normal operating condition [46], [54], [55]. Within the context of transportation systems, reliability is characterized by the probability of maintaining an anticipated operating condition, such as travel time or vehicle speed, across a given time period for a given road segment [54], [56].

Reliability performance metrics are systematically different from other transportation performance metrics - traditional metrics calculate delay as the deviation from an ideal free flow speed (or other discrete speed value). Comparatively, reliability investigates disruptions to scheduled conditions based on deviations from the calculated mean or median of observed speeds [11], [24], [44]. This metric is critical to traveler operations such as public transit, just-in-time delivery, transport of commodities, and other logistics [27], [44]. Reliability metrics are intended to account for variability in vehicle speeds across geographies and time periods by using disaggregate data. Recurrent congestion (e.g., regular slowdown during peak commute periods) is undesirable but can be anticipated and accommodated by travelers when choosing origins, destinations, residence, routes, transportation modes, and other factors [1], [41], [54], [55], [94]. Disruptions are therefore defined by deviations from the anticipated conditions instead of ideal (posted speed limit or free flow) conditions.

Comparatively, delay metrics often use a consistent reference speed (e.g., free flow speed, posted speed, or other) and the delay is measured based on the deviation from the reference speed [24], [47]. This measure of delay deviates from reliability metrics that use mean or median conditions to measure disruption, but the traditional definition of delay (as a deviation from a reference speed) can be used to assess the frequency and magnitude of disruptions. The approach introduced with this chapter is based on existing performance metrics, but the quantitative measure of disruption (from Chapter 2) is modified to represent traveler-centric perspectives of transportation performance by assigning the most frequently observed speed as the reference speed in lieu of the mean speed.

3.3. Risk Analysis of Transportation Planning

The reliability and delay metrics can be applied to a multicriteria risk analytics framework for highway performance. This chapter refers to three components of risk analytics: frequency, magnitude, and exposure (analogous to duration, intensity, and extent from Chapter 2). Frequency is defined by the number of observed delay conditions (by time interval) that deviate from the anticipated operating speeds across a given time period of continuous data collection. The magnitude of disruption is the difference between the observed speed and the anticipated speed. For both frequency and delay, in this chapter we define the anticipated operating condition as the mode statistic – specifically, as the calculated speed that has the maximum kernel density estimate (KDE). Methods of KDE are applied to overcome challenges in binning continuous data and fitting a formal distribution to a set of observed datapoints (such as speed observations) with an unknown probability density function [95]. With this approach, the speed with the highest probability is used to represent the mode statistic, such as the anticipated speed. As evidenced in this work and others, the skew of speed distributions will influence the median such that it is significantly different from the most frequently observed operating condition [11], [57], [96]. If the intent of reliability metrics is to evaluate disruptions as deviations from the typical conditions, then the speed values with the highest probability (maximum KDE) will provide a better representation of the traveler's perspective of typical operating conditions.

For example, within the dataset (referenced in the Demonstration section of this chapter), the median speed varied from the most frequently observed speed by -12 km/h to 15 km/h (-7.7 to 9.4 mph) when the median was 107 km/h (67 mph). Figure 3-1 provides a graphic representation of this condition, where one location (Location ID 7) was evaluated to find the median statistic (represented by a vertical line differentiating the colors) and display the KDE. Within unreliable and congested areas, the median measured significantly less than the most frequent speed condition (peak of the KDE).

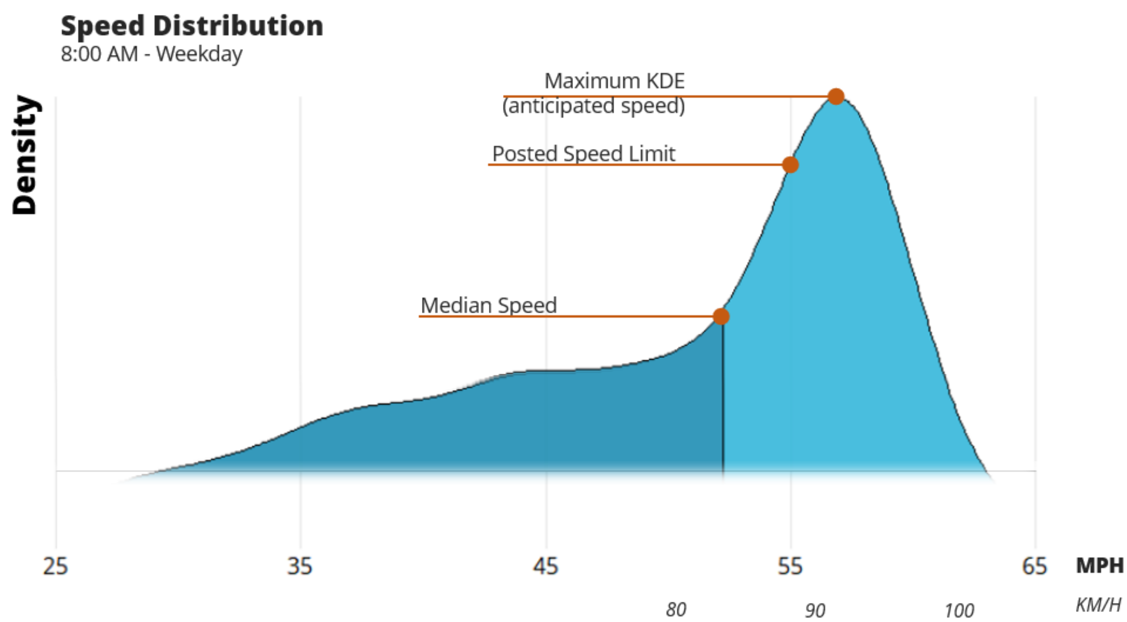

Figure 3-1: Density of speed distribution for a three-lane highway segment from Demonstration data (ID07), depicting differences between anticipated speed (maximum KDE), median speed statistic, and posted speed limit.

From the perspective of land planning, the system reliability and delay metrics should be based on the concepts of driver resilience and perception of typical operating conditions. If we accept that delays and reliability should focus more on traveler expectations, we must also consider that expectations are better represented by the frequency of observed conditions (instead of descriptive statistics, such as mean and median). These expectations are subject to vary across a temporal domain, such as time of day or day of the week [94].

In this chapter, any observations that deviate from the anticipated operating condition (speed that has the maximum KDE) are measured as disruptive events. A buffer is applied around the anticipated speed (e.g., +/- 5%) to consider acceptable operating conditions. We distinguish the risk components from the congestion components (RIDE metrics, in Chapter 2) to emphasize how deviations both above and below the most frequently observed speeds are disruptive. Early arrivals (observed speeds greater than typical operating conditions) also warrant a factor in the measure of system performance. While often a welcomed condition, early arrivals are still categorized as unreliable because they deviate from the anticipated operation and are disruptive to scheduled operations, such as public transit or freight logistics [43]. We have therefore defined two risk factors (frequency and magnitude) as the (i) frequency of observations that deviate from the anticipated condition and (ii) the magnitude as the difference between the observed speed and the anticipated operating condition.

In prior work of infrastructure prioritization through multi-objective risk analytics, the population exposure has been estimated by the average daily traffic (ADT) of a road network [40], [72], [77]. Recognizing that ADT does not describe the variation of traffic volume that occurs throughout a day and week of operations, the measure of exposure can be improved with temporal disaggregation of speed and volume data. The appropriate aggregation of performance observations should be informed by multiple stakeholders to represent the variability of regional transportation systems. Prior work notes the benefits of short intervals (5-15 minutes) but considers practical applications of defined time periods across several hours [54], [55], [65].

The risk components (frequency, magnitude, and exposure) provide new perspectives on system performance to inform the prioritization of infrastructure investments. Within this chapter, these perspectives are based on speed and traffic volume observations within a dataset that spans several years across a diverse geographic region. The remaining sections of this chapter are organized to describe the methods of a risk-based performance analysis before providing a demonstration of methods with a large dataset of highway performance observations. A series of considerations are presented in the summary section.

3.4. METHODS

To achieve the contributions identified in this chapter, the details of methods implemented in the demonstration are listed in this section. There are similarities between the methods of Chapter 2 and those presented in this chapter; however, the methods of KDE in this chapter are applied to volume and speed observations to address limitations of percentile statistics applied to nonparametric data.

3.4.1. Minimum Requirements of the Dataset

The methods of establishing a multicriteria risk analysis requires disaggregated data that includes location identification, date, time, speed and traffic volume. Road characteristics, such as the number of lanes and road classification (e.g., limited access highway) should be documented. Speed data should be available at an interval of 15 minutes (or less), which may be available through continuous count stations (CCS) or probe data analytics (PDA) available from Regional Integrated Transportation Information System (RITIS), which includes INRIX speed data. The traffic volume, at the same 15-minute interval, provides the information necessary to establish volume-weighted speed statistics of the most frequently observed speed. Speed observations from data collection sources (such as INRIX) include confidence levels based on the number of observations [84]. Time periods with low confidence or documented quality conditions should be omitted from the analysis. When traffic volume data is not available through CCS sources, values such as ADT and peak hour factors may be used, or other data sources, such as GPS, may serve to inform the volume weights [57].

3.4.2. Kernel Density Estimation

The mode estimates for the volume and speed are based on kernel density estimation (KDE), a nonparametric method to estimate the density of a continuous random variable. The methods in this chapter use the default Silverman's rule of thumb [95] to set the bandwidth parameter that controls the smoothness of the resulting density estimate. The resulting mode estimate is the value that has the largest estimated density (over a grid of 512 values). When the grid is applied to speed observations for a window from 0 to 80 mph (129 km/h) the resulting grid size is 0.15 mph (0.25 km/h). A graphic representation of the KDE was shown in Figure 3-1. This method is appropriate when computing the most frequently observed speed to consider continuous variables of the dataset [96]–[98]. A statistical programming language, such as R [99], can be used to process the big data sets and establish the KDE to identify the speed for the maximum density estimate.

During a system disruption, the traffic volume documented by a continuous count station will not represent the magnitude of disrupted vehicles because the queuing is not recorded by continuous count station technologies. Instead of referencing observed volumes during a disruption, the exposure and affected vehicles are measured by the demand volume. In Chapter 2, the demand volume was represented as a percentile (90^{th}) value of the volume; however, in this chapter we benefit from methods of KDE to consider the most frequent operating condition. The demand is estimated by calculating the volume with the highest KDE for each time interval, separated by weekday and weekend, across a given year of a road segment. When an observation exhibits a disruption (deviation from the typical speed), this approach provides an estimate to the magnitude of affected vehicles where a capacity reduction would otherwise report a low traffic flow condition.

The demand volume is used to weight the speed observations across an aggregated time period (e.g. morning rush hour, overnight, weekend, or other) before determining the speed with the maximum KDE (similar to volume-weighted mean speed methods in Chapter 2). Aggregating the time intervals benefits the performance analysis by considering distinct operating conditions for a time period, such as morning and evening commute times. This approach also accepts that the performance during a given time interval is subject to preceding time intervals. A complete disaggregation would otherwise neglect adjacent time intervals, which represent the source or recovery associated with observed congestion. The volume weighting of the speed observations represents the anticipated speed as observed by the largest number of travelers during a time period, which is subject to seasonal variability.

3.4.3. Data Processing

To evaluate the frequency, magnitude, and exposure of a transportation system, the observed speed and volume data is processed as described in this section. The data processing described with this chapter, including the determination of time periods and data aggregation, have been informed by transportation professionals; however, the aggregation and parameters may be modified by stakeholders. The use of statistical programming languages and software provides for efficient data processing. The steps in this section provide a sequence of methods for data processing, which is evaluated for each road segment (data collection point) across each year of observation data. The initial steps of quality assurance and establishing time periods, as noted in Section 2.4.2 (of Chapter 2), are applicable to these methods as well; however, the methods differ for calculations of demand volume, reference speed, and measures of risk (frequency, magnitude, and exposure).

1. **Demand Volume**: The Demand Volume is used for the volume-weighted speed observations and measured magnitude (number of vehicles) affected by disruptive events. To account for potential queuing during system disruption, the Demand Volume is the calculated volume that has the maximum KDE for each time interval, separated by weekday and weekend traffic conditions.

2. **Anticipated Speed**: The Anticipated Speed represents the expected operating condition of a traveler. It is calculated as the speed that has the maximum KDE, weighted by Demand Volume. This is calculated for all speed observations for each time interval (e.g., fifteen minutes), separated by weekday and weekend traffic conditions.

3. **Frequency of Delay**: The frequency is determined by counting each observation that deviates from the Anticipated Speed for all 15-minute observations. To account for acceptable variations in speed, the Anticipated Speed can include a buffer (e.g. +/- 10%). The frequency is then identified as the ratio between number of speed disruptions and all observations across a time period.

4. **Magnitude of Delay**: The magnitude is calculated as the speed difference between an observation and the Anticipated Speed (with a buffer condition). The disruption conditions (above or below the Anticipated Speed) should be categorized (delay or early). An average speed disruption can be computed, such as the sum of all observed delay values over the quantity of time intervals with a delay condition, to represent the average delay for when a delay occurs. For example, 1000 cumulative mph delays observed across 200 time intervals classified as a delay condition, would yield a magnitude of 5 mph average delay condition.

5. **Exposure**: The exposure can be plotted with the frequency and magnitude of delay, as calculated by the Demand Volume associated with each observed delay condition.

Data analytics focus on the relationship between the frequency, magnitude, and exposure values. In practice (noted in the Demonstration section of this chapter) the relationship between these values will inform stakeholders of appropriate mitigation measures and prioritization of performance improvements.

3.5. DEMONSTRATION

The dataset used in Section 2.5 of Chapter 2 is used in this demonstration, with data from fifty-five (55) continuous count stations across Virginia, from 2014 to 2017. The dataset includes 6,747,600 speed and volume observations (the geographic location is shown in Figure 2-3 of Chapter 2). The transportation agency associated with this dataset (Virginia Department of Transportation, VDOT) is responsible for the operation and maintenance of nearly 100,000 km (approximately 60,000 miles) of roadways, with 1,800 km (1,118 miles) of limited access highways. This work investigates data collected from fifty-five locations along the limited-access highway corridors and considers regional application of the developed framework.

The statistical programming language, R, was used with the software package RStudio for efficient data processing [86]. The dataset (approximately 7M observations) was formatted as described in the Methods section of this chapter, such that each observation was classified with a time period (morning, midday, evening, weekend, night defined in Section 2.4.2 of Chapter 2) and disaggregated by location and year. For each time period, the demand volumes are estimated through methods of KDE before applying a similar process to identify the speed with the maximum KDE. Figure 3-2 provides a sample pseudocode of this process.

```
FOR every location, year, hour, minute-interval
      Volume_KDE ← density(Volume, from = 0)
      Demand_Volume ← Volume from Volume_KDE which has maximum density
FOR every location, year, time period
      Speed_KDE ← density(Speed, weight = Demand_Volume, from 0 to 80)
      Anticipated_Speed ← Speed from Speed_KDE which has maximum density
FOR every location, year, time period
IF Speed < (Anticipated_Speed * B1) or Speed > (Anticipated_Speed * B2)
      Then Delay_Count = +1
      Then Delay_Magnitude = difference of Speed and Anticipated_Speed * B(1,2)
Delay_Frequency = Delay_Count / n observations
Average_Delay = SUM Delay_Magnitude / Delay_Count
```

Figure 3-2: Pseudocode of identifying the demand volume, anticipated speed, frequency of delay and average delay condition. A buffer condition (B) around the anticipated speed is provided (e.g. 5% above and below) to consider acceptable deviations from the anticipated speed.

The calculated values for each location, year, and time period were evaluated to determine the frequency, magnitude, and exposure condition. Table 3-1 provides the descriptive statistics of the processed data are shown, in which each data point (n) represents a count station, year, and time period (approximately 4,000-14,000 observations).

Table 3-1: Descriptive statistics of data with KDE and risk analysis

	Delay Frequency (hours/year)	**Delay Magnitude mph (km/h)**	**Hourly Volume Exposure**
n (data points)	1065	1065	1065
Minimum	9	1 (1)	60
Maximum	3,959	35 (56)	5600
Median	368	5 (8)	1200
Std Deviation	560	5 (8)	1050

In the next section, the ranked results of each site and time periods are provided, which show relative results in risk metrics.

3.5.1. Demonstration Results

An evaluation of each data point provides a perspective on the risk components of frequency, magnitude, and exposure for the transportation agency. Table 3-2 lists the ranks for each location (ID#) and time period based on the product of the risk components with the most recent data (2017). The values shown in the table provide an indication in how independent metrics would influence decisions of infrastructure investments; however, a comprehensive analysis provides insights into different congestion conditions and different solutions [24], [39]. Some results are expected, with the highest ranked segments located in ultra-urban corridors of a heavily populated region (ID# 7 & ID#12 are north and southbound of the same location in Richmond, VA) and were ranked highest with methods in Chapter 2. The ID#32 (rank 6) station is in a region with low-density development, but along a corridor to an urban center (I-64, westbound to Richmond) that displayed the highest delays on a weekend.

Table 3-2: Ranked location and time period by product of risk factors

Rank	ID#	Time Period	Delay Frequency (hours/year)	Delay Magnitude mph (km/h)	Hourly Volume Exposure
1	7	Morning	1394	12	5188
2	12	Evening	1355	11	5088
3	4	Morning	1004	17	4164
4	7	Evening	1503	8	4904
5	12	Morning	1080	6	5596
6	32	Weekend	1556	17	2380
7	7	Midday	1019	10	4792
8	8	Morning	589	11	4072
9	12	Midday	635	9	4812
10	31	Evening	377	12	4120
…					
940	53	Night	1123	6	64

The risk components of frequency, delay, and volume exposure are evaluated with a multicriteria framework. The relevant weight of each component at different time periods can be considered when categorizing the source of disruption and appropriate solutions.

These risk components are shown in a scatter plot, where each data point is an aggregation of one time period across one year of data collected from a continuous count station, representing about 4,000-14,000 observations (based on the time period and data availability). The depiction of three risk analysis components (magnitude, frequency and exposure) in this format is a traditional interpretation of risk analysis and includes proportional-area point sizes [100], [101]. Within the context of risk and decision-making, work by Berman [102] and Frohwein [16] has applied variables of cost or value to point size of a scatter plot. In this work, the frequency and magnitude are plotted with attribute size based on exposure. To consider heterogeneous road geometry and vehicle classifications, the exposure value should reference the number lanes in the corridor and include passenger car equivalent (PCE) for vehicle volume [26]. Figure 3-3 depicts data from the demonstration, with reference to the magnitude, frequency and exposure of disruptions. Prior work by Xu et. al [42] has implemented the use of contours within a scatterplot to create discrete categories of warranted, marginal, or unwarranted project initiatives. The framework introduced in this chapter uses a scatterplot (or bubble plot) and depicts priority as a range of hues based on a multivariate function. In this chapter, we apply (3.1) to the prioritization assessment.

$$\varphi' = \left[\left(\frac{\omega}{(\omega - \delta)} - 1\right) * \frac{L}{\omega}\right] * \tau * V$$

(3.1)

where

φ' = priority based on risk components magnitude, frequency and exposure (vehicle-hours, per corridor length per year)
ω = speed with the highest KDE (km/h, mph)
δ = magnitude of disruption (km/h, mph)
L = unit length of space-mean speed observation (km, miles)
τ = frequency of disruption (hours)
V = traffic volume exposure (vehicles or passenger car equivalent, per hour)

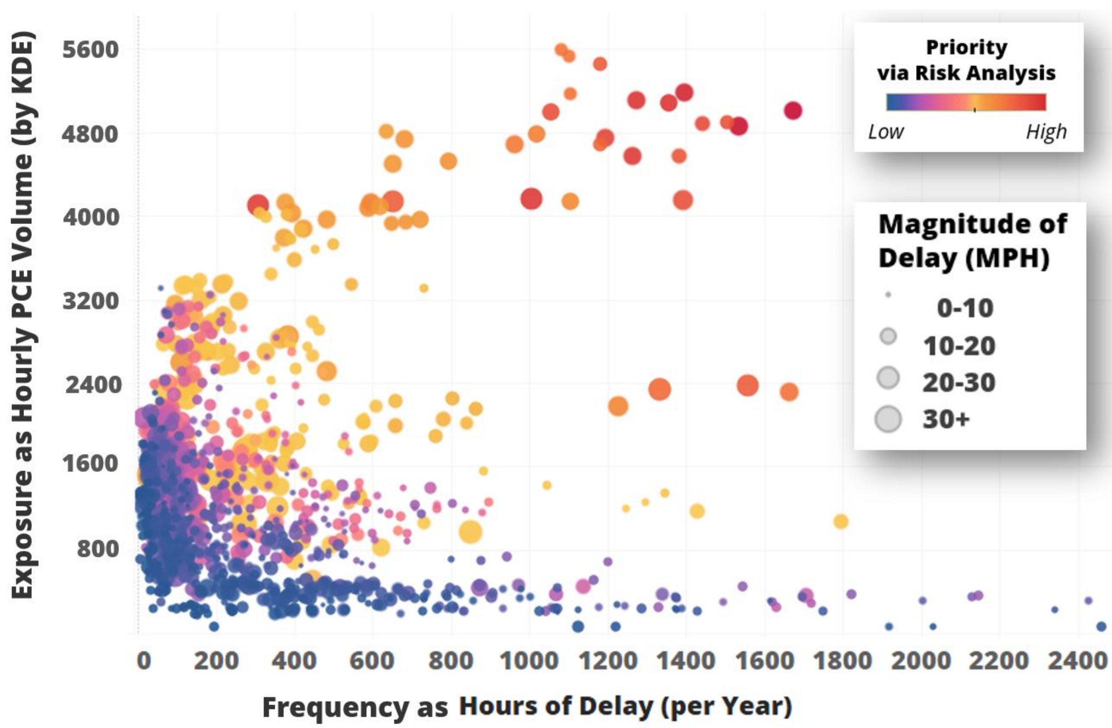

Figure 3-3: Prioritization example with data from highway continuous count stations, 2014-2017 with five time periods. Each data point represents one time period of a given year, giving each count station five points per year. The size represents the magnitude of disruption. The color spectrum represents priority and risk tolerance, based on a user-defined function of magnitude and frequency of delay compared to exposure.

Based on the disaggregation methods of this data, there are several factors to consider when evaluating the results. The data has been isolated into different time periods; each time period carries a different temporal weight associated with the described conditions. For example, the nighttime condition represents almost 42% of the hours each week, but also carries the lowest average traffic volume. The morning and evening rush hours each represent 12% of the hours in a week but carry a significant amount of traffic volume and may be deemed more valuable based on enterprise logistics. An evaluation of risk and prioritization of each time period informs stakeholders of appropriate countermeasures. For example, a nighttime period with high frequency and magnitude of delay may suggest poor visibility conditions and benefit from roadway illumination [78]. The sum of all time series of one segment, across several years, will inform the prioritization of the transportation system.

The example graphic format of risk analysis, shown in Figure 3-3, is one representation of communicating risk analysis in an accessible format to stakeholders, and further analyzed by selecting weights and monetary values to each time period or risk component. For example, project candidates may only include data points that exceed a distinct combination of frequency, magnitude and volume within a given time period. In Chapter 5, methods of assigning temporal weight and value are introduced. This approach is appropriate for a comparative analysis of a large geographic region, but institutional knowledge and local planning expertise is required in the decision-making.

3.5.2. Comparing Disruptions by Mean and Mode

This chapter applies similar methods of evaluating operational disruption as those introduced in Chapter 2; however, a key distinction of the methods in this chapter is an assignment of the reference speed based on the mode statistic (speed with the highest KDE). The exposure (extent) of traffic volume is also modified in the methods of this chapter by referencing the volume with the highest KDE as the demand volume. Table 3-3 provides a comparison of the quantitative operational disruption for both mean and mode reference, based on the sum of results in each of the five disparate time periods (2017).

Table 3-3: Comparison of disruptions by reference of mode speed and mean speed. The value is shown is the sum of five disparate time periods for one year of data.

ID	Disruption Metric	Disruption from Mode	Disruption from Mean
7	Total Disruption	5718	6492
	Delay Disruption	4892	4603
	Early Disruption	826	1890
12	Total Disruption	4818	5358
	Delay Disruption	4108	3658
	Early Disruption	710	1700
4	Total Disruption	2345	2813
	Delay Disruption	2244	2095
	Early Disruption	102	718
32	Total Disruption	1571	2466
	Delay Disruption	1539	1787
	Early Disruption	32	679
8	Total Disruption	1235	1419
	Delay Disruption	1019	959
	Early Disruption	216	460
14	Total Disruption	631	896
	Delay Disruption	549	725
	Early Disruption	83	171
31	Total Disruption	625	724
	Delay Disruption	535	596
	Early Disruption	93	129
18	Total Disruption	808	1379
	Delay Disruption	784	1288
	Early Disruption	24	96
23	Total Disruption	561	708
	Delay Disruption	229	400
	Early Disruption	332	308
00	Total Disruption	548	648
	Delay Disruption	435	545
	Early Disruption	115	102
3	Total Disruption	539	602
	Delay Disruption	420	499
	Early Disruption	119	103
…			
53	Total Disruption	20	30
	Delay Disruption	15	25
	Early Disruption	5	6

Figure 3-4 depicts the ranking and values for all locations to visualize how the prioritization varies based on reference speed, measures of delay, and early arrival conditions. The highest and lowest ranked locations are notably consistent across all measures of disruption, but moderately ranked locations begin to exhibit volatility in prioritization based on the method quantifying disruption.

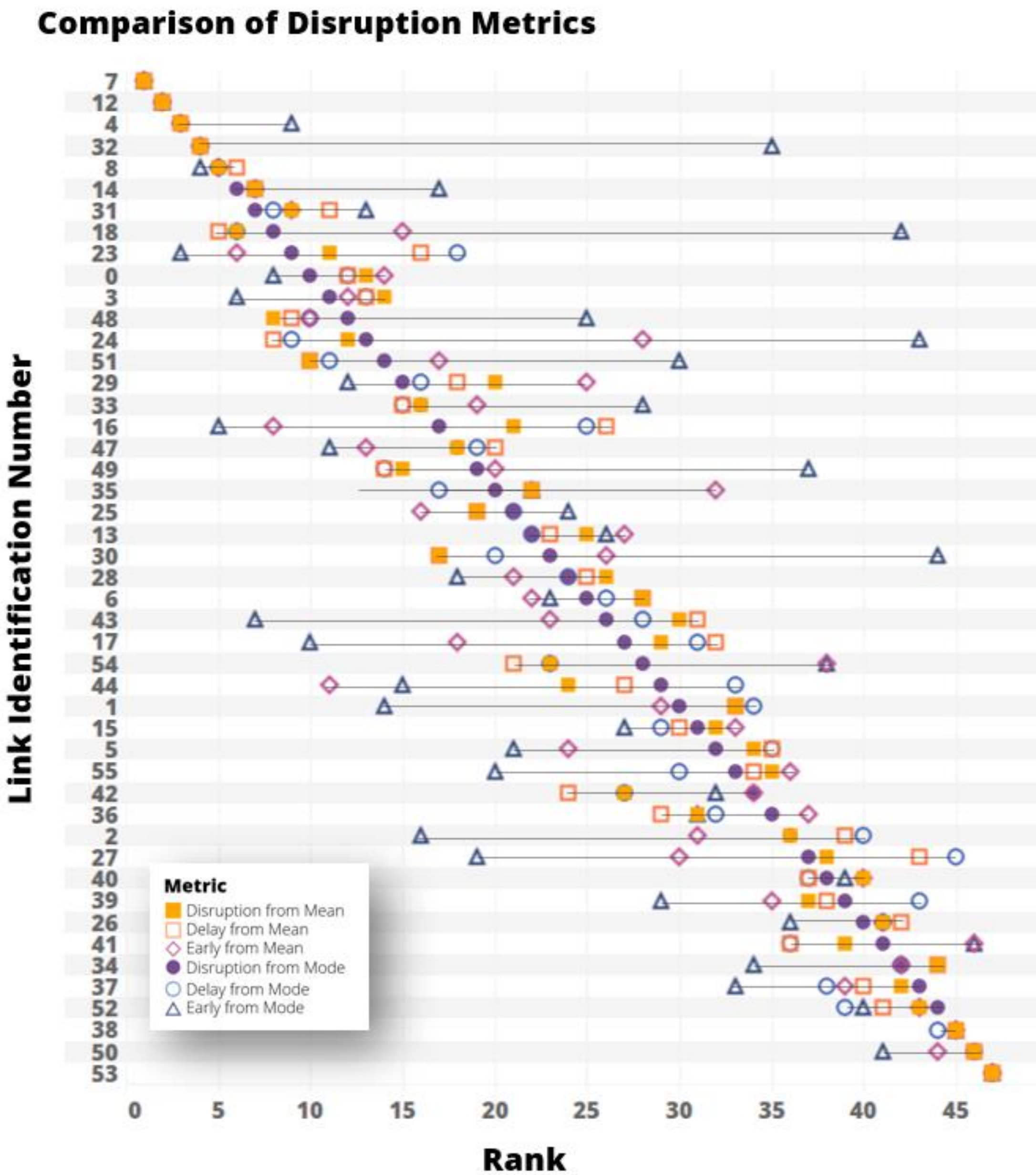

Figure 3-4: Rank and value for each disruption metric, sorted by total disruption from mode reference speed.

3.6. Summary

Prior work has demonstrated how risk analytics informs the prioritization of risk investments associated with traveler safety [29], [40]. The work demonstrated in this chapter extends upon prior applications to identify how risk analytics can inform prioritization of system reliability improvements by evaluating the frequency of a disruption, magnitude of the disruption, and the traffic volume exposure. The classification of a disruptive event refers to the traveler's perspective of the anticipated operating conditions (speed associated with the maximum value of a volume-weighted KDE), which shares similarities with prior work to characterize congestion within a nonparametric dataset [97], [98]. As with all transportation performance metrics, the risk analytics serves as one of many perspectives for monitoring system conditions. Monitoring the mode statistic of speed across each year will also inform transportation planners of system performance, as will visual inspection of the plotted KDE.

An evaluation of road segments by three components of risk analytics (frequency, magnitude, and exposure) provides stakeholders with a method to categorize performance conditions. This categorization informs prioritization of infrastructure investments and appropriate project initiatives. This approach benefits from accessible methods for transportation agency implementation based on business analytics software that provides both quantitative and visual performance reports. The methods were applied across a diverse geographic region with millions of speed and volume observations to demonstrate how available data sources are used with a multicriteria analysis.

The appropriate data aggregation and time periods should be evaluated by regional planners and stakeholders, as informed by observed operating conditions. Benefits of disaggregate data analysis include applications for roadway segments that seek to assign value for different time periods based on regional knowledge of traffic conditions. For example, a large amount of vehicle volume is expected on routes into a city center during the morning time period, and away in the evening. The time periods referenced in this chapter (prescribed by FHWA) are one example of aggregation meant to characterize the variability in volume and speed conditions. Temporal disaggregation for seasonal conditions, operations during adverse weather conditions, peak commodity shipping time, operating hours of public transit, or other conditions may be of interest to different stakeholders. The methods proposed can be modified to accommodate different time periods and performance criteria when evaluating multiple investment priorities. These concepts of temporal weight and value are further explored in Chapter 5.

4. Changepoint Detection of Operations Disruptions

4.1. Introduction

This chapter includes methods for changepoint detection applied to disaggregate vehicle speed and volume data to establish a transportation reliability threshold. In the context of enterprise logistics and surface transportation, reliability is measured by the frequency of deviations from anticipated vehicle speeds associated with a given operating condition. In this chapter, anticipated speeds are calculated as the speed values with the highest kernel density estimate (KDE), with methods defined in Chapter 3. Specific complexities of transportation networks, such as stochastic system capacity, necessitates the identification of operational thresholds associated with rapid performance degradation. Results from a demonstration dataset (comprised of millions of observations) indicates a rapid decline in reliability near half of the capacity defined by traditional traffic models. Variability of the reliability threshold was observed across geographic locations and years of observation, which conforms with concepts of stochastic system capacity based on inherent randomness of exogenous system factors.

4.2. Motivation and Scope

Enterprises in industry, government, military, etc. are susceptible to disruptions from volatile conditions of ground transportation performance. Transportation systems serve as critical infrastructure at a global scale and are an interconnected and interdependent part of a complex system of systems [17], [38], [40], [101]. Monitoring performance of a transportation network has proved challenging, leading to a multitude of metrics that seek to comprehensively define and forecast the operating condition by average speed, frequency of delay, hours of delay, number of bottlenecks, travel time deficit, value of travel time, and many others [46], [47], [67], [83]. A relatively recent metric of *transportation network reliability* has emphasized the importance of monitoring the probability of system failure, defined by deviations from anticipated operating conditions, at disaggregate time periods [48], [54], [55]. The reliability metric advances methods to monitor performance by evaluating adverse conditions as deviations from anticipated conditions evaluated across hours of the day and days of the week.

Infrastructure designers and land planners rely on performance metrics to monitor, manage, maintain and select infrastructure improvement projects [28], [40]. In the multitude of performance metrics, one underlying condition is an abrupt degradation of performance as the traffic volume approaches system capacity. Within the context of a transportation network, a volume-to-capacity (v/c) ratio is correlated to operational performance [103]–[105]. Traditionally considered a deterministic and constant value, capacity has recently been proposed as stochastic to address the exogenous and endogenous variables associated with the seemingly random nature of failure conditions [71], [106], [107]. The capacity of a transportation network has been shown to deviate by time of day, weather, roadway obstructions, number of incidents, vehicle types, and other immeasurable or unpredictable conditions [26], [71], [108]. Both traditional deterministic capacity and the stochastic capacity emphasize rapid degradation of system performance as traffic volume approaches capacity. The conditions of stochastic capacity coupled with variations in demand volume and exposure to exogenous factors form a complex problem for enterprise logistics and transportation planners, which seek to manage performance across large geographic regions.

In this chapter, we identify methods of determining a reliability threshold that extends concepts of stochastic capacity to inform enterprise logistics and transportation planners. Transportation network reliability has a broad range of terms, but primarily measures variations of observed speeds compared to the mean or median speed condition [44], [55], [59]. The transportation reliability metric is fundamentally different from traditional performance measures that monitor deviations from a posted speed limit or ideal performance condition, and instead acknowledge that vehicle operators can plan for recurrent congestion. Measuring reliability by deviations from a mean or median condition assume the statistic is representative of operator perceptions; however, as identified in Chapter 3, there is merit in identifying a failure mode as a deviation from the speed value that has the maximum kernel density estimate (KDE). This approach considers the most frequent condition experienced by vehicle operators at disaggregate time intervals and measures deviations below (late arrival) and above (early arrival) the speed with the maximum KDE. Measuring unreliable conditions by late arrivals is common, and while an early arrival is often a welcome condition for personal travel, it can be disruptive to enterprise logistics that maintain predetermined schedules [43]. In this chapter, the traffic demand volume associated with rapid degradation of reliability is termed the *reliability threshold* and identified through methods of changepoint detection.

The exogenous conditions of transportation networks introduce deep uncertainties for planning applications based on system impact by changes to transportation technologies, policies, environmental conditions, and regional development [37], [72], [73]. The rapid degradation of performance at operational thresholds necessitates the identification and monitoring of system performance. The scope of this chapter includes limited access highway (freeway) transportation networks, which are subject to recurrent and non-recurrent congestion. For context, the demonstration in this chapter includes an analysis of millions of speed and volume observations across multiple years of a geographically diverse region.

4.3. BACKGROUND

This chapter begins with a review of reliability, traffic flow, capacity measures and terminology associated with transportation systems. The abundance of performance metrics and variability in terminology necessitates a review and clarification of reliability measures. While the definition and method of performance measures will vary across planning organizations, there is evidence that a transportation network is vulnerable to adverse performance conditions as traffic volume demand approaches a threshold capacity [26], [71], [88], [109]. The v/c measure is often referred to as level of service (LOS) as described in the Highway Capacity Manual (HCM) and serves as a comprehensive indicator on system operations [26]. The data associated with volume and capacity measures is subject to distinct conditions based on the limitations of data collection methods, current terminology, and the interconnected nature of a transportation network.

4.3.1. Traffic Volume Demand and Capacity Measures

Performance measures require definitions of an operating condition and failure modes within a given timeframe. The operating condition for a limited access highway is defined by the observed traffic volume, often with respect to system capacity. The variability in operating conditions across geographic and temporal domains and the limitations of data collection methods must be considered when referencing vehicle volume and system capacity as the operating condition of the transportation network.

Traditionally, the capacity of limited-access highways has been defined in the HCM as a constant value (around 2,400 vehicles per hour per lane for speeds of 110 km/h) based primarily on the number of lanes [26], [53]. The HCM capacity equation for limited access highways includes parameters for lane width, road geometry, vehicle type (volume of trucks) and others, but is intended as a constant value for a road segment [26]. There are inherent challenges in monitoring capacity reductions from specific disruptions, such as adverse weather, incidents, or construction –

extensive data collection processes are necessary to document events and capacity reductions, which is often cost prohibitive [55], [105].

Current volume data collection technologies capture the observed volume at a stationary location, often with loop detectors and continuous count stations (CCS) [108], [110]. This method faces several challenges when used to represent the traffic volume condition. The volume data collected by CCS is the observed volume, which is notably different from demand volume (how many vehicles are attempting to travel along the roadway). The observed volume by CCS is subject to underrepresenting the traffic conditions caused by an incident, bottleneck, and queuing [60], [111], [112]. For this reason, Chapter 2 references an upper percentile of traffic volume to represent demand and Chapter 3 extends the methods by measuring the volume with the highest KDE [43].

The work by Brilon et al. [71] suggests capacity is stochastic based on a seemingly random nature associated with behavior of travelers and other conditions. This idea of a stochastic capacity is further explored by Shojaat et al. [70] and associated with system failures through a measure they reference as *Sustained Flow Index*. Stochastic capacity considers the foundational terminology of capacity, relating capacity to probability of observed system failure. Instead of a constant value of traffic volume, based on geometric conditions of the roadway, stochastic capacity evaluates observed performance based on demand volume across different time periods [71], [106]. The distribution function is defined by Brilon et al. [71] as shown in (4.1).

$$F_c(q) = 1 - \prod_{i:q_i \leq q} \frac{k_i - d_i}{k_i}; i \in \{B\}$$

(4.1)

where

$F_c(q)$ = distribution function of capacity c
q = traffic volume (veh/hour)
q_i = traffic volume in interval i (veh/hour)
k_i = number of intervals with traffic volume $q \geq q_i$
d_i = number of breakdowns at a volume of q_i
$\{B\}$ = set of breakdown intervals

The metric associated with breakdown or system failure, as referenced in stochastic capacity, requires a definition of both the acceptable operating condition and the failure (breakdown, B) mode. The failure mode of traffic networks is frequently referred to as a transition between two phases: free flow and congested flow [26], [111]. The free flow speed can be calculated as a function of roadway geometry or the speeds associated with ideal driving conditions unrestricted by vehicle congestion (e.g. the 85th percentile speed during low volume conditions) [26], [112]. A three-phase theory of traffic flow considers an intermediate condition of synchronized flow in which vehicle speeds are below the free flow condition but maintain movement without abrupt stops [111], [113]. Synchronized flow conditions are prevalent during peak operating hours when vehicle speeds are below free flow conditions, but the system is still operational [114]. This concept is relevant because it serves as a distinction between system operation (free flow and synchronized flow) and the failure mode (congested flow). The synchronized flow speeds are less than an ideal free flow condition; however, because they can be anticipated during peak traffic periods they are not considered as an unreliable condition from perspectives of enterprise logistics [43], [66], [71], [115]. In this chapter, we address vehicle speeds during recurrent synchronized flow by measuring the speed with the highest KDE during disaggregate time periods and moderate traffic volumes. While the synchronized flow speed may be less than posted or ideal speeds, the speed condition serves as a reference to system reliability performance.

4.3.2. Performance Metrics

The multitude of available transportation reliability metrics is evidence of the challenge in establishing a comprehensive measure of quality. A thorough review by Muriel-Villegas et al. [48] includes numerous classifications of performance metrics and models specific to system reliability. The term *transportation network reliability* is often used to consider how travelers can adapt to recurrent congestion but are disrupted by variable operating conditions. The work by Chen and Fan [46] provides a detailed list of reliability terminology and equations from various perspectives of the transportation industry. Research of reliability practices in Great Britain, Sweden, Japan, Netherlands, and U.S. transportation agencies indicate attention to reliability metrics to evaluate system performance; however, there is often a general dissatisfaction of current reliability measures [27].

The definition and method of these performance measures, specifically a reliability metric, will vary across planning organizations [44], [47]. From a systems engineering perspective, reliability includes: a defined operating condition, a defined failure mode, and a prescribed time scale [56]. In this chapter, we define the reliability of a transportation network as the frequency of an observed deviation from the most probable speed (based on the KDE) associated with a given traffic volume condition during a time of day. This approach overcomes the differences between speed statistics and the anticipated speed. Figure 4-1 is a plot of density and speeds (median, posted, and the maximum KDE), for a three-lane freeway segment across multiple hours of a year.

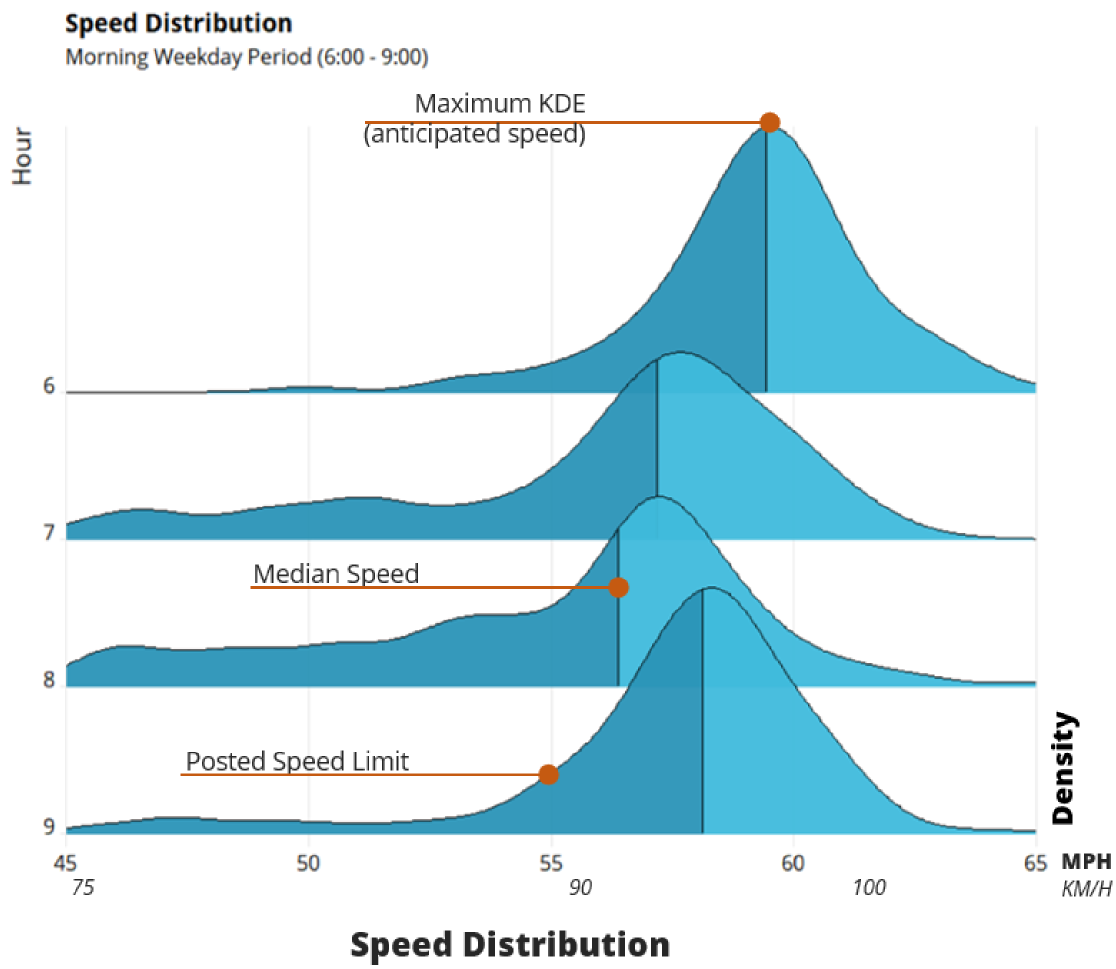

Figure 4-1: Density of speed distribution for a three-lane highway segment from Demonstration (ID07), depicting differences between anticipated speed (maximum KDE), median speed statistic, and posted speed limit across multiple hours.

4.3.3. Threshold Identification by Changepoint Detection

Classic traffic models apply multi-regime linear (broken line) regression models to describe the abrupt change in speed and traffic density patterns [116]. An inherent challenge with multi-regime models is the detection and identification of thresholds, often seeking a balance on model complexity, resolution, scalability and other factors [108]. In traditional traffic methodologies, the Edie model was introduced to improve the single-regime Greenshield's model by using one model for an uncongested state (Greenberg) and a different model for the congested state (Underwood) [111], [113], [117]. Within the context of a three-phase traffic flow theory (uncongested, synchronized, and congested), we use reliability metrics to address conditions of reduced speed during synchronized flow, where performance is reliable but less than free flow speed.

Prior work has successfully applied classification methods to characterize transportation system thresholds based on the operating conditions [59], [98], [118]–[120]. There are a multitude of methods for identifying thresholds; in this chapter we use changepoint detection based on documented success across multiple industries, including intelligent transportation systems [96], [98], [121]. Changepoint detection primarily considers three elements: cost function, search method, and a constraint [120]. The cost function defines the scope of change detection for the input signal. The search method investigates whether the points are discrete (often based on a grid) or continuous. The constraints are determined based on the number of change points, which is intended to balance between detecting too many points (when changes are minimal) or too few points [120], [122].

In this chapter, changepoint detection is applied to reliability measures across multiple states of demand volume. Specifically, we use a statistical programming language to detect the optimal changepoint location based on changes in mean and variance in the frequency of unreliable conditions. This approach provides an efficient method of evaluating changepoint detection across big data associated with transportation systems. In this way, enterprise logistics and transportation planners can monitor and manage the demand volume and schedules associated with time intervals across multiple planning horizons. As noted by Brilon et al. [71], managing highway volumes (e.g. ramp metering) can serve as an effective measure of maintaining a desired operating condition based on the system's performance threshold.

To consider the stochasticity of the transportation system, we acknowledge that it is unlikely that we would observe a universal constant reliability threshold. This approach further acknowledges that enterprise logistics, transportation planners, and vehicle operators can have a different tolerance of unreliable conditions based on context of the local system. In this chapter, we instead identify a changepoint for each geographic location across an aggregated time period (such as one year). Monitoring these changepoints across several years can also inform measures of system performance during exogenous conditions in time periods with disruptions from adverse weather, environmental changes, land development, road construction, or other factors that influence system capacity and demand volume [45], [107].

4.3.4. Considerations for Monitoring Traffic Volume

Traditionally, volume forecasts are developed by transportation planning agencies to estimate future average daily traffic (ADT) and design hourly volume (DHV) conditions. Temporal disaggregation of traffic data has been shown to benefit performance evaluation and traffic planning [59], [65], [123]. Recent U.S. performance metrics have prescribed methods of temporal disaggregation to evaluate and monitor different time periods across multiple years [54]. To apply volume forecasting in context with a reliability threshold, the forecast should consider volume changes at a disaggregated time interval, such as hours, day of the week, months, seasons or others. Anticipated disruptions, such as new land development or hours of construction operations, can be measured against disparate hours of a day and week based on the system's reliability threshold.

Prior to advancements in vehicle data collection, it was not possible to measure transportation network reliability at a regional scale. Transportation agencies have concluded that reliability measures require disaggregate data collection at 15-minute intervals for extended periods of time (several months to a year) [54], [71], [88]. Traditionally, many transportation metrics report and monitor ADT to describe congestion conditions, but the ADT does not describe the variation of traffic volume that occurs throughout a day and week of operations. Acknowledging that transportation agencies are faced with limited resources, it is necessary to consider the cost required to calculate and monitor system performance – complex models and intensive data acquisition places a burden on transportation agencies [29], [40]. Methods of measuring and monitoring performance should be accessible to enterprise and transportation operators.

4.4. Methods

The reliability threshold can be used to assess road networks of a region and, in conjunction with other traffic modeling data, can then be used to monitor the network. This section describes the methods for data processing and identifying the reliability threshold with insights on appropriate monitoring procedures. Figure 4-2 depicts this process.

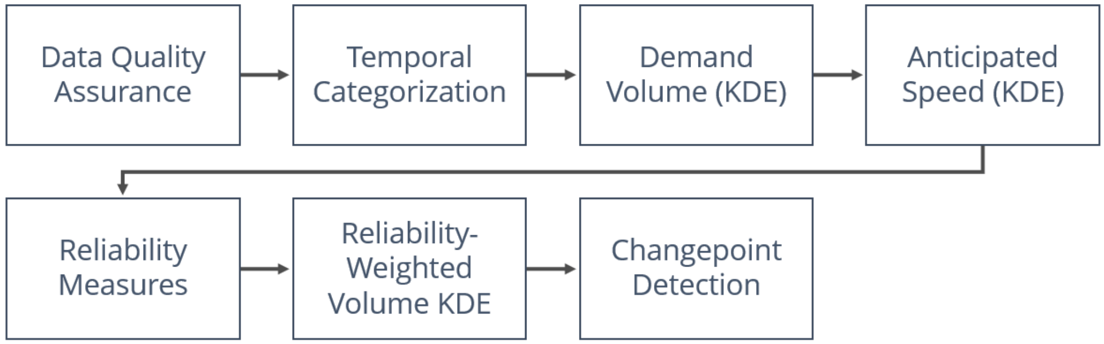

Figure 4-2: Process to identify a reliability threshold that utilizes methods of temporal disaggregation and reference of anticipated operating conditions (by methods of KDE)

4.4.1. Data Collection and Quality Assurance

Transportation systems are inherently comprised of big data, spanning large geographies, continuous operation and dynamic performance conditions. In this chapter, we utilize INRIX probe speed data from the Regional Integrated Transportation Information System (RITIS) [84]. Speed observations are reported at various time intervals and include confidence levels based on the number of observations [84]. Traffic volume data from continuous count stations (or similar systems) provides the data necessary to determine demand volumes at a disaggregate time intervals.

Each geographic location of a regional dataset is evaluated independently and then grouped by an appropriate time interval, such as year, day type (weekday or weekend) and a time of day (e.g., 15-minute intervals). Across a time period, such as a year, the speed and volume data are evaluated to report values with the highest KDE. This approach addresses limitations with data collection systems by representing the most frequent operating conditions. During an incident that reduces capacity and generates queueing, the KDE values serve to represent the demand volume while the data collection system reports the observed volume. The speed value with the highest KDE within each time period represents the speed anticipated by vehicle operators – observed deviations above or below this value (with an appropriate buffer, such as +/- 10%) are classified as unreliable conditions, as previously described in Chapter 3.

The frequency of an unreliable condition is evaluated with context to the observed demand volume for each 15-minute interval. After the data has been processed, the reliability threshold is determined through changepoint detection for each location and each year of data. These methods are based on data collection formats that include location, date and time intervals (15 minutes), speed and volume observations across several years.

Traffic datasets often include a variable to represent confidence of the documented observation based on operating conditions of the equipment. Methods of quality assurance for collected data should be documented, as should technical limitation of the data collection devices and source. Knowledge of special conditions (uncharacteristically severe weather, construction work zones, or others) should be isolated as appropriate.

4.4.2. Temporal Categorization

Data formats are variable and should be systematically categorized based on the appropriate level of disaggregate data. Date and time information of each observation should include separable fields for day of the week, months, seasons, year or other appropriate time period. This process establishes new variables to evaluate performance based on enterprise logistics, such as hours of operations, holidays, delivery schedules, or others. Figure 4-3 is a schematic of this process.

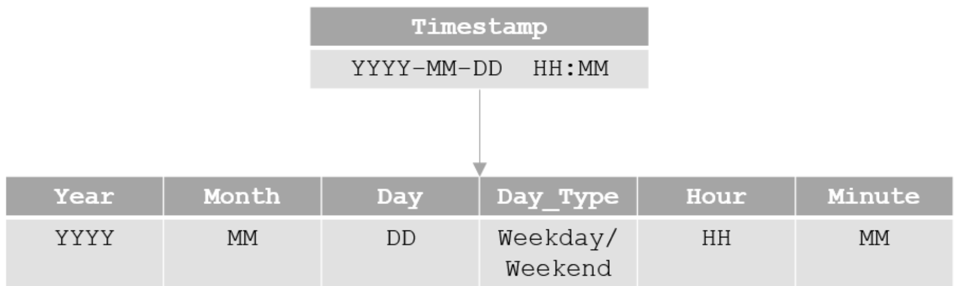

Figure 4-3: Temporal categorization based on variations in performance across temporal domains.

As indicated in the HCM, and other literature, seasonal characteristics should be considered when evaluating system performance. Examples include seasonal changes in hours of daylight, availability of alternative modes of transportation (e.g. bicycles), adverse weather conditions, and others [9], [26], [88]. Availability and aggregation of data collection will influence the appropriate time interval. Prior work indicates that five to fifteen-minute intervals are appropriate when evaluating the influence of an incident on volume and speed observations [55], [70], [71].

4.4.3. Calculation of Demand Volume with KDE

As defined in Section 3.4.2 of Chapter 3, the calculation of demand volume is based on the temporal categorizations, primarily inclusive of day of the week (weekend or weekday) and each fifteen-minute interval across one year of data for each location of interest. When available, the volume of heavy vehicles should be converted to passenger car equivalents (PCE) – methods of calculating PCE values are described in the HCM, which ranges from 1.1 to 7.2 based on terrain and total vehicle volume [26]. Figure 4-4 depicts the KDE of volume for each fifteen-minute interval is calculated, with examples on volume variability across minutes of the day. We associate the volume with the highest KDE as representative of the system demand volume at a given time interval for a day of the week.

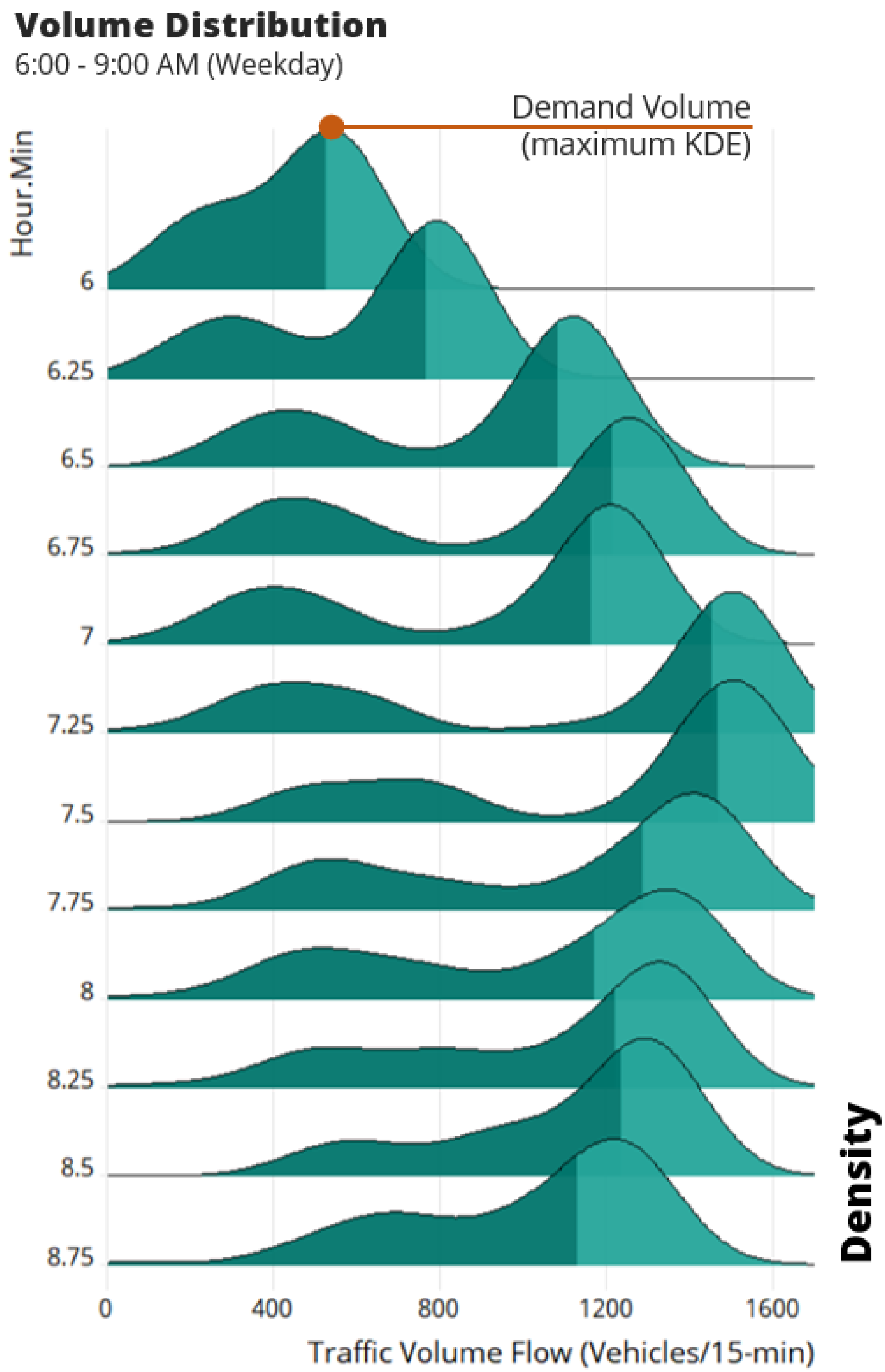

Figure 4-4: Ridgeline plot of density in traffic volume from a three-lane freeway depicting variability in observed volume conditions and location of demand volume, with color difference representing the median volume (Demonstration data ID07, 2016).

An investigation of various volume ranges (based on location and time interval) and bandwidth values will inform the appropriate structure [124], [125]. In this chapter, Silverman's rule of thumb [95] is suggested to set the bandwidth parameter that controls the smoothness. As shown in in Figure 4-4 (Hour.Min values of 6.5, 6.75, 7 and 7.25), road networks that experience high levels of congestions and frequent failure conditions will shift towards bimodal distributions, which should be considered when calculating the system demand volume [57].

4.4.4. Reliability Metric

The speed with the highest KDE represents the condition anticipated by vehicle operators and is calculated within the same time intervals as the demand volume. The considerations given to KDE methods of demand volume are applicable to calculations of anticipated speed, including an evaluation of bandwidth size and trends towards bimodal distributions. Traditional metrics of reliability and delay focus primarily on deviations below a reference speed; however, the reliability metric identified with this chapter measures unreliable conditions based on deviation above or below the reference speed [27], [54]. This approach mitigates bias associated with a network that becomes *reliably bad* as the median or mean reference speed is reduced, and the number of observations below the reference speed diminishes.

The *anticipated speed* used in the reliability metric includes a range of acceptable values, as shown in (4.2).

$$s_a = \{\alpha(s_k) \dots \beta(s_k)\} \tag{4.2}$$

where

s_a = anticipated speed (range of values)
s_k = speed value with the highest KDE
α = buffer associated with the lower threshold (e.g., 0.9 for acceptable speeds above 90% of s_k)
β = buffer associated with the higher threshold (e.g., 1.1 for acceptable speed below 110% of s_k)

The anticipated speed (value with the highest KDE) serves as a reference to monitoring failure conditions for the transportation network. A buffer is established for the anticipated speed (e.g. 10% above or below) to represent an acceptable range of operating conditions. The observation of speeds that deviate from the acceptable range (above or below) are considered unreliable conditions. The frequency of observed unreliable conditions is compared to the total number of speed observations and is associated with the demand volume during the observation period as shown in (4.3).

$$U_i = \begin{cases} 1, & \text{if } s_i \notin s_a \\ 0, & \text{if } s_i \in s_a \end{cases} \tag{4.3}$$

$$\rho_V = \frac{\sum_i^n U_i}{n} \tag{4.4}$$

where

U_i = piecewise function associated with counting unreliable conditions
s_i = speed observation
s_a = anticipated speed (range of values)
n = number of observations for a time interval across temporal domain (e.g., 15-minute interval, one year)
ρ_V = frequency of unreliable conditions, given demand volume of V

4.4.5. Reliability Threshold via Changepoint Detection

The demand volume associated with rapid degradation of reliability (high frequency of unreliable conditions) is defined as the *reliability threshold*. This value can be identified through changepoint detection in the frequency of unreliable conditions (ρ) with respect to the demand volume. All data from an established time period (e.g., year) is aggregated for each location to perform an analysis of changepoint detection. For example, each 15-minute interval grouped by weekdays and weekends would summarize the observations into a set of 192 data points with disparate demand volume observations. Figure 4-5 is representative of the expected relationship between ρ and the demand volume, which is shown with a detected changepoint.

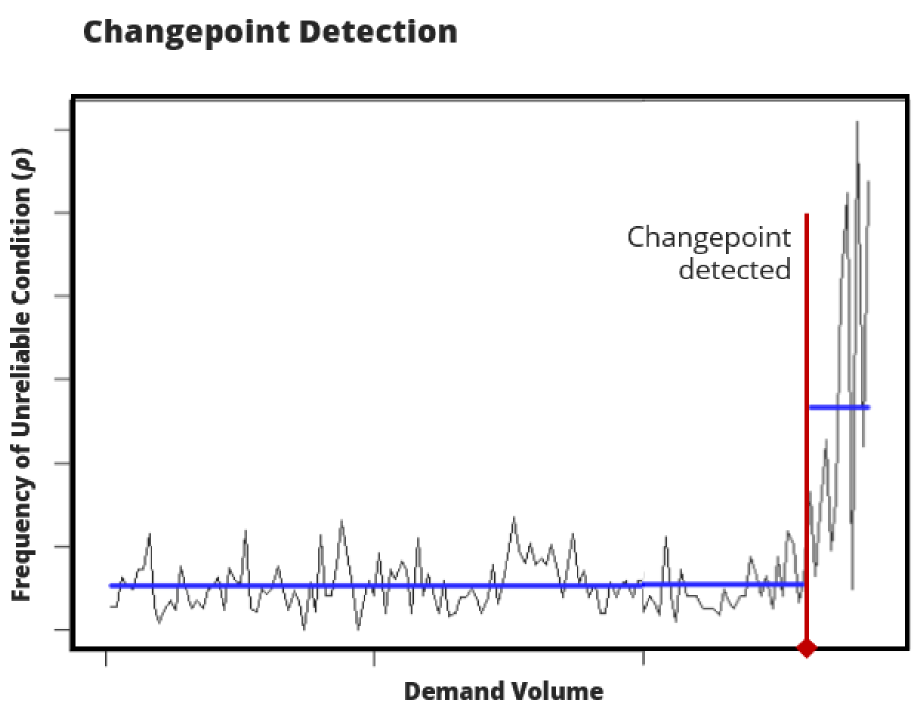

Figure 4-5: Example of changes in the frequency of unreliable conditions based on demand volume (data from Demonstration ID08. 2015)

The calculation of demand volume at each time interval establishes bins of volume observations, which serves as a basis for measuring the frequency of reliability (ρ) associated with each disparate value of demand volume. Changepoint detection is applied to the frequency of reliability (ρ) across demand volumes, evaluated through changes (in mean, variance, or both) with a single changepoint detection method. The general likelihood ratio is traditionally used to test the hypothesis of detecting a single changepoint where the null hypothesis, H_0 corresponds to no changepoints and the alternative, H_1, corresponds to a single changepoint [126], [127]. The relevant values reported with changepoint detection include the location (demand volume) of the change point and the mean of values (frequency of unreliable observations) before (μ_1) and after (μ_2) the changepoint.

Road networks with low daily volumes may return changepoints occurring at an extreme low demand volume. Low demand volumes are often associated with nighttime conditions, which are subject to high incident rates as a result of poor illumination, construction activities, driver imparity, and other factors [128]. To address the conditions of low-volume road segments, a constraint is introduced such that we classify the existence of a reliability threshold if there is a positive change in mean observations of unreliable conditions across the changepoint ($\mu_1 < \mu_2$). Table 4-1 is a confusion matrix to address the classifications.

Table 4-1: Confusion matrix of changepoint classification, based on constraints of positive change in mean.

	Changepoint Detected	**No Changepoint Detected**
True Reliability Threshold	True Positive ($\mu_1 < \mu_2$)	False Negative
True Non-Threshold	False Positive ($\mu_1 > \mu_2$)	True Negative

Changepoint detection algorithms can be assessed on accuracy, sensitivity, and reliability of these conditions in the confusion matrix, as described by Aminikhanghahi and Cook [129]. The penalty value associated with changepoint detection is critical to the results and should be established based on tolerance in the change of frequency in unreliable observations. Specific values and methods are referenced in the Demonstration section of this chapter.

4.5. Demonstration

This section provides a demonstration of establishing the reliability threshold. We refer to the dataset referenced in Section 2.4 of Chapter 2, comprised of almost seven million observations across fifty-five count stations from (2014-2017). Using statistical programming (with R statistical programming language [86], [126]), the collected data was formatted as described in the Methods section of this chapter.

An initial assessment of the dataset provides context to the reliability metrics introduced in this chapter. We deem the frequency of unreliable conditions as the number of observed deviations from the speed with the highest KDE in each fifteen-minute interval of a day of the week (weekend or weekday) for each year. A buffer of 10% (above and below) the speed value is applied to account for acceptable conditions around the anticipated speed. Figure 4-6 depicts a comparison of the anticipated speed (KDE values) and the calculated mean speed. The difference between the anticipated speed and calculated mean ranges from -10 km/h (6 mph) to 21 km/h (13 mph). These differences in speed values signify the importance of establishing an appropriate failure condition. Larger deviations between anticipated speeds and speed statistics are observed with aggregate time data, such as average daily speeds.

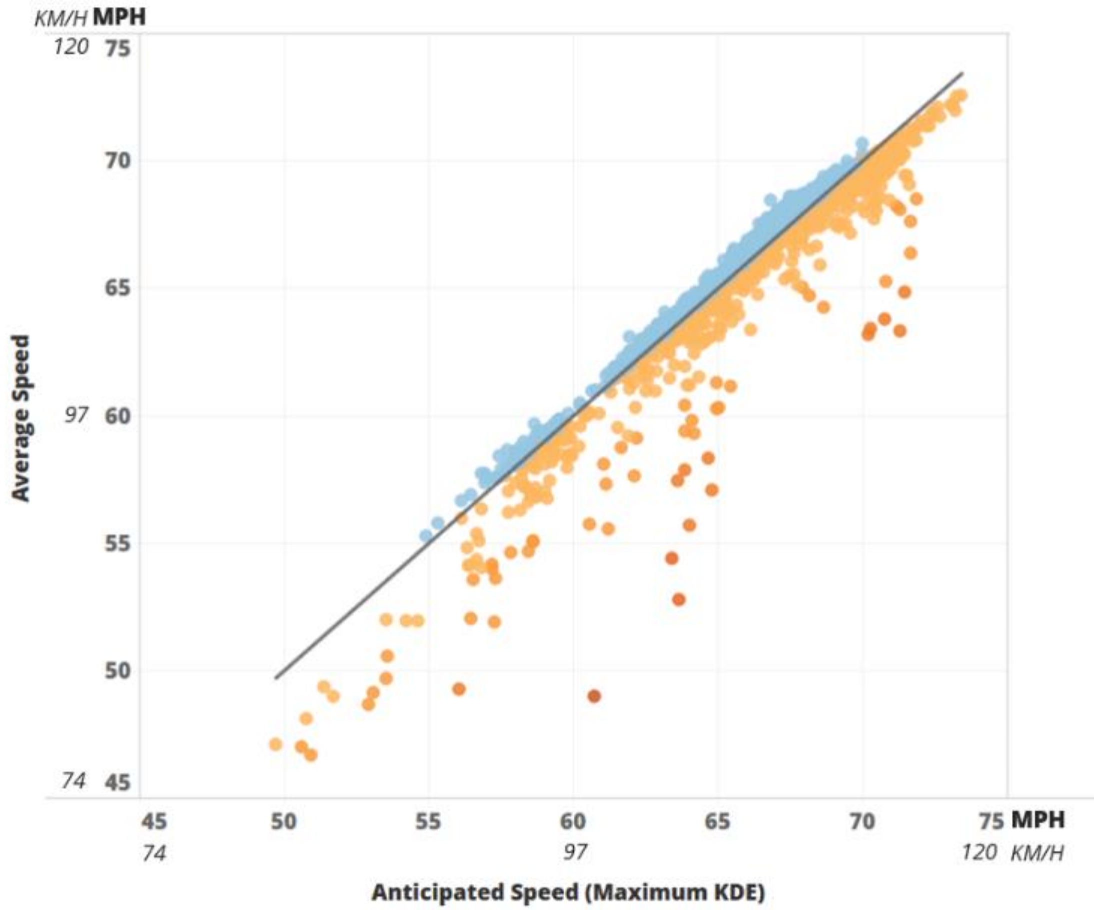

Figure 4-6: Comparison between mean speed and anticipated speed (value associated with highest KDE) to depict importance of selecting an appropriate measure to represent the acceptable system operation metric. A diagonal reference line is shown, and the color indicates the direction and intensity of the deviation.

The frequency of an unreliable condition (above or below the anticipated speed) is computed for each interval and associated with a demand volume. Figure 4-7 depicts the frequency of unreliable conditions, demand volume, and the anticipated speed for two of the road segments of the demonstration dataset (ID08, ID32).

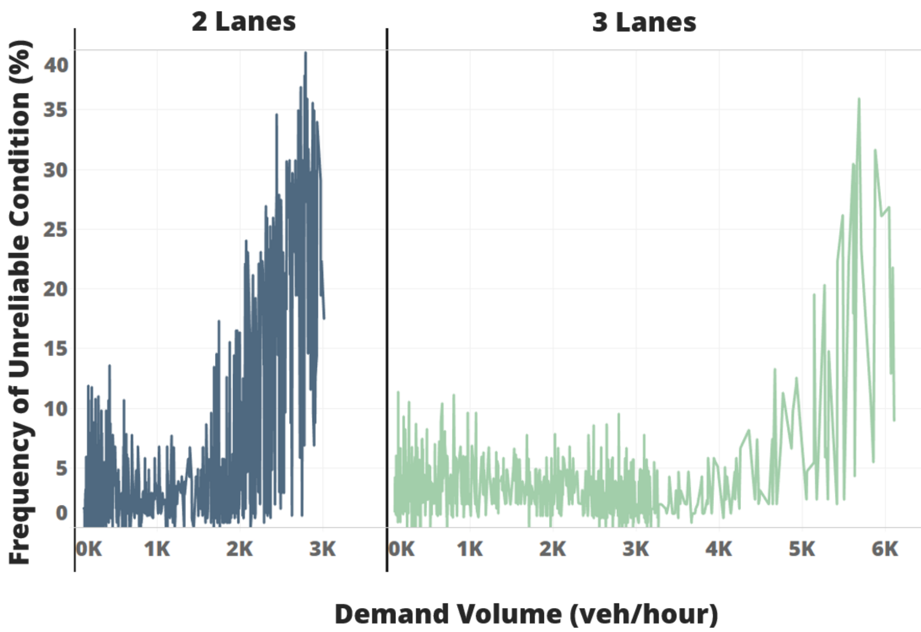

Figure 4-7: Frequency of unreliable conditions compared to hourly volumes for ID08 and ID32.

From Figure 4-7, we observe a rapid increase in the frequency of unreliable observations with an increase in demand volume, which is evaluated through changepoint detection. Compared to the discrete capacity defined by the Highway Capacity Manual [26] for two and three lane segments (4,800 and 7,200, respectively), we observe an exponential degradation of reliability closer to half of that value. The reliability threshold for these two examples was evaluated across each of the four years (2014-2017) with thresholds detected at 2220, 2090, 2050, 1870 (2-lane) and 5270, 4870, 4435, 4240 (3-lane) vehicles per hour. More details on all changepoints are provided in the next section (Section 4.5.1).

4.5.1. Identifying the reliability threshold.

Changepoint detection is applied to all continuous count stations across each year (fifty-five count stations, from 2014-2017) with R statistical programming language and package ‘changepoint’ [126] with a method assignment ‘AMOC’ (at most one change point) on iterations of PELT (pruned exact linear time) and CROPS (changepoints for a range of penalties) to monitor appropriate fitting [99]. Each changepoint analysis is returned with a mean frequency of unreliable conditions before and after the changepoint, which facilitates monitoring system performance and the analysis and detection of false positives (associated with low volume conditions).

Table 4-2 (3 lane highways) and Table 4-3 (2 lane highways) provide results from a selection of road segments, ranked by highest changepoint volume, with information on the reliability threshold (changepoint) and the average frequency of unreliable conditions before and after the changepoint (μ_1 and μ_2). For context, the maximum observed demand volume is provided.

Table 4-2: Selection of locations within demonstration dataset (3 lane highways)

Rank	**ID #**	**Year**	**Reliability Threshold (veh/hr)**	**μ_1 (%)**	**μ_2 (%)**	**Max Vol (veh/hr)**
1	8	2016	5268	3.4	16	6076
2	12	2017	4865	2.9	29	6389
3	12	2016	4721	3.2	26	6419
4	7	2015	4693	3.3	28	6158
5	8	2017	4686	3.9	17	6062
...						
20	4	2014	3058	1.3	9.7	5843
21	14	2017	2392	2.3	4.5	4863

Table 4-3: Selection of locations within demonstration dataset (2 lane highways)

Rank	ID #	Year	Reliability Threshold (veh/hr)	μ_1 (%)	μ_2 (%)	Max Vol (veh/hr)
1	29	2016	2985	1.8	4.2	3001
2	29	2017	2726	1.1	3.5	3070
3	29	2014	2587	1.3	4.2	2802
4	49	2017	2563	2.2	10	2973
5	33	2017	2527	3.1	5.9	2822
…						
30	24	2016	921	1.2	3.9	1986
31	24	2015	843	0.9	3.2	2094

Changepoint detection is applied to all continuous count stations across each year (fifty-five locations across four years of data). Of the 213 datasets evaluated, a reliability threshold (true changepoint) was detected in 21 of the three-lane highways and 31 of the two-lane highways. Five locations were documented with severe congestion with active construction and variable traffic road conditions (lane closures, reduced lane withs, and others), which were subsequently isolated from the ranked analysis in Table 4-2 and Table 4-3. Some locations demonstrated a condition of an emergent threshold, where no changepoint was detected in the early years but appeared in more recent years. Some road segments exceeded demand volumes associated with the reliability threshold of other road networks but did not exhibit abrupt changes in reliability – these conditions warrant further investigation, but initial assessments indicate differences in geometric design (e.g. shoulder width, median type, urban setting, etc.) that influence system capacity.

From the perspective of enterprise logistics, operation schedules are informed by the reliability threshold and system conditions across hours of a day. Figure 4-8 is the relationship between demand volume, frequency of unreliable observations, and the reliability threshold can be evaluated at disaggregate time intervals across days of the week (or other relevant time periods).

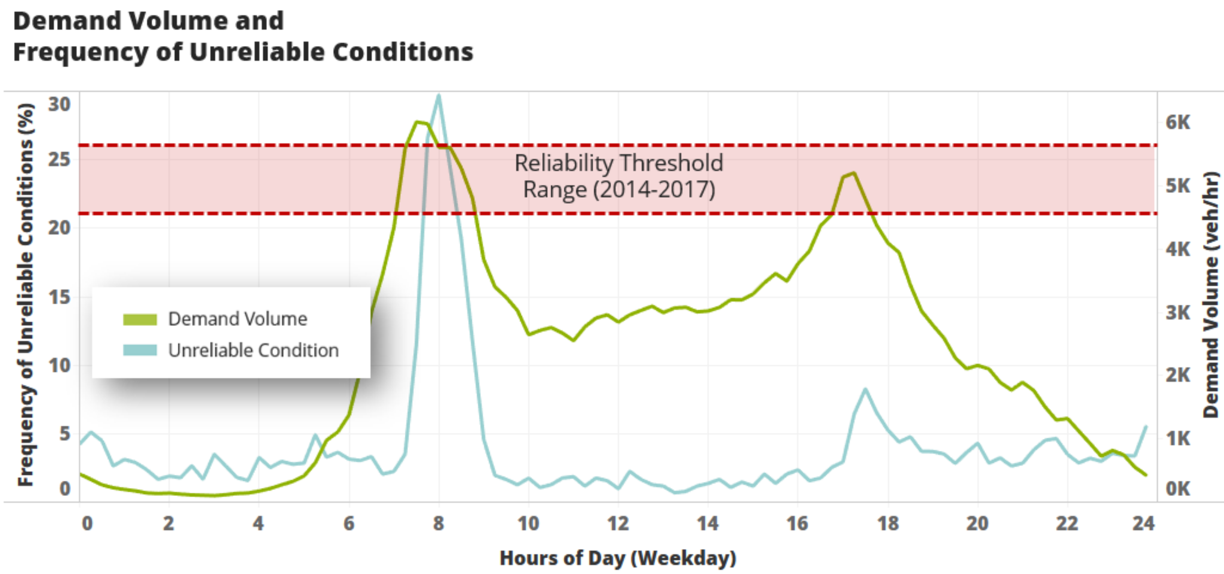

Figure 4-8: Demand volume, frequency of unreliable conditions, and a range of reliability thresholds is shown for one location, based on multiple years of data (ID08, 2014-2017).

Emergent conditions, in which the demand volume for disparate hours of the day begins to approach the reliability threshold, can be monitored based on volume growth across multiple years.

4.5.2. Management and Monitoring Reliability Threshold

The reliability threshold establishes a relationship between the frequency of unreliable conditions and the demand volume. To monitor reliability, an enterprise or transportation operator can investigate the impact of disruptions to volume or capacity of a given network across a timeframe and evaluate when the road segment is expected to exceed the reliability threshold. In Figure 4-9, the variability in demand volume growth is shown by hour and day of the week for one location (ID08).

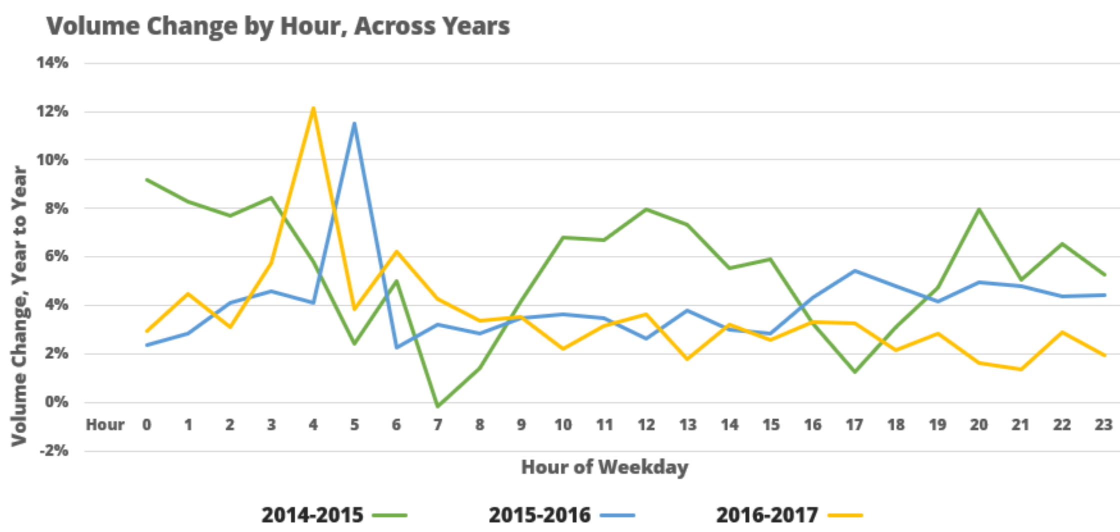

Figure 4-9: Change in demand volume across multiple years for ID08, aggregated by hours of the day and week. Each hour exhibits a different growth rate, which should be considered in operations planning.

Data visualizations of disaggregate performance measures, as shown in Figure 4-8 and Figure 4-9, allow enterprise and transportation operators to investigate trends in the transportation network across hours of the day, day of the week, and years. In this case, there is evidence that several hours exhibit rapid volume growth year over year. Shifts in large growth rates across hours of the day may indicate saturation of the network, where the additional capacity begins to expand across hours of the day.

4.5.3. Review of the Demonstration

The reliability threshold is identified with changepoint detection and frequently observed near half of the road network capacity defined by the HCM. For the three-lane segments, the threshold was observed between 33% and 73% of traditional capacity measures, while two-lane segments varied from 17% to 62% capacity. Intuitively, the capacity of the system is proportionate to the discrete number of lanes; however, traffic models indicate that with one lane of a highway blocked the system operates with 35% capacity for a two-lane road and 49% capacity in a three-lane road [130][26]. The reliability threshold was variable by location and year, suggesting influence by exogenous conditions and concepts of stochastic capacity [71], [106]. The framework for identifying a reliability threshold can support multicriteria evaluation by investigating multiple reliability metrics (or the sensitivity of parameters), which can inform logistics and prioritization of investments [29], [40], [87]. Additional levels of temporal disaggregation, such as months of a year, can be evaluated with context of seasonal enterprise logistics.

4.6. Summary

Time periods with demand volumes approaching the reliability threshold will inform enterprise logistics and transportation planning. A threshold based on demand volume considers traffic management solutions that emphasize metering vehicles entering the road network in lieu of solutions that focus on adding capacity (additional lanes) to the system [55], [71]. As described by Sohrabi et al. [106], similar volume-centric frameworks benefit from methods of determining optimum traffic flow conditions associated with the survival rate (frequency of reliable conditions) for a road network. Monitoring the reliability threshold across several years may uncover deterioration of system infrastructure and rapid emergence of performance issues with vehicle volume growth. When managing and monitoring system performance it is necessary to consider how changes in demand volume across hours is influenced by new disruptions to disparate time periods, such as new centers of traffic demand that increase vehicle volume during peak operating hours [20], [28], [72]. Evaluating data at a disaggregate level informs vehicle operators on accessibility of other transportation modes during times of adverse performance.

This chapter has developed methods of managing and monitoring operations reliability thresholds based on stochastic demand volumes to support enterprise logistics and transportation planners. The methods extend prior models with analysis of disaggregate speed and volume data. Methods of KDE are used to address technical limitations of speed and data collection devices to represent anticipated speeds from the perspective of travelers. Evaluating the anticipated conditions, through KDE, also acknowledges periods of synchronized flow during peak traffic times as an operable and predictable mode of the network. Changepoint detection methods are demonstrated to identify a reliability threshold, which can be used to manage and monitor system performance.

The abrupt transition of reliability observed in the collected data concurs with traditional traffic models that identify a rapid decrease in vehicles speeds near capacity thresholds. The rapid degradation of performance is an indication of the challenges associated with managing the quality of road segments. Methods of traffic volume growth projection and planning can consider the reliability threshold associated with disparate hours and days to identify the decreased performance conditions across a temporal domain (e.g., new time periods begin to exhibit a high frequency of unreliable performance). The reliability threshold was observed near half of the road network capacity defined by the HCM. The threshold was variable by location and year, suggesting influence from exogenous conditions such as adverse weather, driver behavior, special events, and inherent randomness with traffic incidents.

The methods in this chapter provide transportation planners with information to anticipate and prepare for reliability improvements before reliability is problematic. The abrupt change in reliability performance is identified through changepoint detection and other time intervals can be monitored for emergent conditions based on projections in traffic volume. Analysis of disruptions, such as travel holidays, special events, severe weather, global pandemics, road work, etc., can serve as specific measures of reliability analysis. Monitoring the reliability threshold across large temporal domains, such as months or years, considers robustness of the network. The reliability threshold can incorporate various scenarios that influence volume, capacity, or the timeframe. For example, new distribution facilities could significantly increase demand volume of heavy vehicle traffic during peak periods. Proposed changes to working hours could shift the time period of commuter vehicles. Changes to the frequency or intensity of adverse weather could reduce the reliability threshold of the road network. These scenarios are some examples of how enterprise operators and transportation planners could use the reliability threshold to inform logistics.

Scenario-based planning has been successfully applied to the prioritization of operational investments – the methods identified in this chapter will support evaluating performance conditions based on system disruptions, such as traffic volume growth, capacity reductions from adverse weather, new transportation technologies, and others [4], [37], [73], [131]. Scheduled disruptions with measurable durations and capacity reductions, such as temporary traffic controls that reduce lane width and speed, can be investigated to evaluate the effect to system performance and reliability. Emergent and future disruptions are subject to deep uncertainty and benefit from appropriate performance measures, such as the reliability threshold, to support enterprise logistics and transportation planning. Chapter 5 describes methods of spatial and temporal association to monitor and manage performance of transportation networks.

5. Regional Evaluation of Operations Disruptions

5.1. Introduction

Transportation planning for highways is informed by performance metrics with aggregated data that can obfuscate the uncertainty of performance conditions across hours, days and weeks. Prior chapters have referenced a dataset from a set of continuous count stations; however, recent advances in probe vehicle data collection methods provide disaggregated speed data at a regional level, spanning millions of miles of the transportation network at a global scale. Based on the methods of corridor trace analysis (CTA), this chapter extends the framework through temporal disaggregation of highway performance metrics, classified as a temporal corridor trace analysis, t-CTA. This approach introduces a temporal weight and temporal value associated with observed performance during discrete time periods. The temporal value allows stakeholders to address uncertainty in logistics and scheduling, adjusting the significance of a performance condition based on when adverse performance is observed. A demonstration of this approach is provided for a limited access highway and principal arterial road network, with implications of national planning initiatives from multiple perspectives.

5.2. Motivation

The cost of traffic congestion is well documented; however, the definition and value of congestion is variable across stakeholders [16], [72], [77], [132]. Performance metrics are used by transportation agencies in the prioritization of transportation improvements, evaluations on the benefits of an improvement project, identification of improvement needs, funding allocation, and project selection [4]–[6]. With limited resources, agencies refer to performance metrics as a quantitative evaluation that informs regional planning decisions. In a large-scale system, such as a transportation network that spans millions of miles, geographies, demographics, and modes, the analysis of performance metrics requires methods that investigate multiple objectives (e.g., mobility, accessibility, economic development, land access and others) [20], [28], [72].

There are a multitude of transportation performance metrics that investigate conditions such as a travel time reliability, level of service, number of disruptions, hours of delay and others [40], [47], [54]. The use of performance measures varies by transportation agency, with many agencies using several different measures to monitor system performance. The results of these analysis are often portrayed on maps using geographic information systems or other formats that depict the geospatial association of the system elements [133], [134]. As an interdependent and complex system of systems, the analysis of a transportation network must consider multiple performance criteria and perspectives [101]. An additional challenge of the transportation network is the variability of operating conditions across hours and days throughout the year. This variability, and the associated transportation purpose, requires performance evaluation through temporal disaggregation.

5.3. BACKGROUND

As introduced by Thekdi and Lambert [28], a *corridor trace analysis* (CTA) provides a framework for comparing multiple metrics of a transportation network [29]. The CTA framework was developed to supplement transportation planning maps by simultaneously depicting multiple performance metrics across a geographic region. The CTA provides both visual and quantitative methods of comparing different criteria. This method has proven to be accessible to transportation planners that seek to evaluate large geographic regions and multiple performance metrics [87]. Figure 5-1 is a schematic representation of CTA with a set of n criteria (c) are depicted as straight-line diagrams across a series of i number of geographic locations (Location ID of segments, Z), where the locations are formatted in a spatial order.

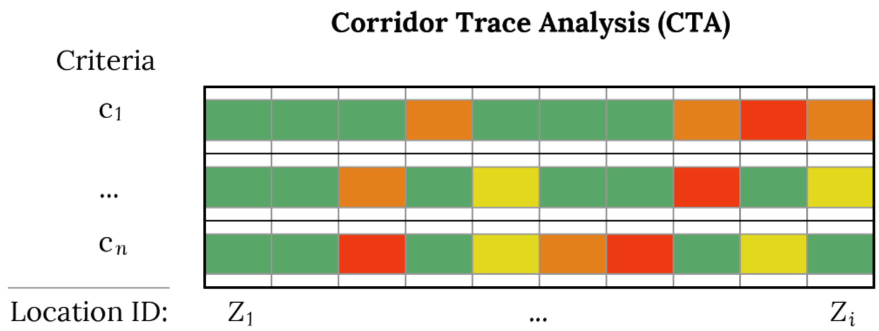

Figure 5-1: Schematic of corridor trace analysis (CTA) providing a visual evaluation of multiple criteria along a corridor system, where the range of ideal (green) to adverse (red) conditions are shown with color ranges. The CTA can be developed with a variety of charts based on criteria evaluations.

In prior work, the multicriteria analysis and CTA have been used to identify transportation networks that are vulnerable to factors such as land development, safety, environmental change, and the movement of commodities by evaluating a set of metrics [28], [29], [74]. Initially developed as a method of visual analysis, the CTA framework was extended by Alsultan et al. [87] to include weight assignments for each criteria (w_c), such that ($\sum w_c = 1$). These criteria weights may be assigned by perspectives from multiple stakeholders, to establish a multicriteria function with a weighted sum. For example, the metric of *number of crashes* may carry a larger weight than the *hours of delay* observed within a transportation system.

Alsultan et al. [87] include a rating value (R_c) based on classifications of each criteria, such that low, moderate and high correspond to different numeric values. This condition acknowledges that some measures may carry an exponential or categorical weight. For example, the access point density (access point/mile) had classifications of ten or less, ten to forty, and more than forty for the low, moderate, and high levels. Classification methods, such as change pointe detection (noted in Chapter 4) and Classification and Regression Trees (CRT), have been used to establish appropriate categories and cutoff values for criteria [96], [135]. Professional experience and stakeholder input can serve to establish rating values and appropriate breakpoints.

The final score of each project initiative is based on the sum of criteria weight and associated score ($S = \sum w_c * R_c$). The score informs transportation operators of road segments that warrant investigation, often categorized in percentiles to manage resources when monitoring a large transportation network [87].

5.3.1. Cost-Benefit Analysis and Deep Uncertainties

Identifying risks and assigning rating values and criteria weights informs traditional cost-benefit analysis used by transportation agencies. In transportation planning, the cost-benefit analysis evaluates projects by estimating the monetary values of project costs (construction, planning, design, maintence, and others) as compared to the benefit [40], [79], [136]. Monetary values of benefits can be ambiguous, as multiple criteria such as safety, social wellbeing, environment, and other factors are more often represented in noncommensurate units, which is further complicated by how the values can vary by different stakeholder perspectives [101]. The cost-benefit analysis is referenced in this work because it is prevalent across the transportation agency and well-studied.

In systems faced with uncertainties, Alsultan [87] provides a thorough review to several works by others. Farrow [137] identifies the variability and uncertainty inherent to risk within the context of environmental and public health issues through cost-benefit analysis informed by risk assessment. Within the context of transportation planning, Xu and Lambert [77] describe a framework for multicriteria analysis and cost-benefit analysis when evaluating project prioritization of highway access management. The use of upper and lower ranges of uncertain costs and benefits provides a useful method of setting priorities, as referenced in Section 3.5.1 of Chapter 3. The priorities are meant to inform resource allocation where additional studies are warranted and does not prescribe a selection process from the quantitative framework. Absent of specific countermeasures and cost estimates, this chapter implements methods of *value* associated with different time periods. Uncertain of specific operating conditions (traffic volume, cargo, number of travelers) or origins and destinations, a value function is informed by knowledge of regional operations to emphasize critical time periods (e.g. morning and evening rush hours based on direction of travel).

5.3.2. Temporal Disaggregation

Traditional transportation performance metrics (including the CTA method) report aggregated data, using annual average daily traffic (ADT) statistics; however, the volatile nature of urban transportation systems across the day and week benefits from temporal disaggregation of data [36], [65], [138]. Prior work by Dutta and Fontaine [65] has demonstrated the benefits of disaggregate speed data when evaluating safety of limited-access highways. Travel time reliability metrics from U.S. Federal Highway Administration have prescribed temporal disaggregation based on distinct time periods throughout a week (morning, midday, evening, weekend, and nighttime) [54]. Recent advances in speed data collection have provided new opportunities for data sciences of transportation networks.

The selection of applicable performance metrics are determined by the transportation agency and stakeholders and vary by agency [4], [47]. Traffic analysis tools for speed observations include metrics such as delay per mile, hours of delay, travel time index, planning time index, buffer index, number of rush hours, misery index and others [29], [47], [139]. With a variety of available metrics, the CTA framework allows each stakeholder to develop an analysis tailored to measures of interest. The temporal disaggregation of these metrics informs transportation operators of when the performance conditions are observed throughout a day or week.

The prior CTA framework is extended in this chapter to investigate multiple performance metrics with an innovation of evaluating temporal disaggregation of data. The temporal component of performance metrics influences the weighted values to further inform stakeholders on segment performance conditions. For example, two road segments may experience the same number of delays, but a greater weight may be placed on delays observed during rush hour time periods compared to nighttime to consider the traffic volume affected by disruptions. Similarly, disruptions that occur during the nighttime may benefit from a different countermeasure compared to disruptions during midday time periods.

5.4. Scope of Work

The method of regional temporal disaggregation is made possible by recent advances in data collection technologies. Extending upon the prior framework, this chapter introduces temporal variables to CTA to account for variability in traffic operations throughout the hours, day and week. This approach establishes a temporal corridor trace analysis (t-CTA) and is demonstrated on a series of road segments across a diverse geographic area in Virginia, USA. The selected unit of temporal disaggregation (hours, days, months) can be modified to investigate planning goals from different stakeholders based on criteria of safety, mobility, environment, economy, and others. The disaggregate speed data focuses on when adverse performance conditions are observed.

5.5. Methods

To achieve the scope of work identified in this chapter, the details of the t-CTA framework and methods are provided in this section. As with traditional CTA, a set of (performance) metrics are established with assigned weights based on the relative importance of each metric to a stakeholder. Each set of criteria, and the associated score ($\sum w_c * R_c$) is evaluated for each time period p within a temporal domain T (e.g. days of a week). A new value, v, of each time period p is defined by an additional score set to account for stakeholder perspectives on the typical volume of traffic, vehicle occupancy, traveler destination, and other factors. This approach modifies criteria scoring framework from the traditional CTA based on when the performance condition is observed. The evaluation of a corridor is presented through data visualization and quantitative values, which provides an accessible method for scanning large geographic regions to identify the location and ranges of adverse performance conditions, evaluated in each time period.

5.5.1. Minimum Requirements of the Dataset

The methods of establishing a t-CTA requires a data source with location identification, date, time, and speed. As prescribed by current U.S. measures of delay and reliability, the data should be available at an interval of 15 minutes (or less), which may be available through continuous count stations (CCS) or probe data analytics (PDA) available from Regional Integrated Transportation Information System (RITIS), which includes INRIX speed data [54]. Comparing multiple road segments based on traffic volume conditions can be achieved by evaluating volume data of local CCS or disaggregating ADT values using k-factor and institutional knowledge of regional traffic patterns. The temporal disaggregation allows transportation agencies to adjust the weight of performance criteria based on the qualitative value of a given time period. For example, enterprise logistics would seek to prioritize the morning rush hour of road networks towards the major work centers. Retail centers may place a higher value on the weekend or evening time periods.

Road characteristics, such as the number of lanes and road classification (e.g., limited access highway) should be documented. Transportation system factors, such as operational hours of public transit, access point density, land use and trip generation, and others should be considered when establishing the system evaluation.

5.5.2. Framework of t-CTA

The extension of CTA, described in this chapter, assigns different weights across a temporal domain. Absent of disaggregated traffic volume data, this approach considers how the value of different time periods will vary based on operational conditions and traveler perspective across the hour, day, week, or month of the year. When disaggregated traffic volume is available, the vehicle count and type can influence the relevant criteria, weights, and time period. The application of criteria weights (w_c) associated with CTA is carried over to the t-CTA methods to reference road and operational characteristics. The criteria weights may be modified for each time period, based on the relevant performance criteria during different operational conditions.

The original criteria weight variable (w_c) from CTA is extended with a temporal weight of a time period (τ_p) in t-CTA, which corresponds with a time period p and proportion of time assigned to a temporal domain (T). The temporal domain and time periods are defined as shown in (5.1), with the temporal weight determined by (5.2).

$$T = \{t_1 \dots t_p\} \tag{5.1}$$

where:
T = the temporal domain, comprised of multiple time periods (t_p)
t_p = disparate time periods of a temporal domain (e.g., hours of a week)

$$\tau_p = \frac{t_p}{\sum t} \tag{5.2}$$

where:
τ = temporal weight of time period t_p proportionate to all time periods in T

For example, current travel time reliability (TTR) metrics begin with speed observation data at 15-minute intervals and aggregate data into five distinct time periods across a single week, as prescribed by the Federal Highway Administration [54]. Table 5-1 summarizes the time periods.

Table 5-1: Assignment of five time periods and the referenced hours and days of the week, as defined by FHWA reliability performance measures

	Time Period	Time	Days of the Week
1	Morning	06:00 – 10:00	Monday – Friday
2	Midday	10:00 – 16:00	Monday – Friday
3	Evening	16:00 – 20:00	Monday – Friday
4	Nighttime	20:00 – 06:00	Monday - Sunday
5	Weekend	06:00 – 20:00	Saturday and Sunday

This aggregation format corresponds to a temporal domain for one week ($\sum t = 168$) for each of five time periods T={t_1:t_5} with a proportionate scale. The Morning time period (t_1) includes four hours, five days a week, or $\tau_1 = 20/168$ (0.12). Similarly, the Weekend (t_5) includes fourteen hours, twice a week, for $\tau_1 = 28/168$ (0.17). A stakeholder may establish a temporal domain across different months of year, or different hours of a single day. Subsets of time periods may also be warranted, such that the five time periods of a week could be evaluated across different months of the year. The selection of time periods should be considered by factors such as seasonal changes, changes in traffic flow, peak hours of commodity transport and others.

A temporal value (v_p) variable is introduced to represent perceived value of each time period p across the temporal domain. The proportionate values should be constrained such that ($\sum v = 100$). Assigning values to each time period should consider parameters such as number of travelers or amount of cargo during a time period and will influence the temporal value. The temporal values follow a similar structure to criteria weights of CTA. The estimates of vehicle volume, including passenger occupancy and travel type (business or personal), are determined by local professionals with knowledge of typical traffic operating conditions. These estimates are informed by local and regional traffic data collection using ADT and traditional practices such as k-factors [11]. The volume and occupancy estimates influence the weight of each time period. The temporal value associated with traffic conditions can also be informed by other data collection methods, such as GPS technologies, that provide insight of vehicle classifications and volumes [57], [140].

The value of a time period should consider economic perspectives of value, often referred to as the *value* of *travel time*, which has been studied immensely within transportation planning [67], [83], [132]. As defined by traditional cost benefit analysis, the unit of measurement is often a monetary amount (USD) per person-hour. As an example, the U.S. Department of Transportation [67] estimates that the value of business travel is more than twice that of personal travel. From a cost perspective, the values are developed based on local income characteristics and consider the estimated vehicle occupancy [67]. From economic perspectives, the value of time is often associated with cost estimates tied to income demographics; however, value is ultimately determined by stakeholders [23]. In a complex system of systems, such as transportation, a multitude of stakeholders will express various perspectives of value [101]. The temporal rating is subjective and will vary by individual stakeholder perspectives. As indicated with prior work of criteria weight assignments, the sensitivity of the assigned weights should be evaluated and monitored [87], [136], [141].

The assignment of temporal value (v_p) is based on procedures determined by a transportation agency and involvement by multiple stakeholders. When evaluating regional infrastructure systems, aggregated traffic volume data, such as ADT, should inform the assigned value based on traffic volumes for different road segments. These will also vary for different directions of the same road network based on regional traffic patterns. Table 5-2 provides temporal ratings (v_p) for a conceptual highway network for the route into a city center and away from a city center based on time periods throughout a week. In this example, a larger value is assigned to the morning route into the city to represent the rush hour commute volume and business category of travel type, which is reversed for the evening condition away from the city.

Table 5-2: Example assignment of temporal values for different routes connecting a city center

Time Period	Route Towards City (v_p)	Route From City (v_p)
Morning	40	10
Midday	10	10
Evening	10	30
Nighttime	10	10
Weekend	30	40
$\sum v$	100	100

Table 5-2 is intended to represent an example of priority and value and transportation accessibility of travelers and transport of commodities in route to employment centers. The temporal value assigned to each time period would change based on the perceived value of a stakeholder. For example, freight and distribution centers may place an emphasis on the midday or nighttime travel conditions as determined by peak hours of truck traffic. Stakeholder bias and sensitivity to the value assignment should be monitored, as is required for subjective system appraisal [142]. As explored through risk analytics, the most robust systems and decisions include multiple perspectives and objectives [18].

The total score for each road segment (or project initiative scope) is calculated by temporal weights and value with each set of criteria weights and rating value from CTA. For a set of i project initiatives for various corridor segments (Z) such that Z = {z_1,…,z_i} defines a set of multiple corridors and initiatives, the numeric score S of each initiative is defined in (5.3).

$$S(z_i) = \sum_{p=1}^{m}(\tau_p * v_p) * \sum_{c=1}^{n}(w_c * R_c) \tag{5.3}$$

where:

$S(z_i)$: the total score of a project initiative, i for the corridor segment z
τ_p : temporal weight τ, for time period p within a set of time periods m
v_p : temporal rating value v, of time period p within a set of time periods m
w_c : weight, w, of a criteria c, within a set of criteria n
R_c : rating value R, of a criteria c, within a set of criteria m

This approach considers the temporal value of each criteria based on value assignments of traffic volume and travel type during the observed performance condition of each criteria. An evaluation across disparate time periods provides opportunities to modify criteria, weights, and value based on transportation planning goals.

5.5.3. Data Processing

To develop the t-CTA, the speed data is processed as described in this section. The use of computer programming languages and software provides for efficient data processing (specific methods are described in the Demonstration section of this chapter).

1. **Selection of Metrics:** Stakeholders will select a series of performance criteria based on measures of interest and available data. The criteria should have a weight (w_c) assigned. Each criteria performance metric is calculated per regulatory requirements.

2. **Criteria Rating:** Quantitative and qualitative metrics are used to assign a rating value (R_c) to each criterion. These ratings can use categorical scores such as low, moderate, and high (as noted with prior CTA methods) or other scoring systems.

3. **Temporal Weight**: As determined by stakeholders, the temporal domain (T) with m number time periods, such that temporal weights (τ_p) of each time period p are calculated by relative duration.

4. **Temporal Value:** Based on institutional knowledge of traffic patterns and stakeholder interests, as supplemented by other available data collection methods, each time period will have a temporal rating assigned (v_p) that corresponds to the time period p. These values should be informed by multiple stakeholders to represent both cost and value of system performance.

5. **Total Score:** Each road segment is assessed by performance metric criteria and temporal values, such that all disaggregated data is computed for a final assessed score, S for each infrastructure initiatives of a set of roadway corridors.

Data analytics focus on the relationship between the performance metrics and temporal association. The total score is not meant as a final determination of priorities, but rather a comparative evaluation of ranks across multiple initiatives that informs transportation agencies of segments that warrant additional investigation. The score also provides a robust method of monitoring performance with multiple criteria and disaggregated data analysis.

5.5.4. Data Visualization Considerations of t-CTA

The data processing for t-CTA provides a tabular output of the variables for each corridor segment across the designated time periods. A foundational element of CTA is the data visualization, which provides an accessible method of communication to transportation agencies, community members, and other stakeholders. Within the civil infrastructure industry, data visualization has been shown to benefit the planning stage and performance and progress monitoring [143], [144]. The production of visualizations, especially for large data sets across multiple geographies, requires careful considerations of human factors and communication. For example, the format and color association of performance charts should be uniform such that an observer can easily distinguish between adverse and ideal performance conditions along a corridor. The axis depicting location information (often through mile markers or traffic message channel, TMC) of t-CTA should be supplemented with contextual landmarks, such as major cities, district lines or other recognizable features. There is no prescribed method provided in this chapter, but data visualization is identified as a critical feature of communicating system performance and priorities with t-CTA.

5.6. Demonstration

This section provides a detailed example of the t-CTA methods introduced in this chapter. The data used in this demonstration is collected through INRIX probe speed data from the Regional Integrated Transportation Information System (RITIS) [84]. This demonstration includes an evaluation of two different corridors: Interstate 66 (I-66), a limited access highway; and U.S Route 50 (US-50), an urban arterial corridor. The methods for developing the t-CTA are identical for each demonstration corridor, but the analysis of the results varies. An evaluation of the limited access highway should consider spatial aggregation – identifying a significant corridor length and adjacent segments that can be improved from major infrastructure investments. Evaluating the urban arterial can identify locations where spot improvements are warranted by improving access management or intersections. Both corridor segments are located in the Washington DC Metropolitan region in Northern Virginia USA. This region is consistently documented as one of the most congested areas in the U.S., which provides for a relevant demonstration [145]. Table 5-3 includes summary statistics for the demonstration corridors.

Table 5-3: Summary of demonstration corridor characteristics

	I-66	**US-50**
Road Classification	Interstate, limited access highway (uninterrupted flow)	Principal arterial (interrupted flow)
Demonstration Length	121 km (75 miles)	32 km (20 miles)
AADT	74,000 – 150,000	32,000 – 72,000
Lanes in Each Direction	Varies (2-4)	Varies (1-3)
Lane Management	High Occupancy Vehicle Lanes (various times)	None
Access Management	Interchange	Controlled and uncontrolled intersections, interchange at interstates

The two corridors follow similar alignments between a western rural region to the east Washington DC Metropolitan area. From west to east there is an increase in traffic volumes, population density, land development access points, and number of lanes. This corridor has a measured ADT (listed in Table 5-3) as documented by the Virginia Department of Transportation [146]; however, absent of disaggregated volume data the t-CTA provides methods of assigning weights and values to disparate time periods associated with institutional knowledge of operating conditions.

5.6.1. Detailed Methods of Demonstration

The statistical programming language, R, was used with the software package RStudio [86] for efficient data processing of millions of observations from INRIX probe speed data. The collected data (millions of observations) was formatted as described in the Methods section of this chapter. The 15-minute observation data was aggregated to five time periods (morning, midday, evening, night, and weekend) as prescribed with other FHWA metrics [54]. Data collection was supported by VDOT's Pathways for Planning (P4P), an interactive mapping and data analysis web-based transportation planning tool [147]. For this demonstration, performance criteria were selected based on local planning criteria and metrics evaluated with the FHWA Urban Congestion Reports: frequency of congested hours, travel time index (TTI), planning time index (PTI) and travel time reliability (TTR) [148].

A summary of the selected performance metrics used in this demonstration are included herein for reference, as defined by FHWA [54]:

1. **Frequency of Congested Hours:** Number of observed observations with speeds below 95% of the FFS compared to the total number of observations as frequency of congested hours (FCH).

$$C_i = \begin{cases} 1, & \text{if } s_i \leq 0.95 \times FFS \\ 0, & \text{if } s_i > 0.95 \times FFS \end{cases}$$

$$FCH = \frac{\sum_i^n C_i}{n}$$

(5.4)

2. **Travel Time Index (TTI):** Ratio of average travel time ($\overline{TT}$) compared to free flow travel time ($FFTT$).

$$TTI = \frac{\overline{TT}}{FFTT}$$

(5.5)

3. **Planning Time Index (PTI):** Ratio of 95th percentile travel time (TT_{95}) compared to free flow travel time ($FFTT$).

$$PTI = \frac{TT_{95}}{FFTT}$$

(5.6)

4. **Travel Time Reliability (TTR):** Ratio of 80th percentile travel time compared to median travel time

$$TTR = \frac{TT_{80}}{TT_{50}}$$

(5.7)

The calculated free flow speed (or free flow travel time) is determined by the 85th percentile travel time during uncongested hours [6]. For limited access highways the free flow condition may also be measured as the travel time associated with 96km/h (60 mph) speeds. This demonstration references the 85th percentile condition for US-50. For I-66, the higher of the 85th percentile condition or 96km/h (60 mph) speed is used. The free flow speed is calculated for each road segment of the corridor based on yearly statistics. Within the calculations of this demonstration, the harmonic mean speed (reported with each observation) is used in lieu of travel time values to assist in comprehension of reported performance conditions for heterogenous road segment lengths.

Each of the performance criteria is assigned a weight (w_c) and point (R_c) system, which provides a quantitative method of comparing corridor segments. In this demonstration, the four performance metrics are assigned equal weights. Each point represents an adverse condition based on performance metric criteria, indicating that the segments with the highest point score are performing the worst. Table 5-4 provides a reference of each performance metric, assigned weight, and a point system assignment that was established by subjective assessment of transportation professionals (the point system is expected to vary by transportation agency). The TTI, PTI and TTR have a base ratio of 1.0, so the calculated R value subtracts 1.0 from the ratio.

Table 5-4: Example of performance metric criteria weights and scores.

	Units	w_c	R_c **Point**
Length	km	-	-
Delay Frequency	unitless	25%	ratio
TTI	unitless	25%	ratio - 1
PTI	unitless	25%	ratio - 1
TTR	unitless	25%	ratio - 1

In this demonstration, the point system for each of the performance measures, TTI, PTI, and TTR are scored based on the calculated value greater than one. These values are then adjusted by criteria weights (w_c). For example, if a TMC has performance measures of 0.3 as frequency of delay, 3.7 TTI, 2.0 PTI and 1.6 TTR, the computed score is (0.3 × 25% + 2.7 × 25% + 1.0 × 25% + 0.6 × 25%) equal to 1.15 points. The length of each segment TMC provides a geometric scale to the segment, which can be used in cost-benefit analysis to estimate the infrastructure investments. Aggregating multiple interconnected segments of various lengths can also inform measures of disruption and estimated costs.

The time periods and temporal weights are established as defined in the Methods section. Table 5-5 lists the values used in this demonstration. As described in the Methods section (Section 5.5), the time periods in this demonstration adhere to the FHWA regulations for TTR metrics, which established five time periods. The first three (morning, midday, evening) are applicable to weekdays (Monday-Friday), the nighttime condition applies to all seven days of the week. The temporal weights (t_p) are calculated based on the time period duration across the temporal domain (T) of a week. Regional knowledge of traffic conditions informs how the temporal values of each direction (eastbound and westbound) should be modified based on peak commute time of day.

Table 5-5: Time periods with temporal weights and values. Values separated by direction, where eastbound leads toward city center (morning commute) and westbound is away (evening commute)

	Time	t_p	v_p *(eastbound)*	v_p *(westbound)*
Morning	06:00-10:00	12%	50	15
Midday	10:00-16:00	18%	15	15
Evening	16:00-20:00	12%	15	50
Night	20:00-06:00	42%	05	05
Weekend	06:00-20:00	16%	15	15

Temporal values (v_p) consider the volume and value of each time period, which should be defined by transportation planners and stakeholders. Other data sources, such as continuous count stations along the corridor, will inform transportation operators of the expected relative traffic volumes (value) across the entire region for each time period. The value placed on each time period will influence the temporal rankings based on origin, destination, or economic factors. Other data, such as the volume of freight vehicles associated with each time period, will inform economic valuations for operational logistics.

5.6.2. Demonstration with I-66 Corridor (Limited Access Highway)

For this part of the demonstration, observations from January 01, 2017 to December 31, 2017 were accessed for a limited access highway, I-66. Disaggregated speed data was collected at 15-minute intervals across 138 TMC (Traffic Message Channel) road segments. The data includes 4.8 million observations of speed conditions for the year of data. Figure 5-2 depicts the I-66 corridor.

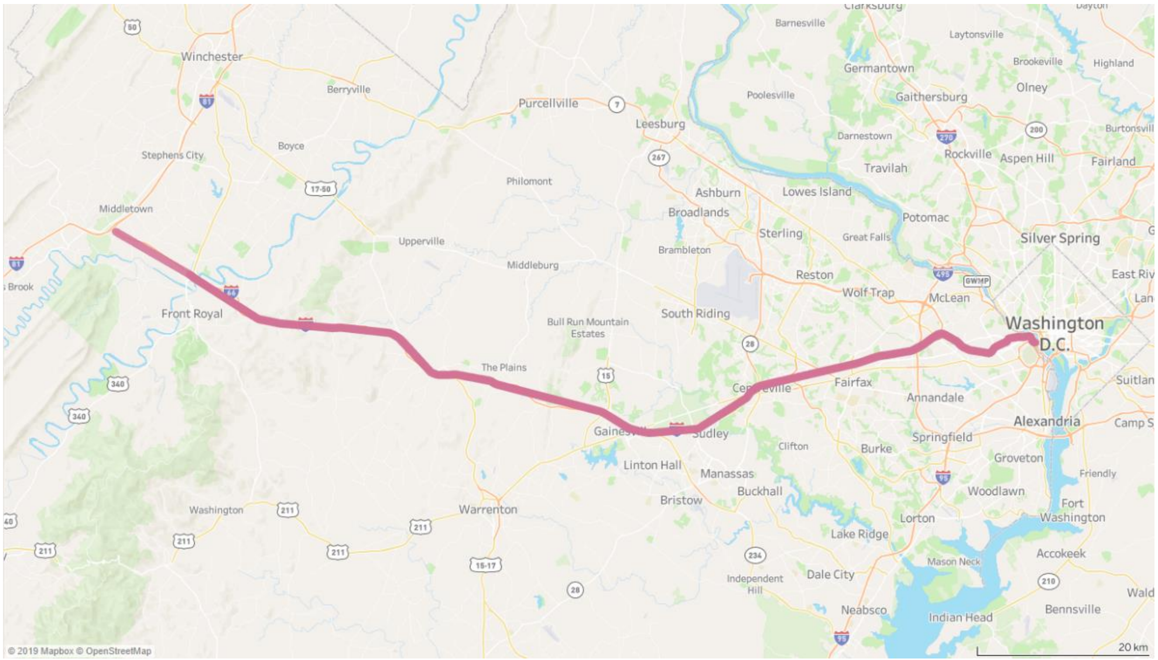

Figure 5-2: The I-66 Corridor, spanning from I-81 to Washington DC, including rural and urban regions across approximately 120 kilometers (75 miles). Both the eastbound and westbound directions were evaluated (map produced with Tableau software, using Mapbox and OpenStreetMap base datasets).

From west to east (left to right on Figure 5-2), the corridor transitions from an active interchange with the limited access highway, I-81, before spanning through rural regions and then connecting to the Washington DC Metropolitan region. The eastern region of the corridor contains increased interchange density, number of lanes, and traffic volumes. Portions of the corridor also include high-occupancy vehicles (HOV) lanes active during peak travel times. Table 5-6 is a set of descriptive statistics of the speed observations along the I-66 study corridor.

Table 5-6: Corridor I-66 statistics of speed data

	Speed (km/h)	Speed (mph)
n (data points)	4,816,611	4,816,611
Minimum	3	2
Maximum	121	75
Mean	95	59
Median	100	62
05th Percentile	61	38
25th Percentile	93	58
75th Percentile	106	66
95th Percentile	114	71
Std Deviation	18	11

The performance criteria scores are evaluated and then adjusted based on temporal weights and values, as defined in Table 5-4. This approach modifies the prioritization scoring of each segment to represent stakeholder perspectives. Different TMCs should have an appropriate temporal value (v) based on direction of travel and proximity to urban centers. Figure 5-3 depicts performance criteria (listed in Table 5-4) within the t-CTA format, with a summary of the final result based on the t-CTA methods (the last rows).

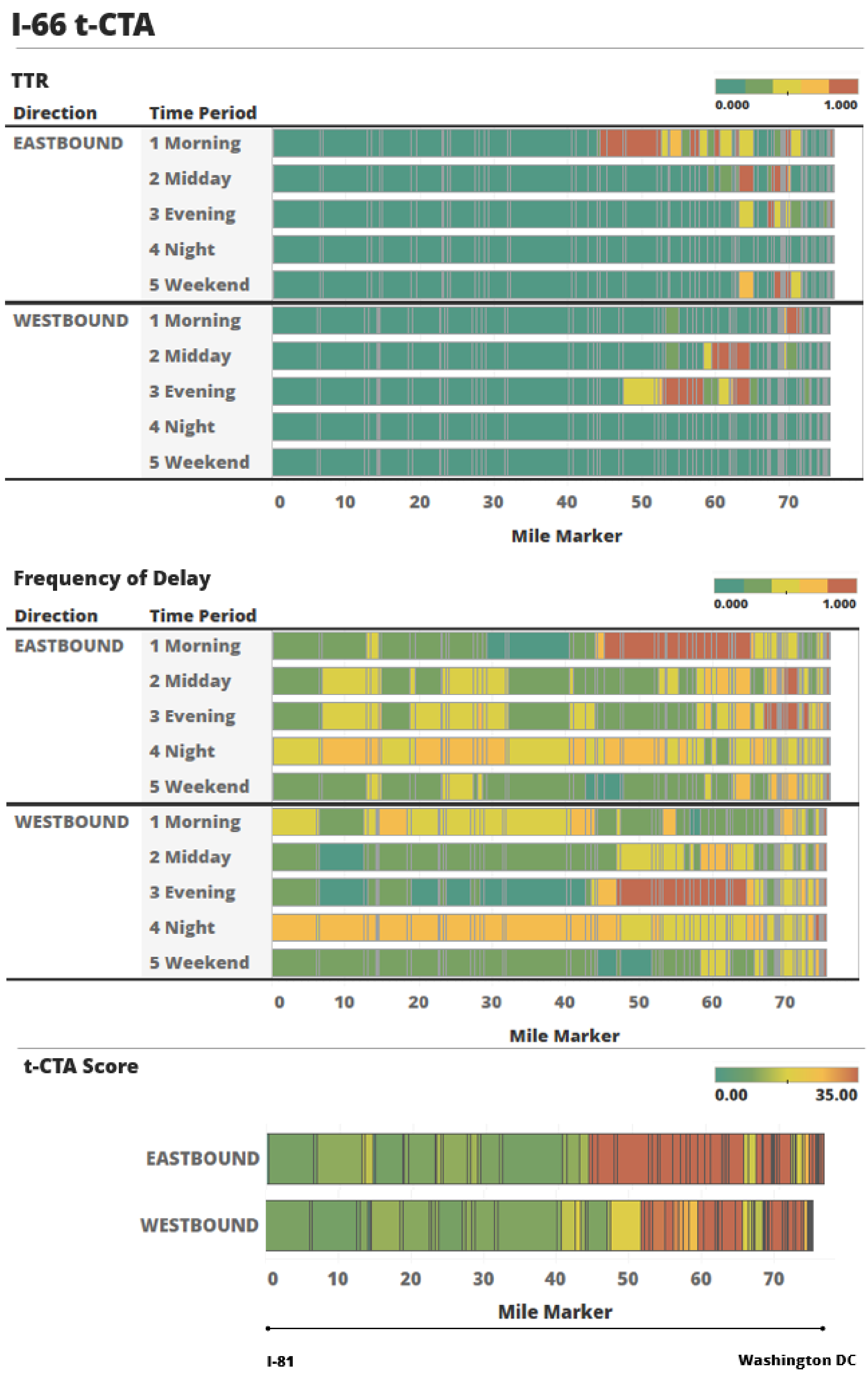

Figure 5-3: The temporal corridor trace analysis (t-CTA) for I-66, depicting two (of four) performance criteria across each of the five time periods with a final t-CTA score that includes temporal weights and values

The quantitative scores for each segment, or set of segments, provides a numeric method of comparing regions. From a quantitative perspective, the rank of each segment (based on the score value) can be evaluated and compared to traditional CTA (without temporal values). Table 5-7 provides a sample of results. The ranking shown is based on the entire corridor (138 different TMCs).

Table 5-7: Quantitative review of select TMCs within Corridor I-66 and the associated t-CTA ranking and performance measures

Direction	**t-CTA Priority Rank**	**CTA Priority Rank**	**TMC**	**Time Period**	**Delay Freq**	**TTI**	**PTI**	**TTR**
Eastbound	1	2	110-04173	Morning	0.62	1.3	6.8	2.2
			MM 67	Midday	0.53	1.2	5.3	1.1
				Evening	0.89	2.3	12	2.1
				Night	0.60	1.1	1.2	1.0
				Weekend	0.47	1.1	2.4	1.1
Eastbound	13	6	110N04171	Morning	0.70	1.4	3.8	1.9
			MM 68	Midday	0.73	1.4	3.4	2.3
				Evening	0.94	2.4	4.7	1.2
				Night	0.51	1.1	1.2	1.1
				Weekend	0.62	1.3	3.2	2.3
Westbound	1	1	110+04169	Morning	0.63	1.4	4.1	2.7
			MM 70	Midday	0.53	1.3	3.4	2.1
				Evening	0.58	1.2	2.7	1.6
				Night	0.52	1.1	1.2	1.0
				Weekend	0.49	1.1	2.1	1.1
Westbound	11	17	110P04175	Morning	0.33	1.0	1.1	1.0
			MM 65	Midday	0.47	1.1	3.2	1.1
				Evening	0.74	1.3	4.7	1.7
				Night	0.54	1.1	1.2	1.0
				Weekend	0.36	1.1	1.3	1.0

The ranking and points shown in Table 5-7 provide context to performance conditions across different time periods as a supplement to the visualization shown with the t-CTA charts (Figure 5-3). The tables depict how the temporal value, influenced by system operations, can change the prioritization of a road segment. For example, this demonstration includes segments with poor operating conditions during the morning or evening time period, which have a short duration relative to the weekly operation, but the large temporal values (corresponding to peak traffic volume periods) have a significant influence on ranking.

5.6.3. Demonstration of US-50 Corridor (Principal Arterial, Interrupted Flow)

For this part of the demonstration, observations from January 01, 2018 to December 31, 2018 were accessed. Institutional knowledge of this region informs outliers that can be considered, such as the U.S. federal government shutdown from December 22, 2018 until January 25, 2019. Disaggregated speed data was collected at 15-minute intervals across all TMC (Traffic Message Channel) road segments, for approximately 1.6 million observations of speed conditions. This corridor is shown in Figure 5-4.

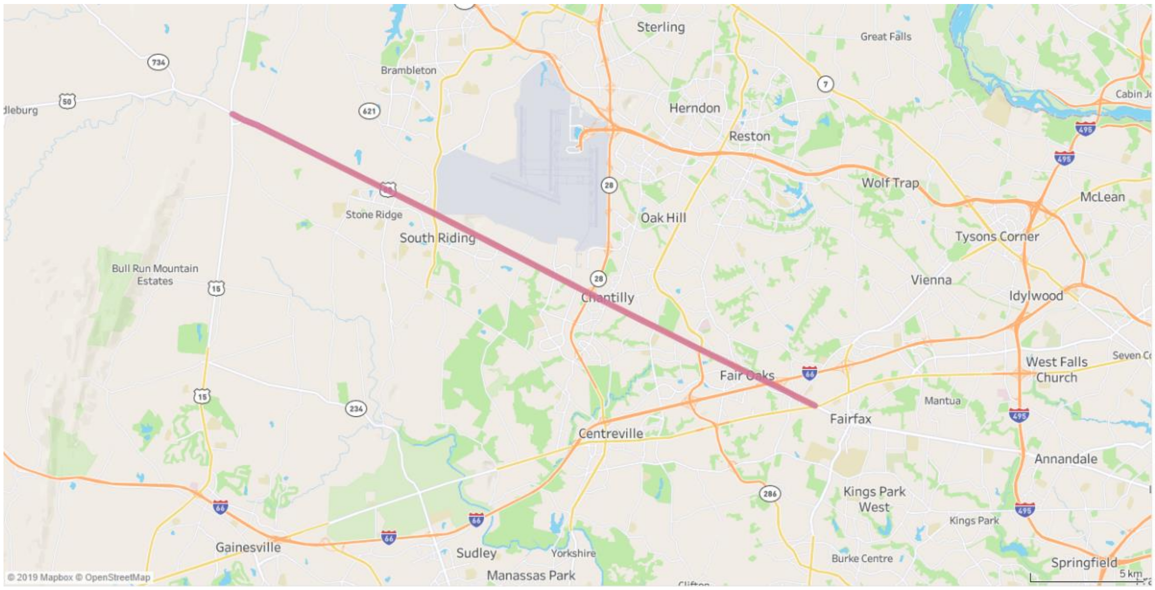

Figure 5-4: Corridor identification of demonstration data along US-50, from US-15 to US-29. Both the eastbound and westbound directions were evaluated (map produced with Tableau software, using Mapbox and OpenStreetMap base datasets).

Intersection control along this corridor includes roundabouts, signalized intersection, retail centers, residential communities, and others. A set of descriptive statistics of the speed observations along the US-50 corridor are shown in Table 5-8.

Table 5-8: Corridor US-50 statistics of speed data

	Speed (km/h)	Speed (mph)
n (data points)	1,605,594	1,605,594
Minimum	3	2
Maximum	121	75
Mean	58	36
Median	60	37
05th Percentile	24	15
25th Percentile	48	30
75th Percentile	72	45
95th Percentile	84	52
Std Deviation	18	11

As with the prior demonstration, the performance criteria scores are adjusted based on temporal weights and values (as defined in Table 5-5). Figure 5-5 is the t-CTA for US-50.

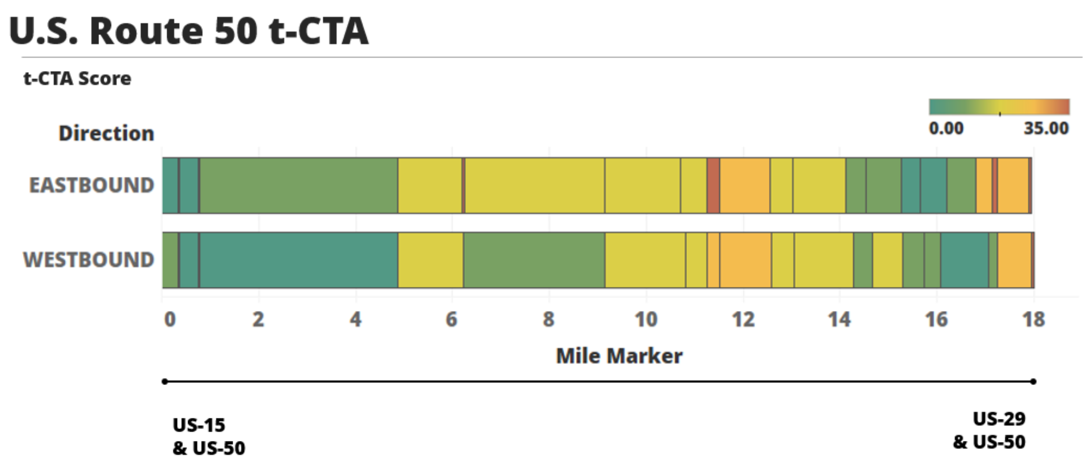

Figure 5-5: The t-CTA for US-50 that includes temporal weights and values for four performance criteria across five time periods.

The data visualization of the t-CTA provides an accessible method of identifying adverse performance conditions and the geographic spread of affected road segments. The red regions of each performance criteria represent adverse performance of a segment. A broad visual analysis of the results is intuitive when evaluated by regional transportation planners, which provides confidence in the model performance. For example, adverse performance is noted towards the Washington DC Metropolitan region (Mile Marker 18) with another peak near a major interchange (U.S. Route 28, Mile Marker 11). The CTA format provides an opportunity to evaluate how the adverse condition of one location will influence the adjacent corridor segments. For example, US-50 (Mile Marker 16) intersects the other demonstration corridor, I-66, with a grade-separated interchange (the location exhibits relatively good performance). The temporal disaggregation of t-CTA identifies when the adverse conditions occur, which informs planners on cost of disruptions and appropriate countermeasures.

The comparison of rankings from multiple perspectives is often measured to determine the robustness of an investment initiative, and serves to inform transportation planners [141], [149], [150]. Figure 5-6 provides the results of the US-50 t-CTA ranked scores to depict how the rankings of each time period compare to the total score and rank of the corridor segment.

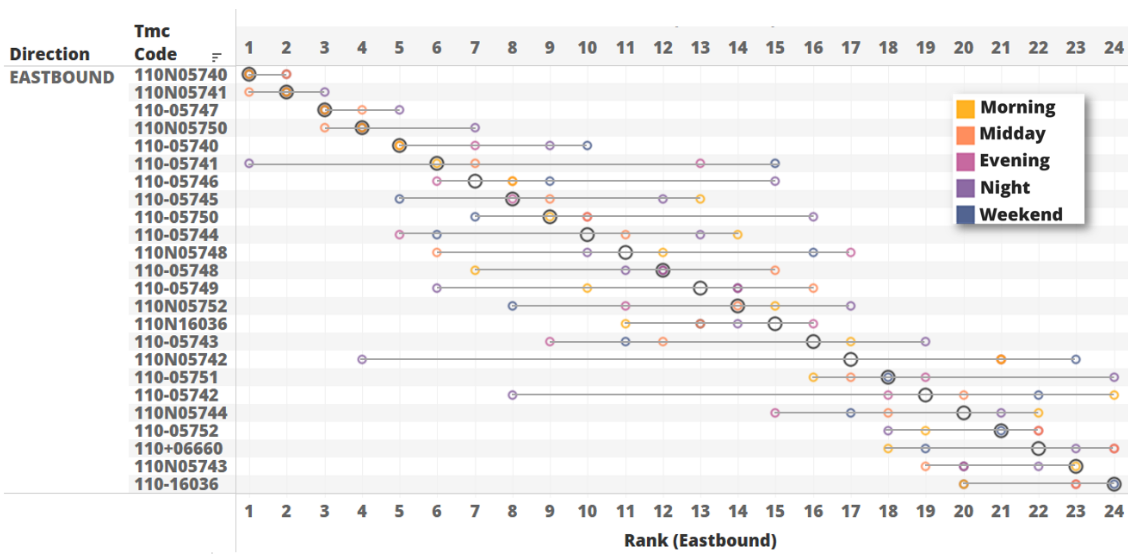

Figure 5-6: Comparisons of rank order to evaluate the influence of temporal values of each time period.

The range associated with each TMC and time period rank informs stakeholders of weekly operating conditions and the influence of temporal values. A smaller range, as shown with the highest ranked TMC (110N05740) indicates that the segment experiences disruptive conditions across all time periods. The 6th ranked TMC (110-05741) depicts a wide range of scores based on the time periods, including the highest rank of all TMCs for the nighttime period. Evaluating ranks and time periods adds context to appropriate countermeasures, such as access management or roadway illumination, which could improve system performance contingent on the source of disruptions.

5.6.4. Demonstration Analysis

The temporal disaggregation of performance metrics, as evaluated through the t-CTA framework introduced in this chapter, provides context of when adverse performance conditions are observed. The visual analysis of the t-CTA (Figure 5-3 and Figure 5-5) depicts the geographic range of disruptions associated with adverse performance conditions during given time periods. This approach allows a multitude of quantitative and visual communication mediums based on stakeholder requirements. This demonstration succeeds in evaluating performance criteria through temporal disaggregation of performance conditions. The comparison of rankings shown in Table 5-7 (I-66) and in Figure 5-6 (US-50) demonstrate how temporal values will influence the prioritization of infrastructure investments. The demonstrations include an evaluation of two corridor types to identify hot spots along the corridor to prioritize localized improvements such as access management, ramp metering, geometric modifications, or others [28], [70], [87], [88]. The framework is applicable to large geographic regions where the evaluation would inform transportation planners of priorities of disparate corridors based on disaggregate performance measures.

The criteria weights and ranking shown in Table 5-4 and Table 5-5 are examples of how multiple perspectives influence temporal values. In the demonstrations provided, an emphasis was placed on time periods associated with direction of travel to major destinations (urban regions). Perspectives from distribution companies, educational institutions, entertainment venues and others can further inform the temporal values based on regional comprehensive planning initiatives. Other criteria, as noted with prior CTA methods, may include crashes, terrain, number of lanes, construction operations, pavement conditions, and others. Selecting the appropriate criteria and time periods will influence the corridor segment score and priority. The t-CTA framework informs transportation planners of operational conditions of the system, but quantitative results are not intended to prescribe project selection – rather, t-CTA is a multicriteria analysis tool to support transportation and land use planning.

5.7. SUMMARY

Prior work has demonstrated how CTA informs the prioritization of infrastructure investments associated with emergent conditions and traveler safety [28], [29], [40], [87]. This chapter demonstrates how CTA can be extended through temporal disaggregation to consider variable criteria weights and values for disparate time periods. Limitations of data collection measures should be considered. As an emerging data source, the probe speed data, used in this demonstration, is subject to limitations of availability and accuracy based on technology. Accuracy of speed data for uninterrupted flow conditions is generally consistent, but the data collection technology is prone to low confidence during low speeds or interrupted and severely congested conditions [110], [151]. Probe speed data does not include a reference to traffic volumes; therefore, assigning temporal values based on relative traffic volume conditions requires regional knowledge (or other data sources or new methods of data collection).

The evaluation of a corridor should consider the context of interconnected road networks. Adverse performance observed on a corridor could be an indication that an adjacent network has created a bottleneck and improvements to the observed corridor may not have a significant influence on system operations. The availability of data and temporal disaggregation of the t-CTA framework provides scalability in corridor evaluation, which allows stakeholders to evaluate multiple connected networks to determine when and where disruptions are propagating along the network.

As with the traditional CTA framework, there are a several considerations with the t-CTA methods. Performance criteria should be selected by stakeholders to represent planning goals and analysis requirements and limitations of the criteria should be documented. For example, the criteria of travel time reliability (TTR) used in this demonstration is challenging to evaluate as an independent metric because a decrease in median speed will improve the reliability score (the system becomes reliably poor) even if the observed performance is undesirable. There is also an expectation that typical operating conditions and posted speed limits will vary across a diverse geography, which means that measuring a disruption is better informed by evaluating a typical operating condition (as noted with methods of quantifying operational disruption in Chapter 3) in lieu of a constant value when calculating delays. This approach would benefit from establishing typical performance conditions based on the same time periods used in the temporal disaggregation of t-CTA, such that disruptions are measured by deviations from standard operating conditions during a given time of day and day of week. This approach would consider recurrent congestion and how a traveler may anticipate system performance.

6. Spatiotemporal Simulation

6.1. Introduction

Traditional methods of transportation performance and land use valuation rely on metrics that emphasize daily traffic volume and ideal travel speeds of transportation systems; however, enterprise logistics is better informed through data-driven models that identify transportation accessibility that considers recurrent network conditions in scheduled operations. There is a critical need to assess and monitor the performance of global supply chains with a perspective of transportation access.

Enterprise and personal logistics are prone to disruptions from the inherent variability of travel times across hours and days of the week. In this chapter, a data-driven agent-based spatiotemporal simulation model is developed with applications to evaluating the variability of successfully completed roundtrips between an origin (distribution center) and destination (maritime port) based on departure time, day of the week, and month of the year. The simulation methods utilize vehicle probe-speed data and road sensors. Based on the success criteria of completed roundtrips, the results are evaluated to compare candidate sites (origins) with respect to scheduled logistics.

6.2. Motivation

Site selection of a new facility and infrastructure development is subject to multiple criteria such as access, utility services, topographic conditions, zoning, regulatory requirements, financial and legal characteristics, geotechnical conditions, and others [15], [72], [152], [153]. Infrastructure systems are vulnerable to land development, which must be assessed in measuring and monitoring scheduled logistics such as public transit, commuting, and the movement of goods [20], [28], [154]. In this chapter, we investigate the operational performance of a candidate site based on agent simulations of transportation networks. Specifically, we investigate the number of short-trip hauls (roundtrips) that can be completed within a given duration (hours of service) for a vehicle operator.

Short-trip regional hauls (defined by trips less than 100 miles) represent 83% of the trips in the transport of goods [155], [156]. The continuous growth of e-commerce and advanced logistics has increased the number of short-trip hauls, which is associated with the development of new distribution centers [155]. The measure of completed trips is an integer problem, where incomplete trips are disruptive to personal and commercial operations. Given the policies that regulate consecutive hours of service, freight vehicle operators must consider the number of trips of trips that can be completed, the duration of each trip, and the variability in duration and completed trips to prevent disruptions to operations logistics.

6.3. BACKGROUND

Prior work has successfully utilized vehicle probe-speed data, from vehicles and devices equipped with GPS receivers and static road-mounted devices, to analyze transportation routes from perspectives of costs, time, and sustainability [59], [77], [157], [158]. These perspectives primarily focus on route optimization from a fixed origin and destination. The methods benefit from accurate data that considers variability in traffic congestion and travel times to inform operations, such as departure times, from an origin to a destination. Route analysis is relevant to real-time operations, but operations logistics is first governed by decisions of where the facilities should be located.

The site selection and development of these facilities must consider multiple criteria tied to operations logistics [159]. There is a finite set of potential development sites, each unique with deep uncertainties of physical and political considerations. Existing evaluation methods include multiple criteria decision making/aiding (MCDM/A) and scenario based planning [153], [160], [161]. These methods rely on mathematical models and computer-based simulations to inform decision-makers in evaluation of criteria with a set of input variations. Within the criteria set, the transportation and logistics is a critical factor with both planned operations and competitiveness [153]. There are a multitude of transportation metrics that serve to inform route performance, including average speeds, daily traffic volumes, level of service, hours of delay, and others [26], [47], [112]. Traditionally, these methods evaluate deviations from ideal driving conditions (referenced as a free flow speed) when assessing performance; however, recurrent congestion conditions are analyzed by real-time traffic data that inform route selection, logistics and operations schedules.

As referenced in preceding chapters, the variability of operations across hours and days of the week is obfuscated by metrics that report daily aggregation statistics. Scheduled operations must account for recurrent conditions based on disparate time periods of a day, week, and month of the year [26], [55], [94]. Relatively newer measures of transportation network reliability have been applied to disaggregate (e.g., 5 to 15-minute intervals) travel time data to identify typical operation conditions for a given time of day. The magnitude and frequency of deviations from the typical condition provides new insights of transportation system reliability [54], [83]. For example, a highway may have an ideal free flow (no congestion condition) speed of 70 mph, but vehicles operate at a speed of 55 mph during rush hour conditions – in this case, reliability is measured by deviations from the typical speed in lieu of an ideal (and infrequent) operating condition.

An investigation of reliability metrics raises questions on appropriate levels of disaggregation, representation of a typical operating condition, value of reliability, and other considerations [44], [55], [61], [67]. From the perspective of enterprise operations, the measures of performance are best informed by a practical application the mathematical and computer-based models. With a given set of constraints (e.g., origin, destination, hours of operations) and a success criterion (e.g., completion of a roundtrip), the critical measure variability in duration and number of completed roundtrips. From this view of the transportation model, site selection of a distribution center benefits from a data-driven approach to identify the variability and frequency of the number of successfully completed trips. The focus of this chapter is to evaluate the performance of the transportation network to inform development site selection and operations logistics. Specifically, the link between a fixed destination (e.g., maritime port) and a set of candidate sites (e.g., distribution centers) is demonstrated with methods of spatiotemporal agent-based simulation with empirical data.

The scope of this work is an evaluation of transportation performance for a set of candidate distribution center sites, which considers the operations of freight vehicle logistics. The primary contribution of this work is the development of a simulation model that informs transportation performance conditions based on a candidate site location and a fixed destination. The results are provided as an integer, number of successfully completed roundtrips, based on site location, departure time, day of the week, month of the year, and other temporal domains. The simulation model includes disaggregate travel times across regional transportation corridors.

6.4. Methods

The parameters and scope identified in the preceding section establish the framework for a simulation model to calculate success of completed roundtrips between a fixed destination and a set of viable origins. The successful trip completion is defined as origin-destination-origin (O-D-O) completion as an integer – incomplete trips are not counted. To address the uncertainty in transportation network performance, we introduce a method of simulating trips based on travel time data collected from probe vehicle speed sources. Data is acquired from vehicles and personal devices equipped with GPS receivers, as well as road mounted systems, covering millions of miles of the road network across multiple years [3], [85], [162]. Travel time collection sources, such as INRIX [84], [162], provide disaggregated data necessary to evaluate roundtrip success by hours of the day and days of the week with variations in departure times, operating hours, origins and destination.

The simulation of a vehicle through an O-D-O roundtrip is based on empirical travel time data collected from probe speed vehicles. In this chapter, we evaluate methods of assessing site valuation based on transportation performance between a maritime port (destination) and a set of candidate sites for a distribution center (possible origins). Other embodiments are referenced in Section 8.5 of Chapter 8. A simulation of an O-D-O trip commences with an agent departure from the origin at a given time of day and evaluated across all disparate days of collected data. A set of departure times is assessed with respect to specific days of interest, days of the week, months of a year, or other temporal domains.

This section provides a background of methods used to develop the simulation and evaluate the results.

6.4.1. Data Availability

Recent advances in probe-vehicle data collection, dissemination and processing provides new opportunities to investigate corridor performance at short intervals (e.g., 10-minute) of travel time and space-mean-speed at a regional level [46], [68], [84]. Methods of probe speed data collection use spatial and temporal information from GPS receivers (personal or commercial) to report space mean speed and travel time associated with a corridor segment [57], [62], [63]. The data availability improves the accessibility of analyzing disaggregate travel time conditions for minutes, hours, and days across several years of data along disparate segments of a corridor. This data is accessed through sources such as the National Performance Management Research Data Set (NPMRDS), sponsored by the Federal Highway Administration (FHWA) and currently provides access to data downloads in a format of CSV files with location information, timestamp, and average travel time (and speed) across a defined time interval [84]. A schematic representation of corridor segments connecting an origin and destination roundtrip is shown in Figure 6-1, where each segment includes a reported travel time at a given interval across multiple years.

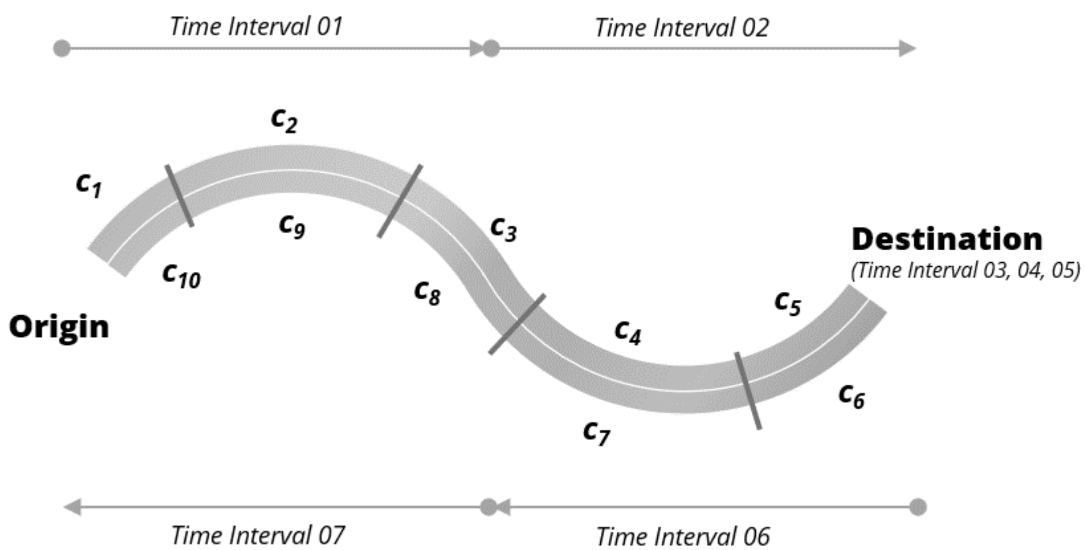

Figure 6-1: Schematic of corridor segments (c) as established by traffic message channel (TMC) segments between origin and destination.

This data availability provides new opportunities to use empirical data in logistics simulation. The variability in travel times along each corridor segment can be evaluated by the time of day and day of the year. In this chapter, we format each day of probe speed data as a matrix (referred to as a space-time matrix) comprised of n columns of time intervals and m locations of the corridor segment (for each direction of travel). This approach removes potential correlation issues of running a simulation with aggregated performance measures or statistical distributions of travel times between segments and accepts the inherent randomness in performance operations. This approach also provides opportunities to investigate specific disruptions, such as days with adverse weather, special events, severe crashes, or global pandemics.

6.4.2. Space-time matrix

A space-time matrix represents a single day of travel times across corridor segment locations (rows) and time intervals (columns). Each space-time matrix includes geospatial and temporal data for a study corridor. Probe speed data is generally formatted in rows for each observation of date-time and location. Data processing methods are used to reformat the data into a matrix, as shown schematically in Figure 6-2.

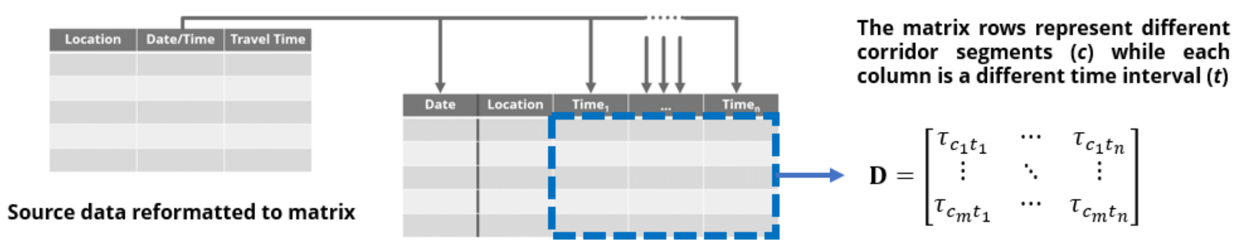

Figure 6-2: Source data is reformatted such that each row represents a corridor location with multiple columns for each time of day. Each day of data is formatted as a matrix (space-time matrix).

A matrix is constructed for each disparate day of the dataset with each cell representing the travel time (τ) for a given corridor segment (c) at a time of day (t). This format is conducive to a simulation in which the travel time value (each matrix entity) is referenced based on the location of an agent and the simulated time of day. As the agent progresses along the corridor, the appropriate time of day is referenced to identify the travel time recorded at the location and time. This approach considers the variability in travel times across hours of the day and days of the week for each road segment, including the randomness associated with events that span multiple hours and geographic locations.

A statistical programming language (such as R [86]) provides for efficient data processing to reformat the source data into a space-time matrix. Each day includes relevant attributes of year, month, day of the month, and day of the week, which facilitates an analysis of performance conditions across various temporal domains.

6.4.3. Simulation Method

Probe speed data includes a timestamp (based on an established interval) for each location and the observed travel time to traverse a corridor segment. The travel time is the average time required for a vehicle to travel from the start to the end of a segment, where a roundtrip is comprised of multiple corridor segments [64], [84]. The corridor segment lengths vary across a geography categorized by traffic message channel (TMC), separated by direction of travel. Travel time data is recorded for each TMC and reported at various time intervals. At a set time of day (e.g., 8:00 – 8:10 AM) and day of the year, empirical travel time data is used to assess the time required for a simulated agent to traverse a corridor segment.

The cumulative travel time for a given column (time of day) should be less than the time interval. For example, if the dataset includes 10-minute intervals, then the next column will be referenced when the cumulative travel time is 10 minutes from the last interval. Recognizing that the final travel time entity could sum to a value greater than the interval, the remainder is included in the accumulation of the next column. For example, if the cumulative travel time is nine minutes and the next row in the column is a travel time of two minutes, there would be one minute of travel time carried over to the next cumulative column value. Figure 6-3 shows a schematic representation of a vehicle traversing across corridor segments (rows) until the cumulative travel time is 10 minutes (0.16 hours), before the next column is referenced.

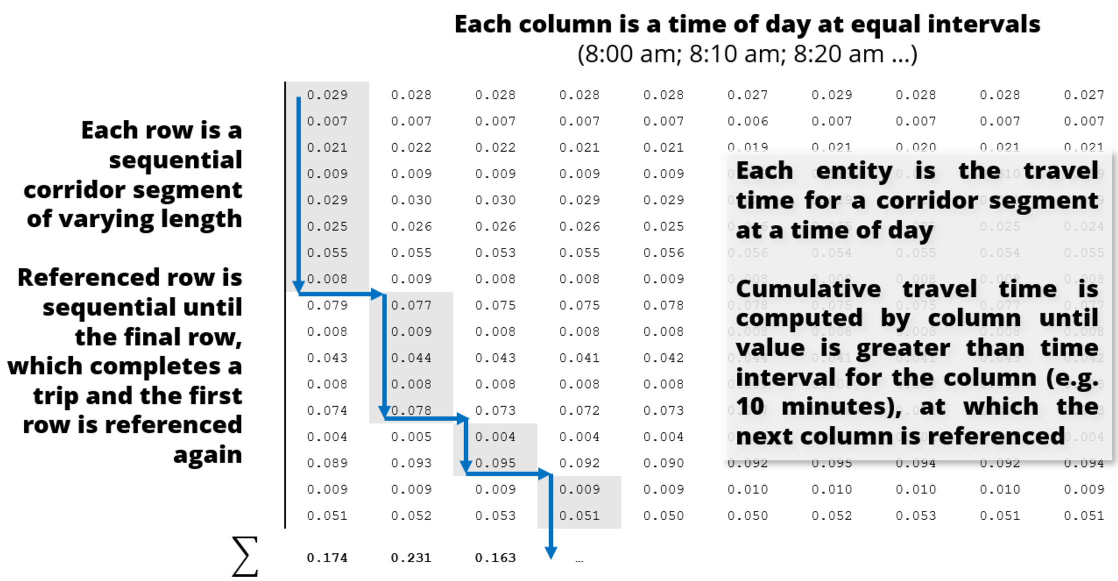

Figure 6-3: Schematic of cumulative travel times for each row, where each cell represents a travel time of a corridor segment (row) at a given time of day (column) as shown in hours.

The simulation starts with an agent (vehicle) at the origin (matrix cell $\mathbf{d}_{11}$) and references the reported travel time, based on the current timestamp (column), to traverse a segment before proceeding to the next segment (row). The agent progresses through the space-time matrix until the final row is reached (return to origin) at which time a trip is counted, and the next entity referenced will be from the first row and the current time column. A discrete or stochastic duration is considered at the destination and origin to account for loading and unloading (truck turn times).

This process is repeated until the sum of all referenced travel times exceeds the allowable drivetime duration (e.g. 11 hours in a single day).

6.4.4. Simulation Framework

The mathematical formulation of the framework is defined in this section. Operations logistics reference in the model will include the operating hours of the origin and destination, which bounds the candidate daily hours of arrival and departure and viable days (e.g., weekdays, non-holiday). Additional parameters, such as handling times (discrete or stochastic) for each the origin and destination are required when simulating a series of trips (round trips).

Model Sets

$S = \{1,2,\ldots,s\}$	Set of candidate sites
$O \subseteq S$	Set of origin nodes ($o \in$ O)
$P = \{1,2,\ldots,p\}$	Set of maritime ports
$D \subseteq P$	Set of destination nodes ($d \in D$)
$C = \{1,2,\ldots,c\}$	Set of corridor segments within route of origin-destination-origin

Parameters

h_o	Handling time at origin
h_d	Handling time at destination
T	Allowable hours of service (consecutive shift time)

Where

D	Space-time matrix, n rows for location and m columns of time interval
loc	row number of **D** for current location of agent
finloc	row number of **D** for final row (return to origin)
time	column number of **D** for current time of day reference

p	period duration, time interval (e.g. 10 minutes)
τ	time in segment (travel time) in cell of **D**, based on *loc,time*
tp	time in period (cumulative travel time in column, *time* across *loc*)

The decision logic for moving to the subsequent time of day interval (column of Figure 6-3) is as follows:

$$\text{if } tp < p, \text{ then } tp = tp + \tau,\ time = time, \text{ else } tp = tp - p,\ time = time + 1 \tag{6.1}$$

This can be represented as:

$$tp, time\colon \big((tp < p) \rightarrow (tp + \tau), (time)\big) \wedge \big(\neg(tp < p) \rightarrow (tp - p), (time + 1)\big) \tag{6.2}$$

Regardless of the result of the evaluation of the time of day interval to be utilized, the location to be utilized in the next iteration is determined as:

$$loc\colon \big((loc + 1 < finloc) \rightarrow (loc + 1)\big) \wedge \big(\neg(loc + 1 < finloc) \rightarrow (finloc)\big) \tag{6.3}$$

This process follows for the total duration (T, hours of service per day) with a returned value on the number of completed trips (when *loc = finloc*). Time values are computed using the increasing time and distance as the trip progresses. While the sum of time values is less than the time limit, a time value is added to the sum. Upon reaching the destination, additional "destination stop time" (handling time) is added to the sum. Similarly, upon reaching the origin, "trip complete stop time" is added to the sum. Figure 6-4 summarize this process.

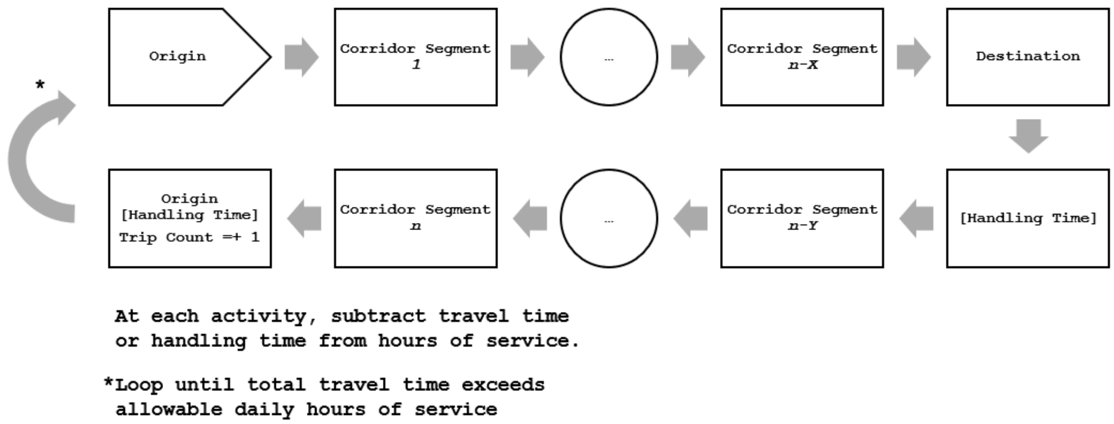

Figure 6-4: Flow chart of agent simulation from origin, through corridor segments, to destination (with handling time), and return through opposite direction of travel to the origin.

Given a space-time matrix of time values with m rows of corridor segments (c) and n columns of time intervals (t), each day of data is evaluated based on variations in start times. The returned value is an integer representing the successful number of completed trips. Other statistics, such as the total trip time of each completed trip, is also returned for context in variability of trip duration.

6.5. Demonstration

The simulation method introduced in this chapter is used to assess the operational performance of a transportation network between an established destination and a set of candidate sites (distribution centers). A region of Virginia, USA, was selected for the demonstration because of the diverse geographic characteristics, variable weather conditions, and proximity to a major maritime port: The Port of Virginia. Regions of Virginia also experience some of the worst traffic congestion in the country, which provides for a relevant case study when evaluating operational performance of the transportation network.

A set of candidate sites was selected based on development studies from the Virginia Economic Development Partnership (VEDP), which focuses on "business recruitment, expansion, and international trade" [163]. For this demonstration, we filtered a group of candidate sites based on site certification from VEDP and proximity to the Port of Virginia, distance from a major highway, and a Tier 4 or Tier 5 in the Virginia Business Ready Sites Program. The Tier rating value indicates that the site is infrastructure-ready or shovel-ready based on permits and plans obtained to date and therefore a viable candidate site. This set of candidate sites yielded two relevant locations along a major highway corridor: Interstate-64.

Table 6-1: Summary statistics of demonstration origin and destination

	Site 1	**Site 2**
Location (lat, long)	37.48375, -77.23519	37.38802, -76.79817
Distance from Port (straight line)	70 miles	42 miles
Distance from Port (route)	80 miles	52 miles
Estimated One-Way Travel Time	1 hour, 15 minutes	55 minutes

Figure 6-5: Candidate site locations and proximity to the Port of Virginia, not to scale. Base map graphic modified from [84].

The route from Site 1 to the Port includes 156 corridor segment TMCs (to and from the Port). A year of data was collected from 2018 at ten-minute intervals, as accessed from the National Performance Management Research Data Set (NPMRDS), which is sponsored by the Federal Highway Administration (FHWA) and hosted through the Probe Data Analytics Suite [84]. The dataset includes 3,688,361 observations when filtered to only include high confidence observations, weekdays and Port operating hours. When reformatted, the dataset includes 40,716 rows (about 257 days of 156 corridor segments) and 90 columns (5:00 AM to 8:00 PM, with 6 observations per hour). Corridor segment lengths ranged from 0.007 miles (37 feet, near interchange sections) to 6.4 miles. Average speed for the study corridor was calculated at 61 mph, with speed observations as high as 84 mph and as low as 2 mph.

Data collected from Port operations indicates an average turn time of 40 minutes, as measured by RFID readings throughout the terminal [164]. The truck turn time represents the duration from entering the terminal gate until the truck leaves the terminal gate (with goods). The truck turn time has been classified as stochastic in prior work, but the average value is used in this demonstration to study variability in transportation network operations [164], [165]. An estimate of handling time at the origin (candidate distribution center) is estimated as 20 minutes based on information from logistics operators.

The allowable duration of truck operations was set as eleven hours based on current regulations in hours of service [166]. Multiple start times were evaluated from 5:00 AM to 8:00 AM (at ten-minute intervals) to consider the uncertainty in operations and evaluate the influence of completed trips and start time. Port operating hours begin at 6:00 AM, which limits the earliest arrival and latest departure from the Port destination.

6.5.1. Simulation Demonstration

The simulation for Site 1 (located near Richmond, VA) yielded 1,738 (46%) conditions of two roundtrips completed in the eleven-hour duration, and 2,039 (54%) conditions of three roundtrips completed across all weekdays of 2018. There were 4,959 potential simulation events (19 different start times across 261 weekdays); however, travel time conditions with low confidence or missing data were removed from the simulation, which reduces the total number of feasible simulations by 25 percent. The reduction in simulations was variable across days and months and is referenced with the simulation results of this section.

The total travel time from Site 1 to the Port of Virginia is estimated by navigation applications as 1 hour and 15 minutes in each direction, with 40 minutes of turn time at the Port and 20 minutes at the site, the base estimate for a roundtrip is 3 hours and 30 minutes. In the simulation, the shortest trip was 3 hours and 24 minutes, with the longest successful trip as 4 hours and 26 minutes. For a simulation yielding three round trips, the duration never exceeded 3 hours and 42 minutes. A distribution of all results for Site 1 is shown in Figure 6-6, as separated by completed trips in each simulation run.

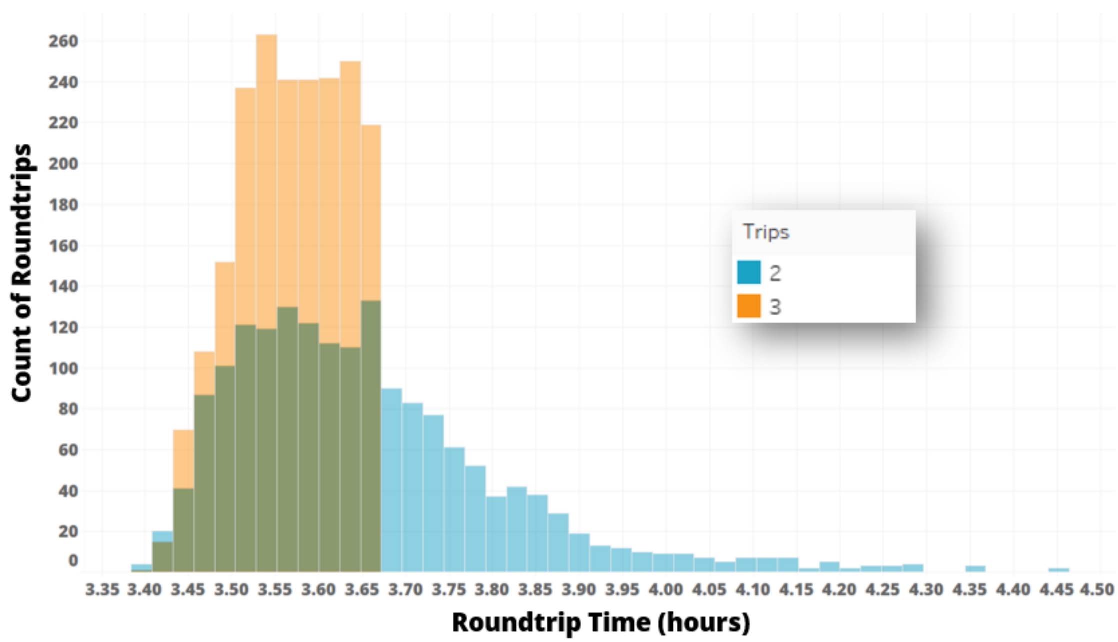

Figure 6-6: Distribution of completed trips and duration, as evaluated across disparate departure times and days of the year

We disaggregate the results to seek additional insights into the variability of transportation performance conditions. The results shown in Figure 6-7, Figure 6-8 and Figure 6-9 are provided to identify how the departure times, days of the week, and months result in two or three successful trips.

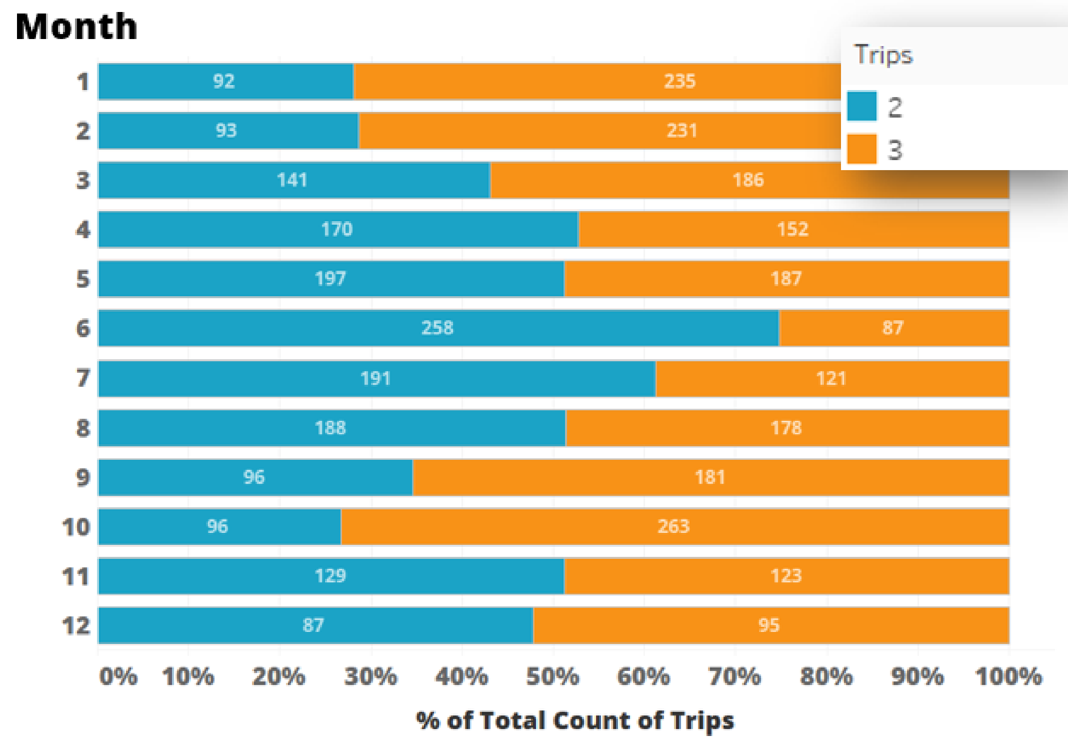

Figure 6-7: Number of trips completed based on month of the year (2018).

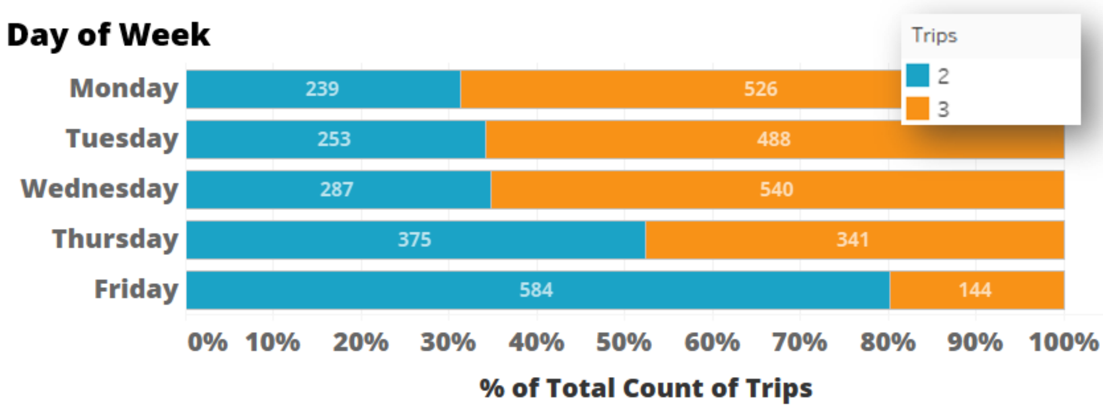

Figure 6-8: Number of trips completed by day of the week

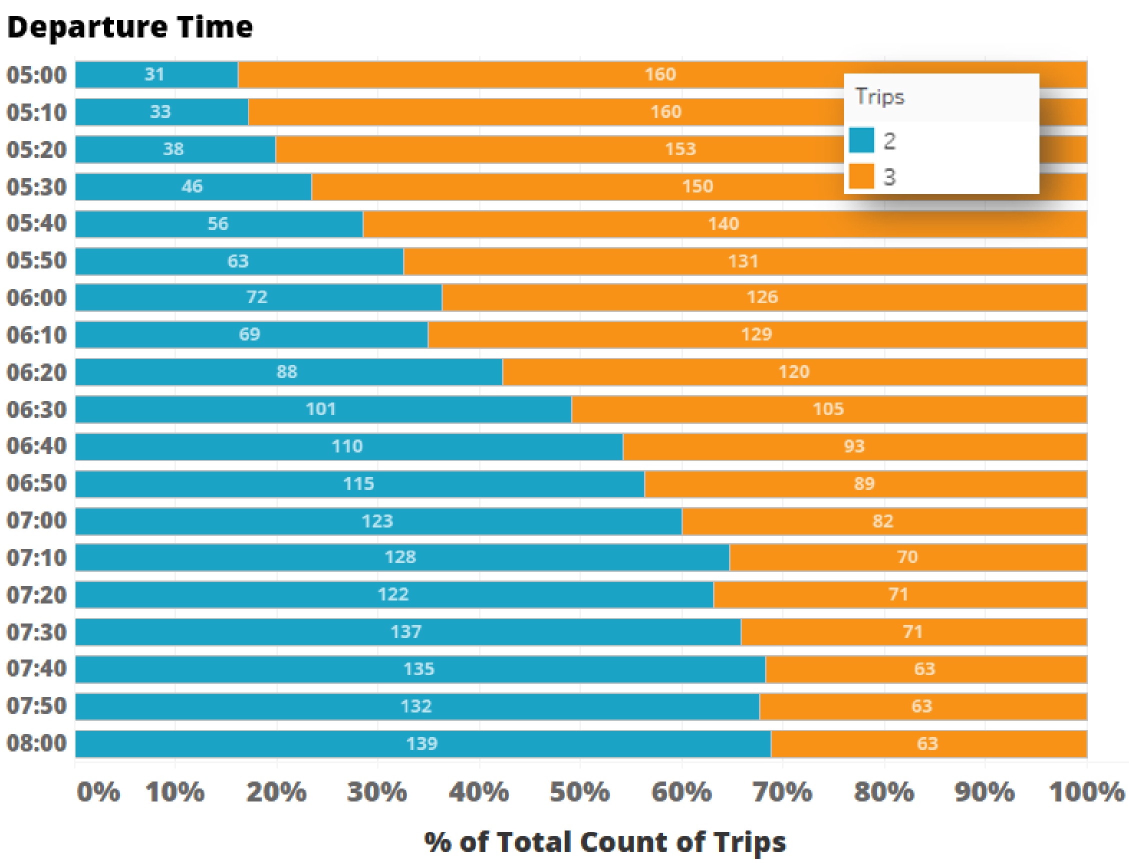

Figure 6-9: Percentage of two and three completed trips by departure time

From the simulation results we observe notable trends in the success of trips based on days of the week and the departure time. Specifically, we see that Monday through Wednesday have a similar result of success where three roundtrips were completed 65% of the time. Comparatively, Friday results show only a 20% success of three roundtrips. The earlier departure times generally result in three completed trips (80% of the time) while the latest departure time reduces success to 30% of the simulated runs. Together, the results of weekdays and the departure times provides information to logistics operations. For example, a Monday to Wednesday departure between 5:00 AM and 6:00 AM yields three roundtrips 85-95% of the time, but three trips are observed less than 50% of the time on Fridays. Other insights, such as evaluations of weekdays of a subset of month (e.g. summer holiday) would further inform site valuation and logistics. Modifications to operational logistics, such as extended hours, would therefore benefit the success of three trips for the part of the week with earlier operating hours.

For Site 2, which is located about 52 miles from the Port (compared to Site 1 at 80 miles), we run the simulation across the same dataset (weekdays of 2018). The variation in successful roundtrips is notably less than Site 1, with 3,326 (88%) of the runs resulting in three roundtrips while only 433 (12%) resulted in four roundtrips. We observe a range of 2 hours and 36 minutes to 3 hours and 33 minutes of roundtrip duration for runs with three roundtrips, and a lesser range of 2 hours and 39 minutes to 2 hours and 45 minutes when four roundtrips were completed. The distribution of roundtrip duration for Site 2 is shown in Figure 6-10.

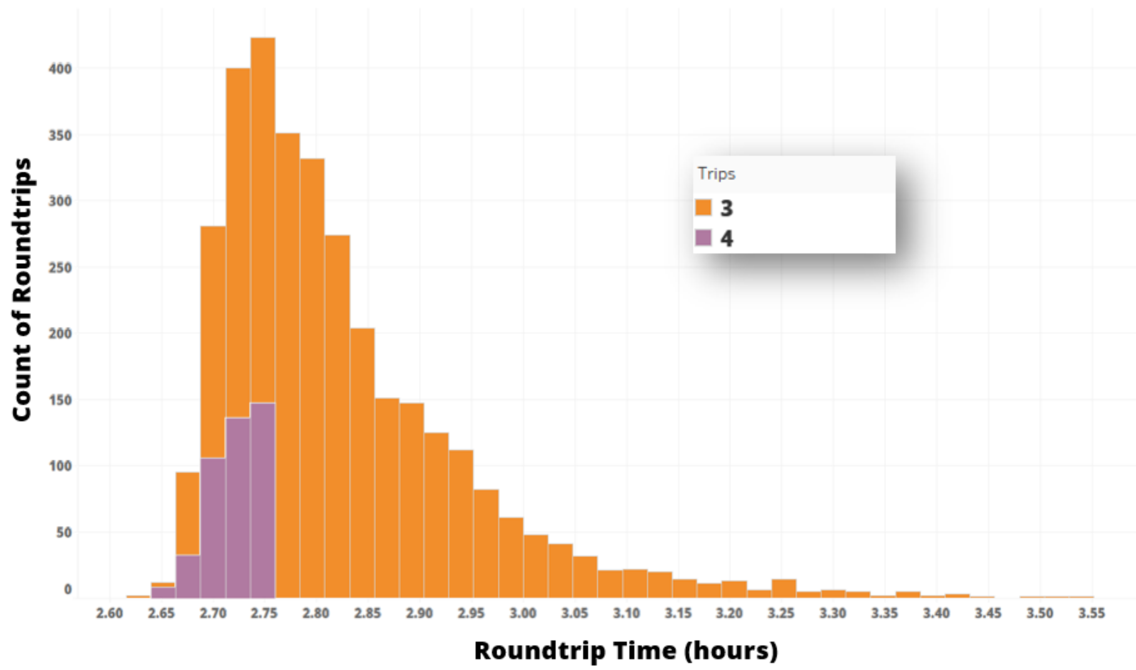

Figure 6-10: Distribution of roundtrip times for Site 2, split between three and four completed trips.

Site 2 simulation results were similar to Site 1 when evaluated across hours, days and months. The early part of the week demonstrated the highest rate of four roundtrips (20%) as compared to later in the week (less than 5%). Similarly, the months of May, June and July yielded four roundtrips less than five percent of the time. Figure 6-11 provides an additional format for data visualization by disaggregation across all simulation days of the year.

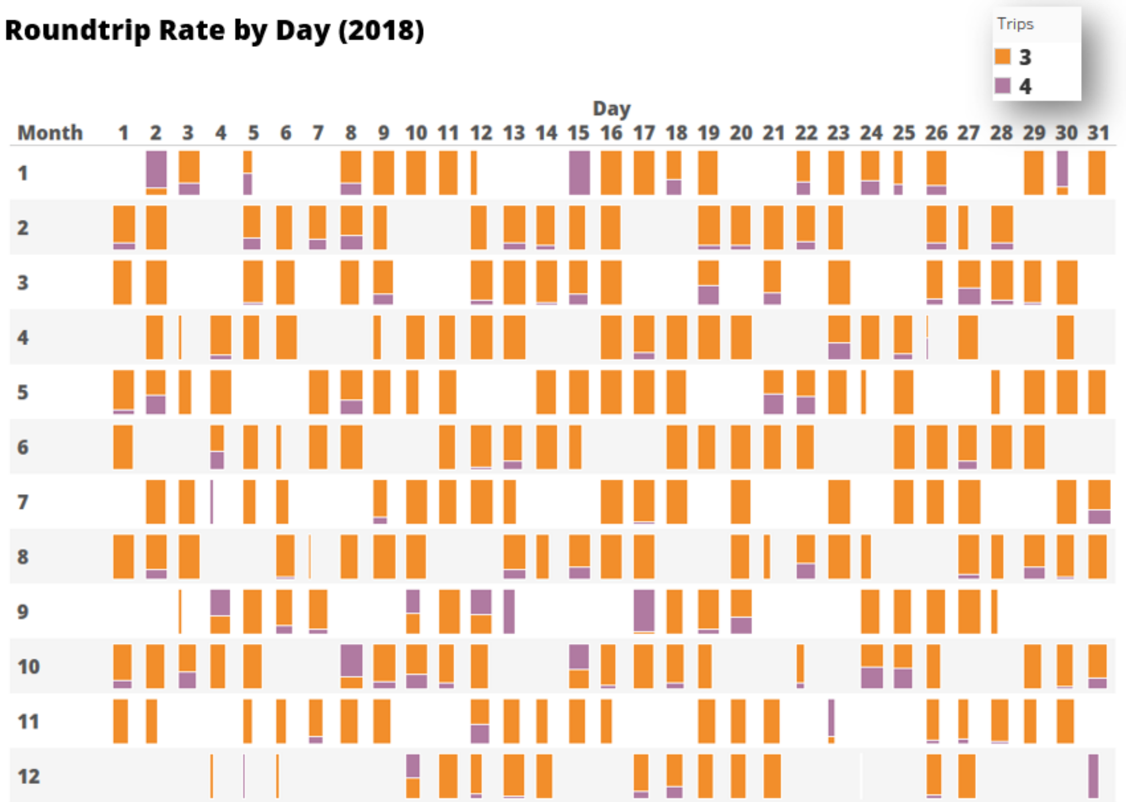

Figure 6-11: Report of successful number of round trips completed on individual days, measured by varying departure times. The width represents the number of successful simulations completed (no missing data). Blank days represent weekends and days with no viable simulation data.

This format provides insight into specific conditions that can be investigated with other recorded data that affects traffic flow, such as adverse weather, temporary road construction, holidays, special events, or severe crashes [55], [81]. The width of each daily plot represents the number of valid simulation runs, where a narrow bar indicates that only a few of the start times resulted in successful simulations (missing data or low confidence values reduce the number of successful runs). Weekends are not included in the simulation.

6.5.2. Analysis of Simulation Demonstration

The simulation methods introduced in this chapter are successful in reporting a novel perspective on site valuation based on empirical data evaluated at variable levels of disaggregation. The results inform criteria of transportation system performance for candidate sites. These results can be evaluated with other criteria and operations logistics for potential developers (or tenants) to investigate how operating hours, handling times, departure times and other conditions will influence the successful number of completed trips. The total number of completed simulations was noted in the preceding section, resulting in completed simulation runs that comprise 75% of the potential number of simulation events across all start times and weekdays of the year.

6.6. Discussion

An empirical simulation model serves to inform scheduled operations, but we must consider the limitations of the approach, as defined in this section. This work does not explore methods of predicting operations in subsequent years after development, but the future work (identified Section 8.5 of Chapter 8) describe methods to extend the model approach to consider scenario-based analysis.

6.6.1. Limitations and considerations

There are noted limitations of data collection methods, often represented by measures of confidence assigned to each observation. Low traffic volumes or complete breakdowns in traffic flow are documented conditions that result in low-confidence of travel time reports. In this chapter, the demonstration studies the transport of goods, which assumes the use of commercial freight vehicles and includes unique constraints. Routes may have restrictions on truck traffic or periodic restrictions based on hours of the day or week. Truck speed, relative to passenger vehicles, is influenced by longitudinal grades of the road corridor, which could be addressed by increasing travel time (decreasing speed) associated with steep road segments [26], [112]. Calibrating the model can be informed by freight and logistics operations.

6.7. SUMMARY

The inherent randomness and complexity of the transportation system has spurred an abundance of metrics to represent operational performance. In this chapter, we extend applications of the perspectives introduced in preceding chapters to evaluate candidate sites based on an empirical simulation model. In a demonstration, these methods are applied to logistics operations in the movement of goods in an origin-destination-origin journey to evaluate the number of successful trips. The variability in roundtrip times, and successful number of trips completed, is analogous to recent metrics of transportation network reliability that seek to measure and monitor traffic volatility. These measures of reliability are an important element for scheduled operations, such as public transit, commutes, and the movement of commodities [48], [88], [92], [94]. Measuring the variation in successful roundtrips between candidate sites and a set destination (maritime port) is a critical measure of site valuation when planning supply chain logistics. The use of disaggregate travel time data informs enterprise logistics in transportation

7. Conclusions & Contributions

7.1. Summary of Work

The preceding chapters identify methods to measure operational performance and inform the prioritization and design of system improvements from perspectives of logistics operations evaluated with disaggregate spatiotemporal data. The methods in these chapters benefit from evaluations of disparate time periods of days and week to assess value, cause, and potential solutions for measured disruptions. The initial chapters of this dissertation (Chapter 2 and 3) provide a review of traditional metrics and methods to quantify disruptions, using kernel density estimation (KDE), to measure deviations from anticipated operating conditions for transportation systems. With the same data source (continuous count stations), changepoint detection is utilized to determine performance thresholds based on traffic volumes, as described in Chapter 4. These methods inform prioritization of project initiatives and monitoring processes of transportation networks, as evaluated by perspectives of accessibility and reliability. Absent of regional traffic volume data, Chapter 5 provides methods to weight performance criteria based on temporal values informed by institutional knowledge and multiple perspectives. In Chapter 6, these perspectives are applied to land use planning initiatives to assess site selection based on simulations with empirical travel speed data. The next chapter, Chapter 8, provides details on planned extensions of these topics. Chapter 8 provides additional considerations for assessing and prioritizing the planning and design of infrastructure systems. In Section 8.6, the physical location of infrastructure projects is assessed to influence project prioritization from coordination benefits. Section 8.7 provides an extension to scenario-based planning by considering the temporal domain of major disruptions associated with disparate scenarios.

7.2. Summary of Contributions

The contributions of this work stem from new perspectives of traffic operations and system performance, which emphasize land use planning and transportation accessibility. Traditional performance metrics rely on temporally aggregated data, which obfuscates the variability of traffic conditions across hours, days, and months. Travelers that seek to maintain reliable accessibility to workforce centers, education, healthcare, and consumer goods can anticipate recurrent traffic congestion but are disrupted by deviations from anticipated conditions. Disaggregate spatiotemporal data informs personal and enterprise logistics by assessing performance variability of the transportation system across disparate time periods. The novel perspectives and metrics provided in this dissertation will inform transportation and land planners in the assessment and prioritization of infrastructure projects to serve the community and enterprise logistics. The identified gaps of traditional congestion metrics (reliability, intensity, duration, extent) are to be considered by transportation agencies that report and monitor transportation performance. The quantified disruptions of transportation systems will inform enterprise and community stakeholders that may adjust origins, destinations, modes, schedules and logistics to maintain reliable operations. Site-specific land planning will benefit from the spatiotemporal agent simulation, which provides methods of candidate site evaluation by logistics of allowable drivetime, departure time, origin and destination handling times, and variability across hours, days and seasons.

Chapter 2 includes a review a of current congestion metrics and outlines new methods to quantify operational disruption as deviations from the mean speed. The contributions include (1) a review of relevant performance metrics and identifies limitations when measuring disruptions; (2) introduction of a quantitative framework of measuring operational disruptions; (3) improvement on prior methods of measuring performance by using disaggregated data that reduces vehicular volume and speed correlation errors; (4) application of the disruption metric to a multi-objective framework to inform evaluation, prioritization, and design of infrastructure systems; and (5) provides a demonstration with considerations of methods while identifying future extensions of related work.

Chapter 3 extends work from the preceding chapter by studying benefits of measuring disruption as deviations from the most frequently observed speed, in lieu of mean speed. The contributions include (6) an introduction of a multicriteria framework established from risk analytics to consider three components of risk: frequency, magnitude, and exposure; (7) an extension of methods for quantity in operational disruption to consider the perspective of travelers, which is achieved by identifying the most frequently observed speed conditions (by methods of kernel density estimation).

Chapter 4 applies methods of changepoint detection to investigate and identify a traffic volume associated with an abrupt change in system reliability. The contributions include (8) an introduction of reliability metrics that emphasize perspectives of enterprise logistics with success and failure criteria; (9) a framework for methods to detect a reliability threshold based on traffic volume conditions; (10) and methods to monitor and manage performance based on the reliability threshold.

Chapter 5 introduces a temporal corridor trace analysis (t-CTA) to (11) allow scaling of performance measures based on stakeholder perspectives of vehicle volumes, vehicle type, travel purpose, and other factors that can be implied by time of day and week; (12) improve identification of appropriate countermeasures for adverse performance by evaluating when performance is observed (e.g. road illumination for adverse nighttime conditions); (13) provide a visual and quantitative evaluation method across a spatial region to allow planners an intuitive method of monitoring changes to duration and location of adverse performance.

The simulation and analysis methods in Chapter 6 (14) provide novel perspectives of site selection based on valuation of successful roundtrips completed within a given duration (hours of service); and (15) the results of the simulation inform operations logistics and reliability of the transportation network.

Chapter 8, Section 8.6, extends methods of infrastructure investment prioritization by considering the geospatial location of project initiatives and opportunities for project coordination. The contributions of this work include (16) a development of methods to investigate opportunities for project coordination based on geospatial proximity; (17) methods to identify geographic clustering of low-ranked projects to seek opportunities for geographic diversity of investments and benefits of coordination; (18) an extension of multicriteria project initiative evaluation with applications of spatial associations. Section 8.7 introduces a multi-objective temporal scenario analysis (MOTSA) to (19) extend prior methods of resilience analytics and scenario analysis by considering emergent and future conditions weighted by temporal factors.

8. Extended Applications

8.1. Introduction

Each topic of this dissertation, introduced across multiple chapters, affords an opportunity to extend the research and provide additional contributions. This chapter provides a summary of planned extensions.

8.2. Cost-Benefit Analysis of Disruptions

Cost-benefit analysis is an industry standard method for prioritizing infrastructure projects, and has previously been extended through risk-cost-benefit analysis frameworks to investigate highway safety [40], [87]. Specific to the congestion cost (300B USD), monetization generally refers to the goods or personnel exposed to a disruptive condition [43], [67]. The priority score can be converted to a monetary value based on the total volume of vehicles (PCE) exposed to the disruptions and other factors [26], [40], [43], [67]. The priority function can be modified by stakeholders and transportation agencies with methods that assign weights to time periods, vehicle classifications, regional conditions, traffic volume and others. This approach recognizes the deep uncertainty associated with data collection and avoids discrete decision intervals to emphasize the necessity of stakeholders in the decision-making process.

The risk-cost-benefit analysis framework is a logical extension and can be applied to multicriteria risk analysis identified in Chapter 3 and benefits from disaggregated speed and volume data (as referenced in this work). The associated costs of system performance will be evaluated across different time periods (morning, midday, evening, night and weekend) to consider the traveler's perceived value. The cost associated with the magnitude of disruption could be measured through breakpoints (e.g., severe delays that cause a missed appointment window) or an exponential cost function. Frequency will also inform the associated costs, as frequent disruptions may be perceived as conditions that can be planned for while rare and severe events could be forgivable [115]. Exposure by vehicle occupancy or type (personal or commercial) will also inform the cost associated with disrupted conditions. These cost factors are anticipated to further inform the prioritization of investments beyond traditional metrics.

8.3. CHANGEPOINTS WITH CLASSIFICATION

As an interconnected and independent system, each of the road segments identified in Chapter 4 are subject to the operating conditions of adjacent segments. Variations in time and location of bottlenecks from connected road networks will influence observed performance conditions, which may inform the appropriate level of disaggregate data (e.g., evaluating Sunday separate from Saturday to account for variable operating conditions). Other time periods of interest to enterprise logistics may isolate seasons or months associated with peak operations.

8.4. EXTENDED APPLICATIONS OF t-CTA

Future work of temporal disaggregation of performance measures will investigate how to group corridor segments by geography and time periods. Changepoint detection or methods of machine learning classification (e.g., CRT or CHAID) can be used to identify consecutive corridor segments that have similar performance characteristics across time periods. Combined with regional institutional knowledge and operational data, this approach informs prioritization and the appropriate countermeasures based on evaluation of where and when adverse performance is observed. The Demonstration provided with Chapter 5 is one approach to the implementation of t-CTA. As a framework, the t-CTA can be structured based on stakeholder objectives. Other methods, to be studied with future work, include those listed in Table 8-1.

Table 8-1: Extended applications and future work of t-CTA framework

Application	Description
Financial Quarters as Time Period	Enterprise logistics with seasonal trends, such as freight transportation, can establish time periods based on financial quarters. The daily and weekly performance conditions can be investigated during each quarter (or season) and compared with enterprise operations.
Public Transit Schedules as Time Periods	An evaluation of local road segments in concert with public transit hours can inform operations or transportation improvements based on observations of adverse performance.
Scenario Analysis Simulation of Emergent Conditions	Future conditions, such as new land development, changes to transportation technologies, environmental changes and others can be evaluated with t-CTA to simulate future performance conditions. New land development can be monitored to investigate performance impact at disaggregated time periods based on trip generation. Changes in the intensity, frequency, and duration of adverse weather conditions can be simulated to evaluated changes in system performance.
Time Series Animation	At a completely disaggregated level, each 15-minute time period can be represented by a different page of a t-CTA chart. Compiling all time periods together, displayed with multiple pages per second, provides an analytical story of the corridor and avoids softening the appearance of peak adverse conditions through aggregation.
Toll Lane Monitoring and Performance	The demonstration corridor includes a portion with access to high occupancy / tolling (HO/T) lanes, with dynamic tolling based on corridor performance. The primary lanes of the corridor could be monitored and compared to restricted access lane operating times and conditions.

The example of extended applications shown in Table 9 are provided for reference on how the t-CTA methods could be used. The temporal disaggregation is an innovation to the traditional CTA methods and serves to further inform transportation planners with an accessible analysis tool and adaptable framework.

8.5. Additional Simulation Embodiments

The framework of the simulation introduced in Chapter 6 affords multiple embodiments that consider multiple perspectives and operational changes across time. Table 8-2 provides a list of extensions relevant to the simulation methods.

Table 8-2: Additional embodiments of simulation methods to be developed with future work.

Extension	**Summary**
Stochastic Handling Times	The work by Thorisson et al. [165] applies methods of Monte-Carlo simulation with historical data of maritime port operations, such as truck turn times. Stochastic handling times, disaggregated by daily or seasonal trends, can be included in the simulation.
Route Choice	An envisioned extension of this work is to accommodate at least one other route choice in the simulation, such that if the primary route experiences severe disruption then an alternate route would be used. This method would consider real-time traffic data that could be communicated to vehicle operators.
Secondary Origins or Destinations	If a final trip(s) could not be completed within the remaining hours of service, a secondary origin or destination may yield additional trips or consider designated breaks (e.g. rest areas).

Continuation of Table 8-2

Extension	**Summary**
Applications to Workplace Commute	Another embodiment of the simulation would evaluate candidate origin sites (commuter residence or public transit locations) compared to a workplace destination. This approach would consider an abrupt failure mode (arrival beyond a given work start time) and evaluate variability in success based on departure times.
Regional Geographic Evaluations	From an origin or destination, another embodiment of this simulation would yield a mapped region of roundtrips based on geographic proximity of an origin or destination, with variable confidence intervals or results based on departure times, days, months or other variations.
Evaluations of Multiple Years	The demonstration included in this paper evaluates results from a single year of data, but multiple years could inform confidence in hourly, daily or seasonal trends while simultaneously considering the transportation network as a nonstationary system. Periodic updates, as new data becomes available, would inform long-term operations and investment decisions.
Scenario Analysis	Based on historic records of unique events of the corridor, or representative transportation models, scenario analysis could be applied to the simulation to adjust any of the constraints. Relative increase or decrease of travel time for some or all corridor segments, extensions or reductions in allowable daily hours of service, interim breaks for electric vehicle charging, modifications or operating hours or handling times, changes in frequency or intensity of adverse weather, new land development, global pandemic, road closures, or other scenarios can be considered in the simulation scenarios.

8.6. Prioritization via Spatial Association

The physical characteristics of infrastructure systems necessitate an investigation of the spatial association of project initiatives. This section provides methods of prioritizing infrastructure improvements by considering geographic location of project initiatives. A demonstration is provided for an existing dataset of ranked infrastructure projects. Future work is outlined in Section 8.6.5 to describe how spatial association can inform project prioritization and selection.

Recent U.S. regulations have mandated project coordination processes that seek opportunities to reduce cost and improve the safety of infrastructure projects by identifying opportunities for collective construction activities. This section includes methods of weighting performance measures and infrastructure investment priorities through spatial association.

Prioritization of system improvements, such as in transportation systems, typically uses multi-objective analysis and cost-benefit analysis but overlooks how geospatial association will influence initiatives. Recent U.S. regulations have mandated project coordination processes that seek opportunities to reduce cost and improve the safety of infrastructure projects by identifying opportunities for collective construction activities. In this chapter, a method is developed to evaluate the geospatial factors in the consideration of transportation project prioritization and coordination. The prioritization of projects is intended to effectively administer resources for improving safety through transportation infrastructure projects. A spatial association factor (Gi^*) is assigned to projects, identifying the geospatial proximity and ranking of other projects under consideration. This finds opportunities of project coordination and addresses the geographic diversity of infrastructure improvements. In this chapter, the approach is demonstrated for a selection of 1,573 intersection improvement projects under consideration by a U.S. state department of transportation. The results and methodology are of interest to systems and enterprises that balance multiple investment projects with geographic attributes.

8.6.1. Background

Performance and priorities for distributed systems is a latest concern of the systems engineering community. For example, prior research has developed a framework for evaluating multiple objectives of project initiatives [87], [167], [168]. Traditionally, each initiative was evaluated independently before being prioritized among all other initiatives; however, the interdependent and interconnectedness of transportation systems requires a consideration of how the geospatial relationship between multiple initiatives may influence the ranking and selection. To consider emergent and future conditions, a multi-objective analysis benefits from evaluating the resilience of initiatives by applying stressors and investigating the resultant numerical rank of various initiatives as evaluated under different perspectives [167], [168].

Resilience Analytics Framework

The term resilience, as defined by the International Council on Systems Engineering (INCOSE) and the Department of Homeland Security Risk Lexicon, describes a system's ability "to adapt to changing conditions and prepare for, withstand, and rapidly recover from disruption" [10], [11]. When evaluated with transportation improvements, such as those that address spatial implications of safety projects, a resilient project would maintain value under disruptive conditions, such as construction activities, population growth, new transportation technologies, changes in land development, and others.

A framework for *resilience analytics* has previously been defined to investigate the ability for various project investment initiatives (p) to withstand different stressors (s) as evaluated under a defined set of success criteria (k) [167], [168]. A numeric score value (z) is used to compare the initiatives for ranking and prioritization. This score value is influenced by a weight criteria (w) that is used to investigate how stressors will influence the ranking and prioritization of each initiative. As previously defined by [169], the framework is identified as:

- Initiatives – different infrastructure projects
    - $P = \{p_1,\ldots,p_n\}$, with n initiatives
- Stressors – disruptions, such as natural disasters
    - $S = \{s_1,\ldots,s_q\}$, with q initiatives
- Criteria – economics, environments, and others
    - $C^k = \{c^k_1,\ldots,c^k_{mk}\}$, with k sets of mk
- Score – numeric method to evaluate initiatives
    - $z = [1,\ldots n]$ as a rank by stakeholder

From [168], the weighted values are balanced around a neutral option (w_j) with scenario-based multipliers applied (a_1, a_2) as provided in (8.1).

$$w_{jk} \propto \begin{Bmatrix} a_1 w_j & \textit{major increase in importance} \\ a_2 w_j & \textit{minor increase in importance} \\ w_j & \textit{no change} \\ (1/a_1) w_j & \textit{major decrease in importance} \\ (1/a_2) w_j & \textit{minor decrease in importance} \end{Bmatrix}$$

(8.1)

A linear additive value function has been previously developed to define the relationship of these variables as shown in (8.2).

$$V^k(p_j) = \sum_{i=1}^{m_k} w_i z_{ij}$$

(8.2)

The weight of each score is influenced by various stressors under the multiple perspectives of a set of criteria and is generally defined with a normalized weight for each stressor. For example, a project that focuses on roadway drainage improvements may be deemed more important when considering stressors such as climate change or sea level rise.

This model can be extended to consider the spatial relationship of candidate projects. Following the previously prescribed process, the initiatives will have a numeric rank that has been investigated through various stressors, which provides the most resilient initiatives and informs decision-makers. The spatial association of each project can further inform the selection criteria of ranked projects based on planning goals for coordination or geographic diversity. In this way, projects can also benefit from being evaluated in groups based on geographic proximity (as opposed to independent investments), which could change the value (rank) of the projects.

Spatial Association and Project Evaluation

Spatial analytics has significant implications within the transportation industry (and others) to assess events and geospatial attributes, which informs the evaluation of project initiatives [28]. These frameworks can be used to evaluate the selection of ranked investments based on the geospatial proximity of similar projects. The connectedness of certain variables across a geographic location is referred to as *spatial association* [170]. The variables of different attributes, such as traffic accident intensity or duration, can be evaluated through a geospatial information system (GIS) to investigate termed *hot spots*. Within GIS analysis methods, the hot spots (and cold spots) signify the clustering of data points with high (or low) attribute values, like project rankings. Spatial association can also inform the resilience of project initiatives when evaluating geospatial disruptions, such as adverse weather events, flooding, road construction, land development, public transit systems, and others.

8.6.2. Methods

This section briefly describes the extension of spatial association to prior work efforts for resilience analytics and project coordination.

Spatial Association

Transportation improvements (as compared to policy, procedure, or other non-geographic initiatives) have a geospatial attribute, which creates an opportunity to evaluate resilience analytics with spatial association methods. As an inferential statistic, spatial correlation investigates patterns based on the variables and location of different attributes. When investigating the clustering both the high (hot) and low (cold) values of a variable, the Getis-Ord Gi^* (spatial statistic) analysis is typically applied and includes an attribute value [171], [172]. The measure of correlation is generally defined as shown in (8.3).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{8.3}$$

In this case, G_i^* represents the spatial association with x as the attribute value (initiative rank) for a feature (project, p) and w (notably different from the weight variable shown in (8.2)) is the spatial weight between projects i and j with a total of n features [171]. Additionally, the variables X and S are defined in (8.4) and (8.5).

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{8.4}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \tag{8.5}$$

Each attribute (or project initiative) is evaluated against all others based on the associated ranking value z, as defined by (8.2). These methods are proposed to seek clusters of highly ranked projects or those that are ranked low. If hot spots are identified it's a sign that a series of highly ranked projects could benefit from coordination, as they are likely candidates for investment. Conversely, a cold spot would signify a region that may have been inadvertently excluded from investment initiatives. The lack of a hot or cold spot would indicate geographic diversity of projects, which may increase robustness of the initiatives.

Additional spatial metrics, such as *Moran's I*, could be used in conjunction with the *Gi** analysis to determine if there are geographic clusters (regardless of ranking). Clustering could indicate a previously unrealized benefit of investing in multiple projects that were independently ranked low but could collectively be ranked higher based on geographic proximity.

This application relies on assumptions of quantity and geographic relationship of various projects. In spatial association analytics, there is an anticipated minimum quantity of objects (e.g. at least 30 projects) and proximity that meets expectations of project coordination benefits. The benefits of spatial proximity also rely on similarities in project scope. Other work has been successful in applying spatial association analytics to cases of traffic crash locations, crime locations, and other spatial events [134], [173].

Spatial disassociation informs stakeholders seeking to diversify infrastructure investments. If the physical location of different infrastructure projects is not considered, then the prioritized projects may inadvertently be geographically constrained. This impedes the robustness of the system (especially with geographic disruptions, like sea level rise) and likely agitates the multiple planning organizations that must consider large geographic regions.

Resilience Analytics & Spatial Association

These methods describe how *resilience analytics* can be extended with *spatial association* of various initiatives. When seeking positive spatial association, the intent is to identify geographic clusters of projects that are ranked highly (likely project candidates) to minimize resource requirements, increase safety, and reduce traveler disruptions by combining multiple projects. Identifying projects that achieve geographic diversity can ensure all localities are seeing a share of transportation resources. These objectives should also be evaluated across the temporal domain and consider prior project work and initiatives planned beyond the immediate future.

The spatial association statistics (G*i** value) are combined with the resilience analytics to reevaluate the prioritization of project initiatives. In seeking project coordination goals, the emergence of hot spots indicates highly ranked projects, whereas geographic diversity goals may investigate regions with cold spots, signifying a cluster of low ranked projects.

8.6.3. Demonstration

This section provides a demonstration of resilience analytics and spatial association applied to infrastructure project initiatives with potential for safety improvement (PSI) for investment projects throughout Virginia, USA. A dataset from the Virginia Department of Transportation (VDOT) includes 1,537 project initiatives throughout Virginia. The PSI data points include geospatial attributes, a reference to the planning district, and rank value of each project initiative. The geospatial attribute is used to reference the physical location of each project initiative and the spatial association of initiatives. The data used in this demonstration was acquired through the VDOT

Pathways for Planning interactive data analysis application, which includes PSI data for 2018 (updated on February 13, 2019). The ranking values are based on analysis results from years 2013 – 2017.

Identification of Projects

The map shown in Figure 8-1 provides a geographic reference to various PSI projects that are distributed throughout the state of Virginia, USA.

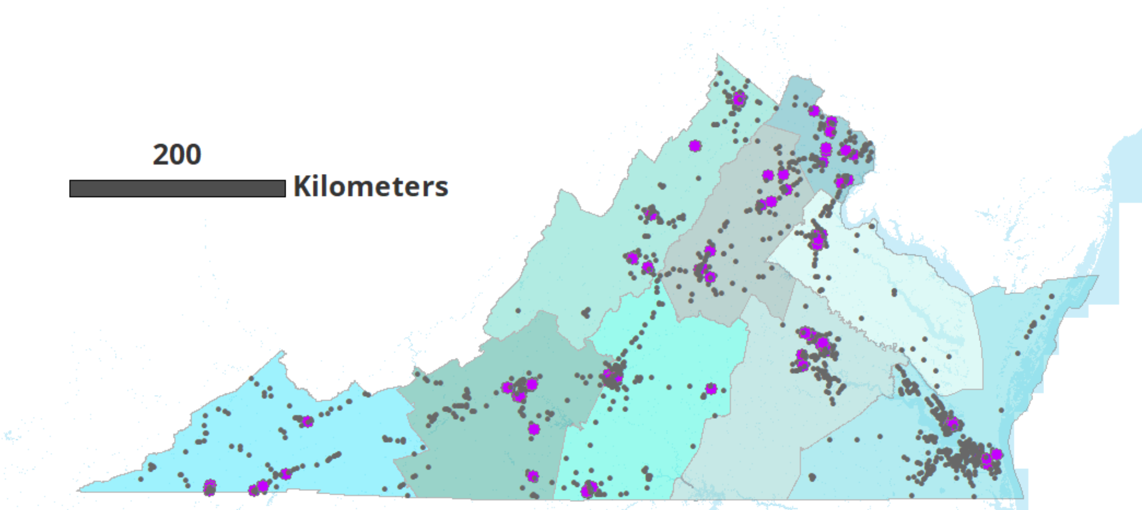

Figure 8-1: Distribution of 1,573 potential project locations throughout Virginia, where the highest ranked projects (top ten) are shown in purple for each of eight districts (teal polygons).

The scoring of these projects is developed by systematic safety improvement policies through multiple criteria with various weights, as defined in [174] and shown in Table 8-3. The scoring process evaluates each initiative independently prior to ranking all eligible projects.

Table 8-3: Scoring rubric for initial project improvement ranking.

Criteria	**Weight, w**
Benefit/Cost Ratio	40%
Problem identification (PSI)	25%
High Number of Targeted Crashes	10%
Cost Estimate	5%
Project Schedule	5%
Multiple Funding Sources	5%
Supporting Documents	5%
Location Information	5%

Initial eligibility into project consideration requires an inventory of crashes and an associated risk assessment [174]. The benefit-cost ratio is also required to be greater than 1.0, which is established by a prescribed method of calculating each benefit and cost. The cost variables include (a) construction cost, (b) service life, (c) preliminary engineering, (d) right of way acquisition, (e) contingency and (f) maintence costs [29], [136], [174]. Benefits of the improvements are based on documented crash modification factors (CMF) for different safety improvement methods as associated with the crash types and severities [174].

Absent of a geospatial reference and projection, the multi-objective analysis provides an abbreviated list of ranked projects as shown in Table 8-4. This list includes roadway identification information (route number) but there is no reference to the proximity of projects.

Table 8-4: Ranked projects with roadway route number, traffic control device (TCD), and the rank

Route Number	TCD	Rank
R-VA029SC00657NB	Traffic Signal Control	1
R-VA053SC00637NB	Traffic Signal Control	2
R-VA029SC02864NB	Traffic Signal Control	3
R-VA235UR06662NB	Traffic Signal Control	4
S-VA076PR	Traffic Signal Control	5
R-VA029SC05401NB	Traffic Signal Control	6
S-VA253PR	Traffic Signal Control	7
R-VA SR00028NB	Traffic Signal Control	8
R-VA US00001NB	Traffic Signal Control	9
R-VA SR00236EB	Traffic Signal Control	10
…	…	…

As represented by the map in, the projects contain unique geographic attributes throughout a dispersed region. The location of these attributes is generally represented by mapping coordinates such as longitude and latitude or by a projected state plane coordinate system. Within Virginia, the coordinate system is the North American Datum of 1983 (NAD83), split into a north and south zone across Virginia [175]. The x and y values of the project location are identified as northing and easting of the NAD83 system. The coordinates provide the information necessary to perform the Euclidean distance algorithm used in the determination of spatial association, as shown previously in (8.3).

Project Coordination Benefits

Evaluating the spatial association of infrastructure projects can be completed based on the geographic location of initiatives associated with each project. A select region of Virginia is shown in Figure 8-2, with text referencing the ranked value of each PSI initiative. The ranking is based on criteria attributes, as shown in Table 8-3, for all initiatives that meet the eligibility criteria. Spatial association is not initially considered with the rankings shown in Figure 8-2 and Table 8-4.

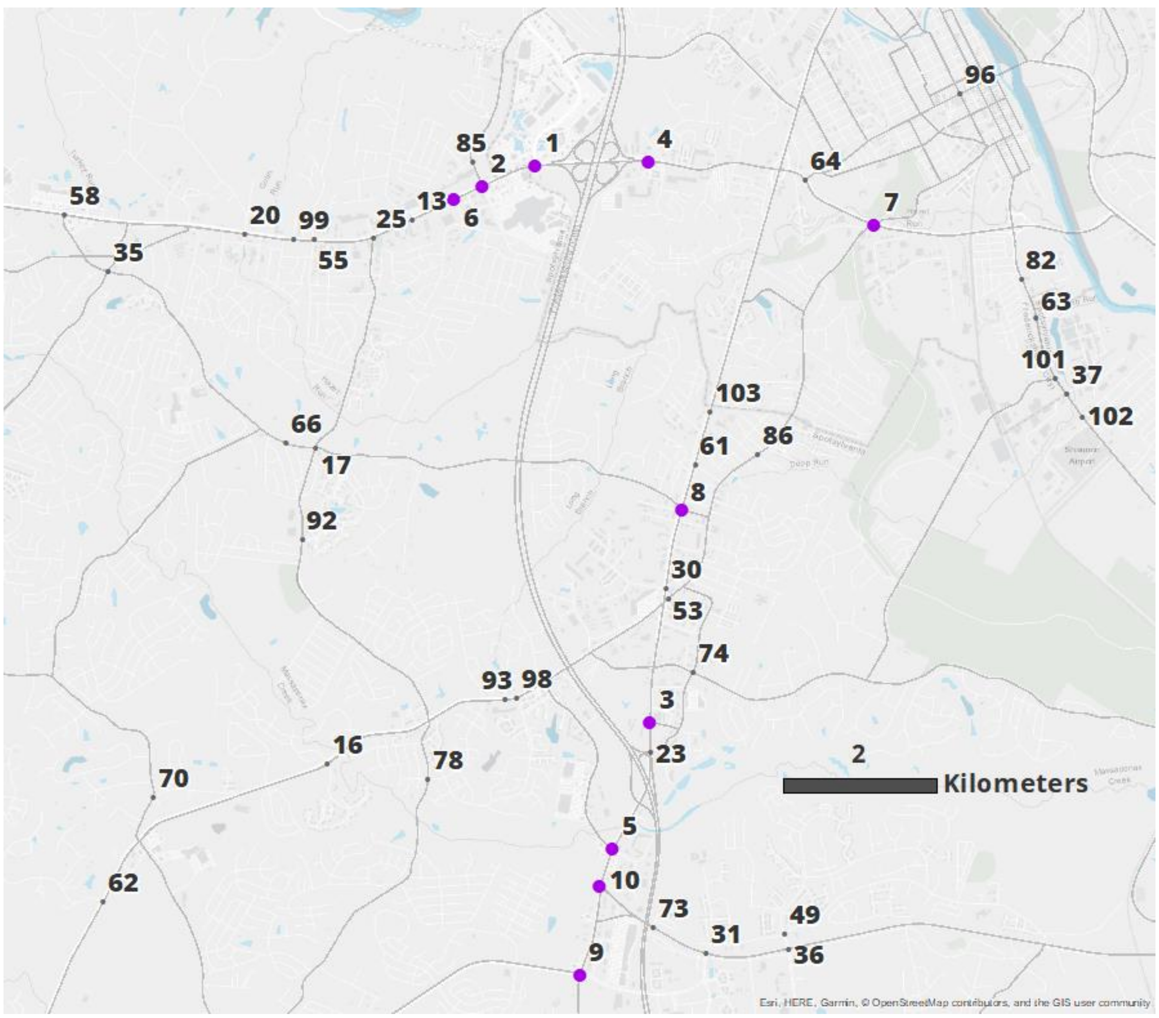

Figure 8-2: Intersection improvement projects and associated criteria ranking within a select region of the dataset. The top ten projects are shown in purple.

With the extension of spatial association, each ranked project is evaluated with considerations of the project's geospatial correlation (*Gi**). All projects that are highly ranked represent a hot spot as shown (with red dots) in Figure 8-3.

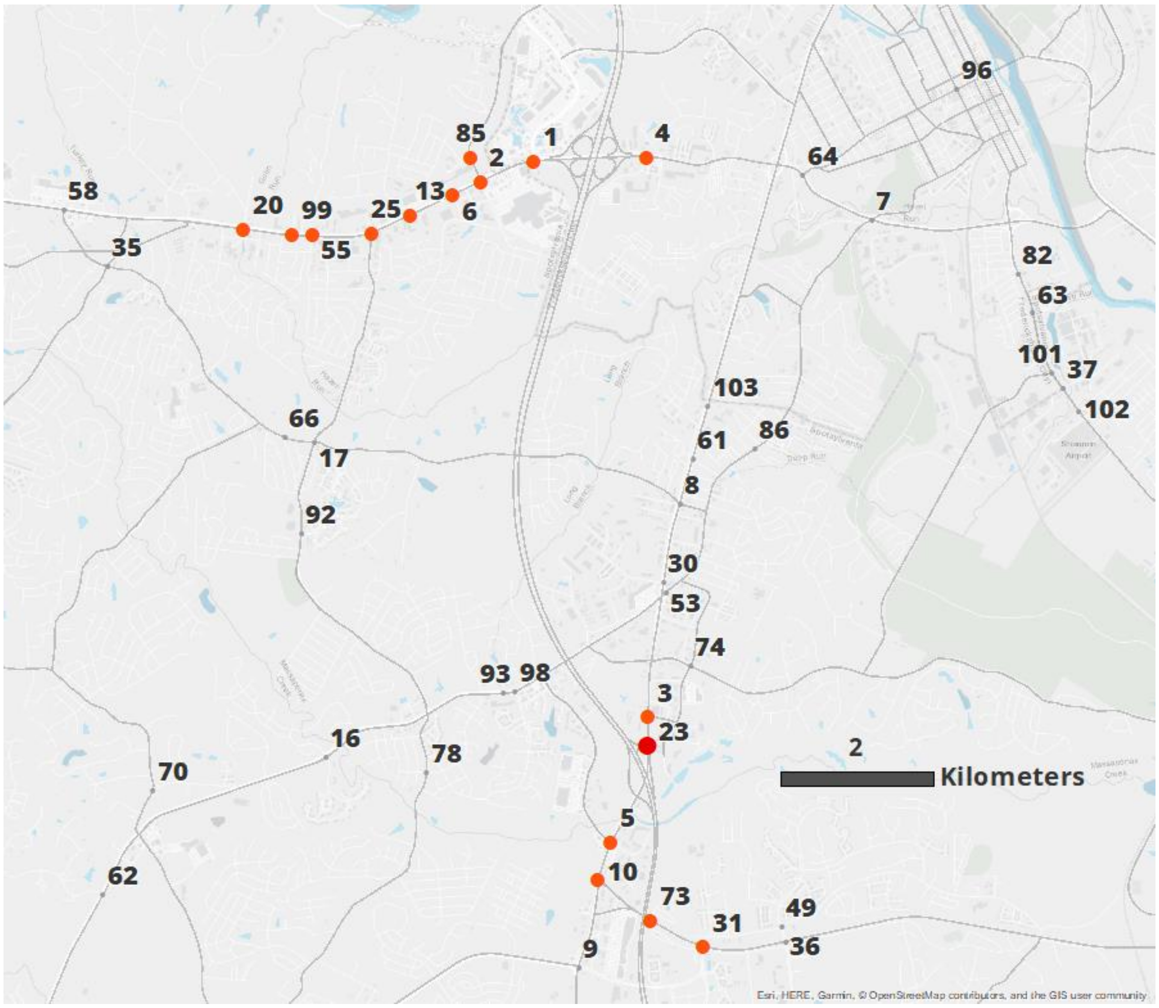

Figure 8-3: System hot spots (highly ranked projects) based on spatial association and project rankings. The brighter red represents a stronger spatial association (95% confidence), light red indicates a moderate spatial association (90% confidence), and the smaller gray dots do not carry any spatial association significance.

Regions that include clusters of low ranked projects are referenced as cold spots and would be shown in blue (Figure 8-4). Other groups of projects with relevant spatial association are depicted as gray dots (based on the Gi* analysis). The indication of hot or cold spots informs planning agencies of geographic clusters and potential project coordination benefits to influence project selection.

Under the premise of project coordination goals, the hot spots indicate an opportunity to investigate projects that could be combined based on geographic proximity and a high priority rank. Note that some projects with only moderate ranking might be included within the hot spots, indicating an unforeseen coordination opportunity in combining projects that might have ancillary benefits. Figure 8-3 shows hot spots for project initiatives that are not within the original top ten rankings (Figure 8-2); however, because the projects are evaluated based on spatial association there is potential opportunity to select these projects based on cost savings or coordinated safety benefits.

Geographic Diversity Goals

The presence of cold spots indicates that a region does not include potential project candidates as the projects have been ranked low by multi-objective analytics. The identification of cold spots could be used by stakeholders to revisit the projects within the given geography and determine if some investments are warranted. For example, Figure 8-4 depicts a group of lower ranked projects within a localized region of Virginia that does not have any highly ranked projects.

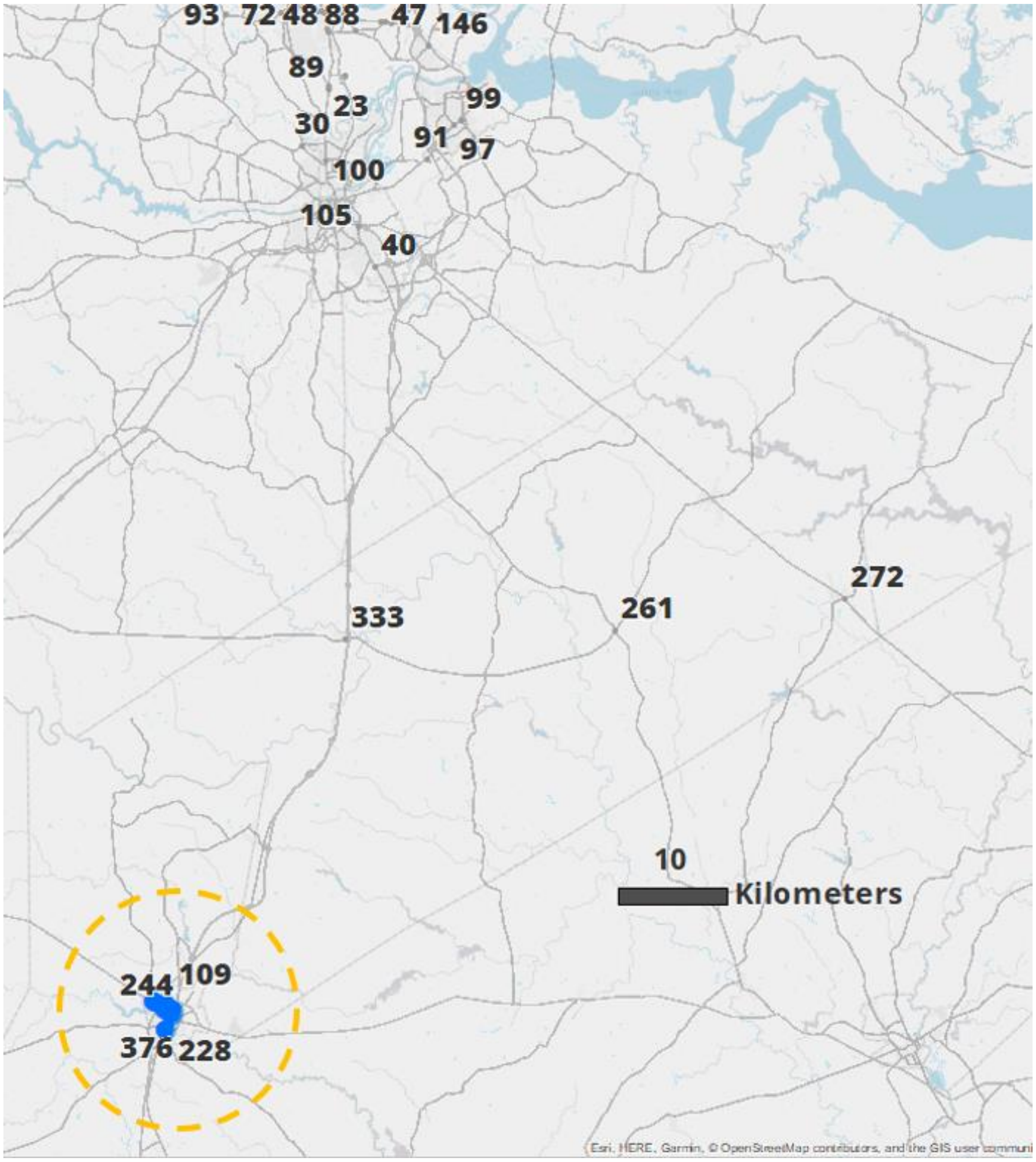

Figure 8-4: Region of the transportation system with a group of intersection improvements that have a low rank indicated by a cold spot (95% confidence) that informs planners of a potentially underserved area.

The spatial association analysis informs planners that this region might be underserved by safety improvements. The cold spots highlight a series of points that have a low global rank; however, if these project initiatives are evaluated as a group it may uncover compound benefits or potential cost savings. This perspective could increase the ranking of the initiatives, which may otherwise go undetected if evaluated independently.

Geospatial Resilience Analytics

The spatial association analysis can be extended to consider how the initial ranking could be informed by geospatial information such that the proximity of multiple projects can uncover unforeseen program coordination benefits. The resilience analytics framework can be correlated to location-specific intensities of various disruptions [168]. As shown in Figure 8-5, the geospatial relationship to disruptions can further inform planning agencies of project selection.

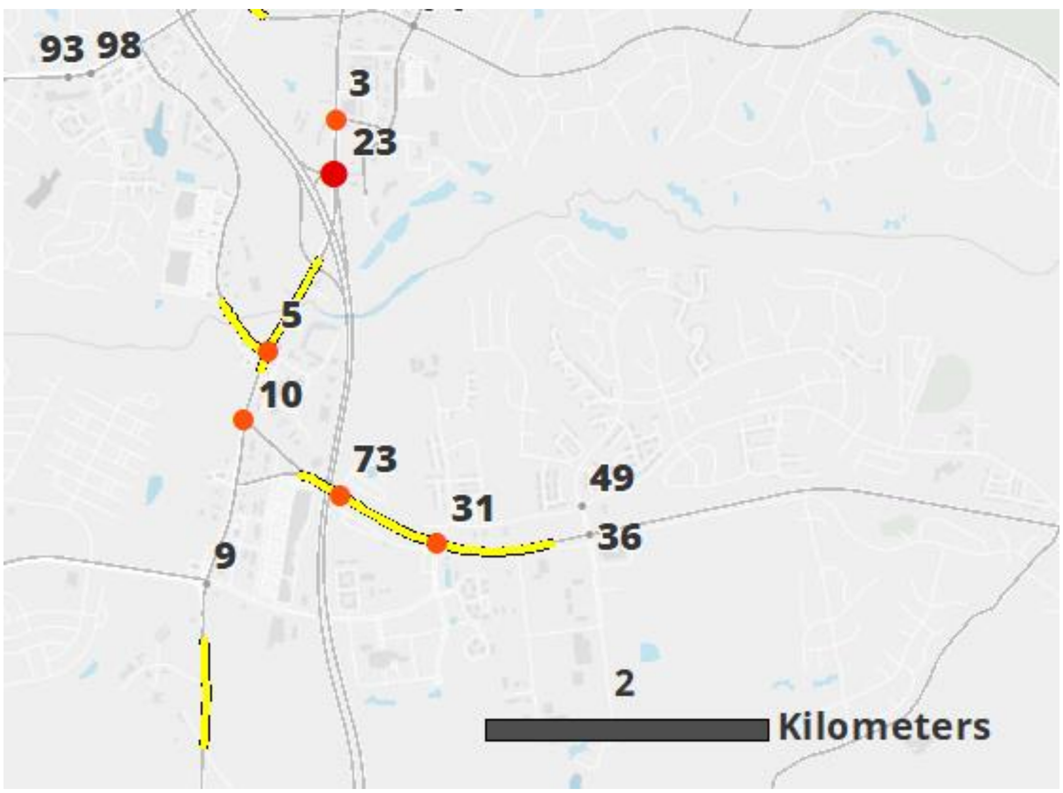

Figure 8-5: Project initiatives with a disruption to the system (other planned transportation projects, shown as yellow lines).

The Virginia transportation agency has 1,448 planned transportation projects within the six-year improvement plan (SYIP) dataset (as acquired from the Virginia Department of Transportation Pathways for Planning geospatial analytic tool, updated September 2019). Any safety improvements made to intersections that are coincident with other planned transportation initiatives require additional coordination and evaluation. The intersection safety improvement may be obsolete after a SYIP project is constructed and should be considered in investment selection. The intersection initiative ranked five (5) in Figure 8-5 may not be relevant in the prioritization because a separate investment initiative may resolve adverse condition. Similarly, the initiatives 73 and 31 could be incorporated into the project scope of the coincident SYIP project.

8.6.4. Summary

The contribution of this chapter is to inform a systems-based multi-objective analysis of a transportation system by evaluating the geographic spatial association of project initiatives. Multi-objective analysis, and the ranking of investments, is an iterative process [176]. The result of ranked values is not meant as a prescribed method of project investments, but a means of informing stakeholders of how each project performs under multiple criteria. Adding spatial association statistics provides an extension to the analytics by investigating the physical relationship of the interconnected transportation systems. Multiple spatial associations (*Moran's I and Gi**) can be investigated to identify clustering of project locations and evaluate the clustering of high rankings (signifying project coordination opportunities) or a clustering of low ranked projects (indicating geographic diversity of projects). Specifically, corridor projects would benefit from a *Moran's I* autocorrelation of network analysis, which evaluates if clustered projects are located on the roadway or disparate corridors.

Addressing geospatial resilience in transportation systems engineering can further inform project prioritization by considering geospatial (and non-geospatial) disruptions. Evaluating other geospatial attributes extends the concept of system resilience. These analyses can further inform the system owners and operators in the prioritization and evaluation of infrastructure investments.

8.6.5. Scenarios of Spatial Association

In the preceding sections, a post-facto spatial association analysis was applied to safety improvement initiatives to inform transportation agencies of project coordination opportunities. In future work, the scoring rubric for project selection can be modified to include spatial attributes of project initiatives. A spatial score could be disaggregated based on different objectives associated with geospatial attributes. A sample list of location-specific project criteria is shown in Table 8-5.

Table 8-5: Sample of geospatial criteria that should influence project initiative score and ranking

Geospatial Criteria	**Geospatial Weight (φ)**
Located along bike corridor	φ_1
Proximity to residential area	φ_2
Proximity to retail center	φ_3
Proximity to school zone	φ_4
Located within a designated economic growth zone (comprehensive plan)	φ_5
…	φ_n

The geospatial weight would follow the same framework as other criteria weights associated with resilience analytics, such that:

$$\sum_{n=1}^{N} \varphi_n = 1 \text{ and } \varphi_n \in [0,1]$$

(8.6)

where the geospatial weights (φ) could vary based on disruptive scenarios associated with geospatial attributes. For example, an increase in vehicle congestion and population growth could result in rapid growth of bike transit, creating a higher weight value for intersections along existing or planned bike corridors [9].

In coordination with stakeholders from various positions (regional, local, community, government, scientists, and others), a series of geospatial disruptions and relevant scenarios can be identified for project stressors. The sensitivity of stakeholder influence and objectives should be evaluated to determine the sensitivity of influence and monitor potential bias that is inherent is benefit analysis [142]. As disruptive scenarios are established, they can be evaluated against prior published and researched work to identify which of the disruptions (or combination of disruptions) has the most influence on project prioritization [75]. In some cases, a disruption is established as a baseline that is also influenced by other conditions – for example, population growth and congestion growth is (likely) inevitable and could be evaluated with environmental change, additional freight vehicles, or other stressors.

The following list provides several different scenarios related to spatial association.

1. **Scenario S1 (Regional population growth):** Base scenario, in which regional population growth increases vehicular and pedestrian traffic, where the growth volumes are based on population and traffic conditions of the locality.

2. **Scenario S2 (+Environmental change):** In addition to Scenario S1, this evaluates how sea level rise or additional adverse weather conditions disrupt operations. The influence of these disruptions would vary by geography. For example, the coastal area would have a higher risk of sea level rise whereas colder climates would be influenced by increased frequency and intensity of snowfall.

3. **Scenario S3 (Increased freight growth):** In addition to Scenario S1, this considers how increased commercial operations will add more heavy vehicles to road networks, which influences operations and safety. Regions near major industrial hubs would see more disruptive conditions.

4. **Scenario S4 (Freight and land development growth):** In addition to Scenario S1, this considers a significant increase in freight surface transportation and new development areas. New development provides coordination opportunities between public and private developers.

5. **Scenario S5 (Land development):** In addition to Scenario S1, this considers how new development will influence local road systems and provide coordination opportunities between various project types.

These scenarios are listed with various conditions, as shown in Table 8-6. In practice, these conditions originate from research that has identified the importance of evaluating the possibility of these disruptions and scenarios. The inclusion of a diverse set of stakeholders (environmental scientists, land planners, transportation engineers, community members, and others) can better diversify the scenarios and conditions. These scenarios should be developed with stakeholders that evaluate the critical list of emergent and future conditions.

Table 8-6: Disruptions and the relationships to identified scenarios

Disruptions	Scenarios				
	s1	s2	s3	s4	s5
Regional population growth	✓	✓	✓	✓	✓
Sea level rise	✓	✓			
Increase in snow accumulation		✓			
Increase freight growth			✓	✓	
Land development growth				✓	✓
Coordination opportunities				✓	✓

The influence of each disruption varies by geographic location. U.S. Census data, environmental studies, comprehensive planning documents, commercial business plans, and other sources of information would inform the scoring.

When evaluating the spatial association of project initiatives, other geospatial layers can add context to benefit, cost, risk and disruptions with each project location. Census data (geospatial layers) include population growth data, which could be used to evaluate how crash risk may increase with anticipated population growth of a region. Detailed geospatial data may include locations of bus shelters, streetlights, parks, or other information that could increase crash risk. Planning data, such as areas with anticipated growth, transportation improvements, trail extensions, and other infrastructure can be evaluated in coordination with intersection improvements. The geospatial analysis of resilience analytics provides a new perspective on project prioritization and planning decisions.

8.7. Emergent and Future Conditions

As technology has changed at an exponential rate since the turn of the 21st century, so too have the industries and systems impacted by the resulting changes or disruptions. This section provides content on the initial work for methods of scenario-based planning that considers *when* a disruption may occur. Within the real estate industry, the influence of new technologies is readily apparent in certain areas such as the adoption of Building Information Modeling (BIM) in design and construction, the incorporation of smart and sustainable systems into new buildings, and a shared economy approach to travel behavior and space use (e.g. ride shares and AirBnB). However, there is an extensive network of critical interrelated institutions connected to real estate that is often overlooked, making the effects of disruption less transparent in the context of the larger system. This chapter section will emphasize the complexity of the system that supports the real property and its relevance for infrastructure and market interests.

8.7.1. Applications of Resilience Analytics to Real Estate

Real estate development is challenged by limitations in resources and the uncertainty of future conditions. It is further bounded by political and physical conditions that must consider the long-term operational requirements and the continuous shift of social, environmental, technological, and economic conditions. This complexity can be served by systems engineering. While the potential applications of systems engineering to real estate are extensive, this section will highlight conceptual examples in infrastructure development and marketing.

With the rapid emergence of technologies, infrastructure planning is challenged to serve current needs while also being adaptable to future conditions. These challenges are especially prevalent in infrastructure design because (i) the planning, funding, design and construction of a project will span multiple years; (ii) the technology, policies, economics and other factors change during the years of design and construction (and continue to change over the life of the development); (iii) each project is unique; and (iv) the scale of infrastructure projects prohibits testing, prototyping, and agile development.

The planning, design, construction, operations and maintenance of civil infrastructure is interconnected and interdependent within a community and the economy. Water, transportation, energy, and communication infrastructure are critical to the economic system [16], [17]. The multitude of stakeholders and contending objectives are constantly negotiated between local, regional and global environments. This interconnected state is not restricted to the physical infrastructure of the built environment – the rapid and continuous emergence of technology and communication channels adds to the complexity and risks of community development. This complexity requires processes that serve, plan, and adapt to economic, social, physical, spiritual and environmental objectives.

Once developed, real estate projects are expensive and difficult to modify. In some cases, extensive retrofitting or rehabilitation is simply not possible due to design or site constraints. Unanticipated future changes in space use, technology, or other areas can limit functionality, increasing operating costs, or impact demand, leading to increased vacancy, slower rental/sales rates, or the need to discount prices. Thus, it behooves land use planners and developers to account for future disruptions that may impact their projects before each asset reaches its natural point of functional obsolescence. A contemporary example of a future disruptive threat centers around the eventual impact of autonomous vehicles on parking structures. Changes to automotive technologies are generally considered unrelated to real estate. However, a rise in the use of autonomous vehicles may change the way parking structures are designed and used. While autonomous vehicles are already a part of mainstream industry discussions, other potential disruptions have likely not yet been identified. Applying a systems engineering approach to evaluating projects during the design stage can help developers consider what unanticipated disruptions or seemingly unrelated technologies may become relevant in the future, allowing the developer to plan accordingly.

Assessing the technical, managerial, and philosophical applications of a real estate project serves to inform infrastructure planning subject to deep uncertainties [101],

[177]. From the technical perspective, systems engineering investigates the applied mathematics of topics such as optimization and statistical modeling. Decision and risk analysis can fall under the managerial content of systems engineering. Perhaps most importantly, the philosophical element of systems engineering considers how multiple systems, objectives, and stakeholders are interconnected and interdependent. The philosophical perspective acknowledges the inherent challenges associated with models, risks, and decisions for systems with noncommensurate variables (e.g., financial investment costs versus risk of life) and multiple objectives. These topics are not independent within the realm of systems engineering and must also consider the shifting base of the system across time [18]–[20].

The application of systems engineering is not prescriptive or uniform across domains, geographies or projects. It would be impossible to create a systems-based process or model that could appropriately represent the complexity of the built and natural environments. Instead, systems engineering is a catalyst for stakeholders to be engaged in the evaluation of multiple objectives, perspectives, tradeoffs and risks associated with development.

Applied to real estate development, systems engineering can function as a tool to investigate the challenges associated with the risk, uncertainty, and shifting conditions that are inherent to land development projects. Real estate projects seek rapid design and development while attempting to consider uncertain long-term conditions. Specifically, three critical practices of systems engineering can be applied to real estate development processes:

(i) considering *multiple objectives* and perspectives
(ii) evaluate the systems across a *temporal* domain, and
(iii) *scenario analyses* to investigate possible outcomes associated with future conditions.

In this way, the multiple objective temporal scenario analysis (MOTSA) provides a framework that benefits developers, stakeholders, landowners, and decision makers.

The MOTSA process supports developers and stakeholders in decision-making. The approach demonstrated in this chapter describes a philosophy of planning that considers the complex interconnected and interdependent conditions of real estate development, with implications for different market-rate product types, infrastructure, and humanitarian initiatives. While it is impossible to find an optimal design solution (when attempting to identify optimality from multiple perspectives) the intent of the MOTSA process is to introduce necessary actions into traditional land development planning in order to minimize regret. It would be unreasonable to assume that regret could be accurately measured except by a post-facto analysis; instead, the MOTSA process is meant to inform stakeholders of conditions that may not be self-evident in the consequences of current actions on future decisions.

8.7.2. MOTSA Overview

The MOTSA process can be defined as a tool for resilience analytics. The term *resilience*, as defined by the International Council on Systems Engineering (INCOSE) is a system's ability "to adapt to changing conditions and prepare for, withstand, and rapidly recover from disruption" [177]. When evaluated with real estate development projects and disruptive technology, a resilient project would maintain value under disruptive conditions and regret would be minimized. The disruptions may come as technological discoveries but in many cases it is the policies and social perspectives that establish the influence of technology [23].

Prior work has applied resilience analytics to infrastructure systems as a means of ranking and prioritizing investment initiatives [19], [37], [167], [168]. The prior research developed a framework for evaluating the resilience of multiple initiatives by applying system stressors and investigating the numerical rank of various initiatives as evaluated under different perspectives (or conditions) [29]. This framework has previously been defined to investigate the ability for various project investment initiatives (p) to withstand different disruptions (d), where one or more disruptions are defined by scenarios (s). Each project is evaluated and ranked by a set of multiple objectives (mo) and then re-evaluated under different scenarios [167], [168], [178].

- Project Initiatives – different investment initiatives for a given project
  - P = $\{p_1,\ldots,p_n\}$, with n initiatives
- Disruptions – technological disruptions that could influence the ranking of initiatives
  - D = $\{d_1 \ldots, d_m\}$, with m number of disruptions
- Scenarios – one more disruptions defines a scenarios
  - S = $\{s_1,\ldots,s_k\}$, with k scenarios based on sets of disruptions
- Multiple Objectives – economics, environment, aesthetics, and others
  - Mo = $\{mo_1,\ldots,mo_m\}$, with m objectives based on multiple perspectives

A weight value (w) is assigned to each objective (mo_m), where $\sum_{j=1}^{m} w_j = 1, 0 \leq w_j \leq 1 \; for \; j = 1, \ldots m$. In this way, the weight assigned to each objective is normalized. The weight can change for each scenario and temporal domain. For example, if the primary objectives are economy, safety, and environment, the weights might be 30%, 50% and 20% respectively. Each objective also has a maximum score (z) proportional to the weight (30, 50, and 20 from the prior example).

Each project initiative (p_i) is scored (a_i) based on the ability to meet an objective, as measured with the associated weight (w_j). Continuing with the prior example, a project initiative might score 15 (of 30), 45 (of 50), and 20 (of 20) points (for a total of 80 out of 100 possible points). The scoring is best performed by a group of stakeholders with multiple perspectives. Score values are based on relevant research and expert opinion. The scoring process is repeated across all projects. Mathematically, this is defined as shown in (8.7).

$$v_{s_k}(p_i) = \sum_{j=1}^{m} w_j^k a_{ji}^k \tag{8.7}$$

This method represents the project prioritization value (v) for a given project (p_i) based on the total value of each objective weight (w) and the assigned score (a) across all objectives (j) for a given scenario (s_k).

Resilience analytics process traditionally begins with a baseline condition, in which there are no disruptions. Each scenario introduces one or more disruptions, often with a common (inevitable) disruption, that could modify the weight values of each objective. Each scenario also requires a new set of scores assigned to each project initiative to consider the effectiveness under the given scenario. For example, under a baseline (no disruption scenario), a site's surface parking may be designed to accommodate current transportation systems. However, under a disruption such as the emergence of electric vehicles, the investments in vehicle parking systems such as charging stations might be scored higher. Each stakeholder must evaluate the development program to determine a list of project initiatives that can be influenced by multiple objectives and disruptions. A sample set of project initiatives is shown in Table 8-7 for reference.

Table 8-7: Example land development project initiatives that are influenced by disruptive technologies

P	Project initiatives
P_1	Provide underground infrastructure to support electric charging stations
P_2	Install electric charging stations
P_3	Provide infrastructure to support hydrogen vehicle fueling
P_4	Provide conduit, electrical systems and structural support for rooftop solar
P_5	Plan for surface parking redevelopment
P_6	Install additional (empty) communication and electrical conduits
P_7	Reserve building space for battery backup systems
P_8	Reserve site area for alternative transportation modes
P_9	Provide drop off and queuing areas for autonomous vehicles
P_{10}	Design roof layout (and structural support) to accommodate UAVs
P_{11}	Design structured parking with raised clear heights to accommodate future conversation to useable space (subsurface or above grade decks)
P_{12}	Design structured parking layout with side ramps to facilitate AV navigation
P_{13}	Change plenum depth to accommodate new sustainable heating/cooling mechanisms
P_{14}	Provide drone docking and delivery drop off stations (aerial or vehicular)
P_{15}	Increase building central computing capability and dedicated mainframe space for systems upgrades and/or to engage with future Smart City initiatives

The source of these initiatives may come from the developer, stakeholders, design team, academic works, or other sources. The list of project initiatives should consider similarities and the ability to disaggregate initiatives that may establish more resilient investments. For example, when faced with an unknown condition of the next dominant vehicle fuel source (e.g., electric or hydrogen), a resilient project initiative would include infrastructure elements to support additional onsite electrical demands.

Multiple Objectives

There is no system with a single objective or perspective. The *multiple objective* component of MOTSA acknowledges that most stakeholder objectives will face competition between project priorities, available resources, community support, and others. For example, water infrastructure projects may compete on objectives of supply, hydropower or replenishment of natural systems [179]. Businesses located along a highway may compete for customer access to promote economic development, but transportation agencies may seek to minimize access points to reduce vehicle conflicts [28], [29]. A residential developer seeks to maximize profits but must consider the physical and political boundaries of development – and should also consider the humanitarian responsibilities of providing affordable and accessible housing.

Hierarchical holographic modeling (HHM) is a framework to consider multiple perspectives and objectives of a system [16], [101]. Originally demonstrated though large-scale complex infrastructure systems (energy distribution and water resources), the development of an HHM requires the decomposition of a system into multiple subsystems but expands across multiple models to consider different structures associated with political, economic, environmental, and functional conditions across time [18], [101]. While HHM fundamentally relies on a mathematical representation of a complex system, the development of a graphic representation of the HHM will promote active discussions about a project's objectives, risks, stakeholders, and perspectives.

As an example, we can consider the complexity of evaluating multiple objectives and perspectives of a land development project. A new residential community might consider a high-density development that would promote population growth and increase the number of available homes in the region;

however, constructing high-rise structures can limit convenient access between homes and open space (increasing the distance between parents seeking to watch over their children playing in a park). Similarly, the transportation network within a residential development might benefit from increased connectivity and complete streets (parking, bike lanes, vehicular travel lanes) through the neighborhood, but maintaining the safety of children with narrow low-speed streets would oppose goals of adding on-street bike lanes and encouraging public street connections. Similarly, narrow streets and traffic calming can promote reduced vehicle operating speeds but can challenge emergency vehicle access. Clearly identifying the existence of multiple objectives requires a diverse group of stakeholders engaging with mutual respect. Each stakeholder (or stakeholder group) must also recognize that communication, objectives, perception, and priorities will vary between individuals (or groups). There is no single method to ensure inclusive design practices – each project requires a determination of the appropriate processes and technologies. Most importantly, an accurate representation of multiple objectives (and associated perspectives) requires a common language of understanding.

Table 8-8 provides a list of several stakeholders that contribute to multiple objectives of a project. Each objective should have a maximum score that can be achieved with different project initiatives (p_i) and each project is scored (a) with respect to the a given project meeting each objective (mo). The weight (and maximum possible score) of each objective is determine by stakeholders.

Table 8-8: Sample list of the sources of multiple objectives from perspectives of different stakeholders

M_o	Multiple Objectives of Stakeholders
MO_1	Developer
MO_2	Legislative Bodies
MO_3	Courts & Police
MO_4	Land Records Office
MO_5	Zoning & Planning
MO_6	Lending & Finance
MO_7	National Data & Technology Policies
MO_8	Education
MO_9	Taxation & Economy

Each stakeholder objective can be disaggregated to consider additional objectives based on the composition of the entity. For example, the zoning and planning authorities likely include offices of environment, affordability, mobility, utility services, and other divisions that each have their own objectives. A merchant builder, who builds with the intention of selling, may consider only immediate costs and the returns of a project and may not be concerned with aesthetics, future technological disruption, future policies, or operation and maintenance costs [14].

Temporal Considerations

The management of real estate is often focused on the immediate needs and costs. These initial objectives struggle to recognize the impact of future decisions, or perhaps surrender to the uncertainty and challenges associated with predicting the conditions and requirements of future timeframes. Land development is especially challenged by timeframe considerations of a project. Architecture and infrastructure projects are designed to last for decades but relies on current technologies, policies, and market conditions for design and decision-making. Additionally, the due diligence, research, design, funding, and construction of real estate development requires years – during this time the technology, policies, and market conditions continue to change. This variability creates a vulnerability in the project. The temporal considerations should not be limited to future conditions but should also investigate historic and concurrent influences on the project requirements. For example, today we may consider that autonomous vehicles are inevitable and will dramatically change the transportation infrastructure, but current policies and development decisions are still made under the traditional transportation requirements and regulations.

When decisions are not evaluated across the temporal domain, parties fail to anticipate how current actions can limit the future options and the associated long-term costs. The design and material choices for the infrastructure construction will influence the social, environmental and financial costs of the operators and the community. An inadequate capacity of infrastructure will lead to operational challenges and limit growth, while over-investments in infrastructure will create unnecessary burdens on the operations and maintenance.

The political and physical conditions that bound the initial infrastructure development are subject to change across the temporal domain of the project. The development legislation of a jurisdiction is not static – the policies are subject to change with new environmental discoveries, the shifting vision of a community, and new technologies in design and construction. Additionally, changes to exogenous factors such as technology, weather, sea level, and population growth create deep uncertainty for infrastructure planning.

These temporal conditions provide an additional dimension to the scenario planning associated with the MOTSA process. For many of the scenarios the question of “when” is more relevant than “if” a disruption will occur. When prioritizing investments, a stakeholder must consider when a disruption will occur, how stakeholder objectives may change over time, and how current actions can limit future decisions. The process of temporal decomposition is an extension of resilience analytics and considers the time frame associated with each disruption. The original framework, as referenced in Equation (8.7), can be expanded to consider different planning horizons associated with a scenario. A technological disruption might be inevitable, but other disruptions could be prioritized based on immanency of the disruptions.

To consider the planning horizons and temporal domains, a new temporal weight (τ) is introduced to the resilience analytics, where $\{\tau : 0 < \tau \leq 1\}$. The temporal weight modifies the ranked value for scenarios based on when they are anticipated to occur. The timeframe of the scenario must be less than the life expectancy of the project, or else it is not deemed relevant to the project. Based on a planning horizon in years (T), the anticipated timeframe of a scenario (t_{sk}) is evaluated as shown in (8.8):

$$\theta = \sum_{k=1}^{s} \frac{(T - t_{sk})}{T}$$
$$\tau_k = t_{sk} \times \theta^{-1}$$
$$\{ t_{sk} : 0 < t_{sk} \leq \mathrm{T}\}$$

(8.8)

Each scenario (s_k) holds a temporal weight (τ_k) associated with the expected timeframe of the disruption. The variable τ represents a proportional weight of a given scenario to all other scenarios evaluated across the temporal domain. The variable θ represents the sum of all temporal values of the project. As an example, if the planning horizon of project infrastructure is estimated at 50 years and the disruptive scenarios are expected to occur 15, 25, and 40 years from project origination, then θ would equal (1.0+0.7+0.5+0.2=2.4). Each value of t is then evaluated as a proportional weight to calculate τ_k, such that τ_k= {0.42, 0.29, 0.21, 0.08}. The temporal weight is assigned to the (8.7) as defined by (8.9).

$$v_{s_k}(p_i) = \tau_k \sum_{j=1}^{m} w_j^k a_{ji}^k$$

(8.9)

As shown in (8.9), the temporal weight does not influence the score (a) or weight (w) assigned by multiple objectives, and instead applies an adjustment to the entire project initiative value (v) for each scenario. In this way, scenarios that are anticipated to occur later in the planning horizon will carry less weight than those in the near term. These temporal weights should not preclude an investigation into which decisions could obfuscate future project initiatives, such that a project in the future is no longer an available option. The value of t_{sk} does not reference the time of invention of a relevant technology but instead evaluates the expected timeframe of market penetration such that it would influence project initiatives.

Scenario Analysis

Scenario analysis is a method to changes to policies, environment, community, and technology across time, which will all influence the priorities and value of investment decisions. By accepting the uncertainty, scenarios inform the current decisions with an investigation of a variety of effects across different time frames. These scenarios are key to the temporal considerations of MOTSA and are based on prior work that demonstrates the value of scenario-based planning [38], [51]. While the scenario development is meant to inform stakeholders, it is not reasonable to assume the scenarios are inclusive to all possible futures. Instead, the development and analysis of scenarios should prompt discussions about possible futures and the prioritization of initiatives that establish resilient designs, The determination of the appropriate metric of resilience should be prompted by the multiple objectives of stakeholders and informed by the scenario planning and analysis. A scenario analysis begins with identifying a list of disruptive conditions, as shown in Table 8-9.

Table 8-9: sample list of disruptive technologies that would influence the ranking and resilience of development project initiatives

D	Disruptive Technology
D_1	Blockchain
D_2	Autonomous ground transportation
D_3	Artificial intelligence (building systems)
D_4	Drone delivery systems
D_5	Electric vehicles
D_6	Hydrogen-powered vehicles
D_7	Smart building materials (flooring, walls, sensors)
D_8	Enhanced communication (5G)
D_9	Autonomous air transportation
D_{10}	Renewable energy production (cheaper systems or policy requirements)
D_{11}	Robotic delivery or assistant services
D_{12}	Biometric security
D_{13}	Unknown unknowns

The disruptions in Table 8-9 are provided as an example and should be developed by stakeholders and state of the art research. Based on a selected set of disruptions, each scenario will consider one or more disruptions. A base disruption (e.g., an inevitable condition) can be used across all scenarios. Similar disruptions can be grouped into a single scenario, as shown in Table 8-10, which considers a (0) baseline, (1) consistent disruption, (2) transportation technologies, (3) artificial building intelligence, and (4) energy technology scenarios.

Table 8-10: Sample list of scenarios that group various disruptions by similar technology conditions or anticipated timeframes. Each scenario may have a common disruption or represent independent disruptions.

S	Scenario Disruptions
S_0	*No disruptions*
S_1	D_1
S_2	$D_{1} + D_2$, D_4, D_5, D_6
S_3	$D_{1} + D_3$, D_7, D_8, D_{10}, D_{11}, D_{12}
S_4	$D_{1} + D_9$

Scenario analysis can be used to prioritize different projects based on a defined set of objectives through various futures that consider emergent conditions [141], [176]. Each objective has different weights assigned, which can be modified across various scenarios. Each scenario prompts a new assigned score on how well a project meets objectives given the disruptive conditions of a scenario. The scenarios can be opportunistic or disruptive and are meant to inform decision-makers. The development and analysis of scenarios promotes conversations across subject matter experts with different perspectives and objectives. Scenarios are best authored by a diverse team based on technical review of potential disruptions. Initially, each stakeholder may lobby for a set of project initiatives to meet one objective; however, scenario-based planning evaluates how the initiatives rank when considering all objectives. Resilience of each project initiative is evaluated by the scenarios that can most disrupt the system. There is a growing recognition of the applicability of this technique and the American Planning Association (APA) supports scenario planning methods as a complimentary framework for traditional planning processes [160], [180], [181].

8.7.3. Summary

Systems engineering has a range of applications related to real estate, including infrastructure delivery, humanitarian projects, and private sector investment and development. The use of a systems engineering approach can enable developers and policy makers to consider a more robust, holistic view of the real estate system rather than limiting focus to individual industry sectors or institutions. The intentional application of the MOTSA process can support an analysis of potential disruptions to projects, build resilience against future threats, prevent or limit unintended policy consequences, and lead to early adoption of best practices.

Despite its potential, however, systems engineering is often poorly understood outside of the engineering profession and military applications. This inherently limits its value to members of the real estate community who might otherwise benefit from its use. Thus, further development is required to increase the approachability of the MOTSA processes in order to support the engagement of non-engineering stakeholders. This includes the need to build a framework tailored for different real estate applications. Such a framework would guide users through an outline of considerations with prompts for defining and considering multi-objectives, temporal factors, and scenario analysis components. A fully developed MOTSA tool could become, in its own way, a type of disruptive technology used to improve the results of real estate planning and projects.

REFERENCES

[1] C. Marchetti, "Anthropological Invariants in Travel Behavior," *Technol. Forecast. Soc. Change*, vol. 47, no. 1, pp. 75–88, 1994.

[2] P. Newman, "Transport priorities shaping the urban fabric: New methods and tools," *Methods Sustain. Res.*, pp. 17–31, 2017.

[3] INRIX, "Global Traffic Scorecard," 2019.

[4] J. H. Lambert, Y.-J. Wu, H. You, A. Clarens, and B. Smith, "Climate Change Influence on Priority Setting for Transportation Infrastructure Assets," *J. Infrastruct. Syst.*, vol. 19, no. 1, pp. 36–46, 2012.

[5] H. You, E. B. Connelly, J. H. Lambert, and A. F. Clarens, "Climate and other scenarios disrupt priorities in several management perspectives," *Environ. Syst. Decis.*, vol. 34, no. 4, pp. 540–554, 2014.

[6] TRB, *Highway Capacity Manual*. Washington, DC: U.S. Transportation

Research Board, 2010.
[7] D. Schrank, B. Eisele, and T. Lomax, "2014 Urban Mobility Report, Appendix A: Methdology," 2019.
[8] K. Kelobonye, G. McCarney, J. (Cecilia) Xia, M. S. H. Swapan, F. Mao, and H. Zhou, "Relative accessibility analysis for key land uses: A spatial equity perspective," *J. Transp. Geogr.*, vol. 75, no. January, pp. 82–93, 2019.
[9] A. Mondschein and B. D. Taylor, "Is traffic congestion overrated? Examining the highly variable effects of congestion on travel and accessibility," *J. Transp. Geogr.*, vol. 64, no. September, pp. 65–76, 2017.
[10] J. Scheurer and C. Curtis, "Accessibility Measures: Overview and Practical Applications," 2007.
[11] FHWA, "National Performance Measures for Congestion, Reliability, and Freight, and CMAQ Traffic Congestion," Washington DC, 2018.
[12] UN-Habitat, *Urbanization and development: emerging futures. World cities report* 2016, no. 8. Nairobi, Kenya, 2016.
[13] United Nations, "Transforming our World: The 2030 Agenda for Sustainable Development," 2016.
[14] Dewberry, *Development of the Built Envrionment*. New York: McGraw Hill, 2019.
[15] Dewberry, *Land Development Handbook*, 4th ed. New York: McGraw Hill, 2019.
[16] H. Frohwein, J. Lambert, Y. Haimes, and L. Schiff, "Multicriteria Framework to Aid Comparison of Roadway Improvement Project," *J. Transp. Eng.*, vol. 125, no. 3, pp. 224–230, 1999.
[17] Y. Y. Haimes, B. M. Horowitz, J. H. Lambert, J. R. Santos, C. Lian, and K. G. Crowther, "Inoperability Input-Output Model for Interdependent Infrastructure Sectors. I: Theory and Methodology," *J. Infrastruct. Syst.*, vol. 11, no. 2, pp. 67–79, 2005.
[18] Y. Y. Haimes, *Risk Modeling, Assessment, and Management*, 3rd Editio. Hoboken: Wiley, 2009.
[19] Z. A. Collier and J. H. Lambert, "Time Management of Infrastructure Recovery Schedules by Anticipation and Valuation of Disruptions," *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.*, vol. 4, no. 2, 2018.
[20] A. S. Linthicum and J. H. Lambert, "Risk management for infrastructure corridors vulnerable to adjacent land development," *J. Risk Res.*, vol. 13, no. 8, pp. 983–1006, 2010.
[21] Z. A. Collier, J. H. Lambert, and I. Linkov, "Interdisciplinary mathematical methods for societal decision-making and resilience," *Environ. Syst. Decis.*, vol. 40, no. 1, pp. 1–2, 2020.
[22] S. Angel and A. M. Blei, "The productivity of American cities : How densification, relocation, and greater mobility sustain the productive advantage of larger U.S. metropolitan labor markets," *Cities*, vol. 51, pp. 36–51, 2016.
[23] M. Maier and E. Rechtin, *The Art of Systems Architecting*, Third Edit. Boca Raton: CRC Press, 2009.
[24] T. Lomax, "Quantifying Congestion NCHRP 398," Washington, DC, 1997.

[25] L. Gong and W. Fan, "Developing a systematic method for identifying and ranking freeway bottlenecks using vehicle probe data," *J. Transp. Eng. Part A Syst.*, vol. 144, no. 3, 2018.

[26] Transportation Research Board, *Highway Capacity Manual 6th Edition: A guide for Multimodal Mobility Analysis*. Washington, DC: The National Academies Press, 2016.

[27] Cambridge Systematics Inc, "Incorporating Reliability Performance Measures into the Transportation Planning and Programming Processes," 2013.

[28] S. A. Thekdi and J. H. Lambert, "Integrated risk management of safety and development on transportation corridors," *Reliab. Eng. Syst. Saf.*, vol. 138, pp. 1–12, 2015.

[29] H. Thorisson and J. H. Lambert, "Multiscale identification of emergent and future conditions along corridors of transportation networks," *Reliab. Eng. Syst. Saf.*, vol. 167, pp. 255–263, 2017.

[30] C. A. Pennetti, S. Sreekumar, K. Hollenback, M. D. Fontaine, and J. H. Lambert, "Quantifying Operational Disruptions as Measured by Transportation Network Reliability," *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.*, 2020.

[31] C. A. Pennetti, D. J. Andrews, M. D. Porter, and J. H. Lambert, "Traveler Perception of Transportation System Performance Using Kernel Density Estimation to Prioritize Infrastructure Investments," in *ASCE International Conference on Transportation and Development*, 2020.

[32] C. A. Pennetti, M. D. Fontaine, J. Jun, and J. H. Lambert, "Relating Disruptions of Enterprise Logistics to a Highway Reliability Threshold with Methods of Changepoint Detection," *Reliab. Eng. Syst. Saf.*, 2020.

[33] C. A. Pennetti, J. Jun, G. Jones, and J. H. Lambert, "Temporal Disaggregation of Performance Measures to Manage Uncertainty in Transportation Logistics and Scheduling," *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.*, 2020.

[34] C. A. Pennetti, D. J. Andrews, T. L. Polmateer, and J. H. Lambert, "Geospatially Distributed Safety and Performance Benefits for Projects of a Transportation System," in *IEEE SysCon*, 2020.

[35] C. K. Grimsley and C. A. Pennetti, "Applications of a Systems Engineering Approach to Improve the Effectiveness and Sustainability of Land Policy Regulatory Reform and Tenure Security Projects," in *Annual World Bank Conference on Land and Poverty*, 2020.

[36] A. Skabardonis, P. Varaiya, and K. F. Petty, "Measuring Recurrent and Nonrecurrent Traffic Congestion," *Transp. Res. Rec.*, no. 1856, pp. 118–124, 2008.

[37] A. Quenum *et al.*, "Resilience of business strategy to emergent and future conditions," *J. Risk Res.*, vol. Advance on, no. 10.1080/13669877.2018.1485172, pp. 1–19, 2019.

[38] T. P. Bostick, E. B. Connelly, J. H. Lambert, and I. Linkov, "Resilience science, policy and investment for civil infrastructure," *Reliab. Eng. Syst. Saf.*, vol. 175, pp. 19–23, 2018.

[39] S. Anam, J. S. Miller, and J. W. Amanin, “Managing Traffic Forecast Uncertainty,” ASCE-ASME J. *Risk Uncertain. Eng. Syst. Part A Civ. Eng.*, vol. 6, no. 2, 2020.
[40] M. Alsultan, J. Jun, and J. H. Lambert, “Program evaluation of highway access with innovative risk-cost-benefit analysis,” *Reliab. Eng. Syst. Saf.*, vol. 193, 2020.
[41] T. Thomas, A. Mondschein, T. Osman, and B. D. Taylor, “Not so fast? Examining neighborhood-level effects of traffic congestion on job access,” *Transp. Res. Part A*, vol. 113, pp. 529–541, 2018.
[42] J. Xu, J. H. Lambert, and C. J. Tucker, “Highway Access Safety Program Evaluation with Uncertain Parameters,” *J. Transp. Eng.*, vol. 140, no. 2, pp. 1–11, 2013.
[43] National Academies of Sciences Engineering and Medicine, “Value of Travel Time Reliability in Transportation Decision Making: Proof of Concept Portland, Oregon, Metro,” The National Academies Press, Washington, DC, 2014.
[44] T. Lomax, D. Schrank, S. Turner, and R. Margiotta, “Selecting Travel Reliability Measures,” 2003.
[45] A. A. Ganin, M. Kitsak, D. Marchese, J. M. Keisler, T. Seager, and I. Linkov, “Resilience and efficiency in transportation networks,” *Sci. Adv.*, vol. 3, no. 12, pp. 1–9, 2017.
[46] Z. Chen and W. Fan, “Data analytics approach for travel time reliability pattern analysis and prediction,” *J. Mod. Transp.*, vol. 27, no. 4, pp. 250–265, 2019.
[47] Virginia Transportation Research Council, “Considerations for Calculating Arterial System Performance Measures In Virginia,” Charlottesville, VA, 2017.
[48] J. E. Muriel-Villegas, K. C. Alvarez-Uribe, C. E. Patiño-Rodríguez, and J. G. Villegas, “Analysis of transportation networks subject to natural hazards - Insights from a Colombian case,” *Reliab. Eng. Syst. Saf.*, vol. 152, pp. 151–165, 2016.
[49] L. Gong and W. (David) Fan, “Applying travel-time reliability measures in identifying and ranking recurrent freeway bottlenecks at the network level,” *J. Transp. Eng. Part A Syst.*, vol. 143, no. 8, p. 04017042, 2017.
[50] Washington State Department of Transportation, “Development of a Freight Benefit/Cost Methodology for Project Planning,” Pullman, WA, 2013.
[51] M. Leung, J. H. Lambert, and A. Mosenthal, “A risk-based approach to setting priorities in protecting bridges against terrorist attacks,” *Risk Anal.*, vol. 24, no. 4, pp. 963–984, 2004.
[52] Office of the Federal Register, *Title 23 Highways*. 2017.
[53] FHWA, “Simplified Highway Capacity Calculation Method for the Highway Performance Monitoring System,” Washington, DC, 2017.
[54] FHWA, “MAP-21 Proposed Measures for Congestion, Reliability, and Freight,” Washington, DC, 2016.
[55] National Academies of Sciences Engineering and Medicine, “Incorporating Travel Time Reliability into the Highway Capacity Manual,” The National Academies Press, Washington, DC, 2014.

[56] INCOSE, "The Guide to the Systems Engineering Body of Knowledge (SEBoK), v. 2.0," 2019. [Online]. Available: www.sebokwiki.org. [Accessed: 01-Jun-2019].
[57] W. Zhao, E. Mccormack, D. J. Dailey, and E. Scharnhorst, "Using Truck Probe GPS Data to Identify and Rank Roadway Bottlenecks," *J. Transp. Eng.*, vol. 139, no. January, pp. 1–7, 2013.
[58] Code of Federal Regulations, 23 CFR § 490.711 - *Calculation of Peak Hour Excessive Delay metric*. 2017, p. 23 CFR § 490.711.
[59] C. Kamga and M. A. Yazici, "Temporal and weather related variation patterns of urban travel time: Considerations and caveats for value of travel time, value of variability, and mode choice studies," *Transp. Res. Part C Emerg. Technol.*, vol. 45, pp. 4–16, 2014.
[60] Transportation Research Board, "Traffic Monitoring Data, Successful Strategies in Collection and Analysis," Washington, DC, 2007.
[61] G. List, B. Williams, and N. Rouphail, "Establishing Monitoring Programs for Travel Time Reliability," 2014.
[62] P. Olszewski, T. Dybicz, K. Jamroz, W. Kustra, and A. Romanowska, "Assessing highway travel time reliability using probe vehicle data," *Transp. Res. Rec.*, vol. 2672, no. 15, pp. 118–130, 2018.
[63] S. M. Turner, W. L. Eisele, R. J. Benz, and J. Douglas, "Travel time data collection handbook," 1998.
[64] P. Puangprakhon and S. Narupiti, "Allocating Travel Times Recorded from Sparse GPS Probe Vehicles into Individual Road Segments," in *World Conference on Transport Research - WCTR 2016*, 2017, vol. 25, pp. 2208–2221.
[65] N. Dutta and M. D. Fontaine, "Improving freeway segment crash prediction models by including disaggregate speed data from different sources," *Accid. Anal. Prev.*, vol. 132, pp. 1–16, 2019.
[66] C. Carrion and D. Levinson, "Value of travel time reliability: A review of current evidence," *Transp. Res. Part A Policy Pract.*, vol. 46, no. 4, pp. 720–741, 2012.
[67] U.S. DOT, "The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations Revision 2 Introduction," Washington, DC, 2011.
[68] S. Heshami, L. Kattan, D. Ph, P. Eng, Z. Gong, and S. Aalami, "Deterministic and Stochastic Freeway Capacity Analysis Based on Weather Conditions," *J. Transp. Eng. Part A Syst.*, vol. 145, no. 5, pp. 1–9, 2019.
[69] B. E. C. Sullivan and U. T. Division, "New Model for Predicting Freeway Incidents and Incident Delays," *J. Transp. Eng.*, vol. 123, no. 1, pp. 267–275, 1997.
[70] S. Shojaat, J. Geistefeldt, S. A. Parr, C. G. Wilmot, and B. Wolshon, "Sustained flow index: Stochastic measure of freeway performance," *Transp. Res. Rec.*, vol. 2554, pp. 158–165, 2016.
[71] W. Brilon, J. Geistefeldt, and M. Regler, "Reliability of Freeway Traffic Flow: A Stochastic Concept of Capacity," in *16th International Symposium on Transportation and Traffic Theory*, 2005, no. July, pp. 125–144.
[72] J. H. Lambert, S. A. Theckdi, and Q. Zhou, "Land Development Risk Analysis for

Multimodal Transportation Corridors (VCTIR 12-R7)," Virginia Department of Transportation, Richmond, 2011.
[73] J. L. Tsang, J. H. Lambert, and R. C. Patev, "Extreme Event Scenarios for Planning of Infrastructure Projects," *J. Infrastruct. Syst.*, vol. 8, no. 2, pp. 42–48, 2002.
[74] Y. Y. Haimes, S. Kaplan, and J. H. Lambert, "Risk filtering, ranking, and management framework using hierarchical holographic modeling," *Risk Anal.*, vol. 22, no. 2, pp. 383–397, 2002.
[75] K. Y. Teng, S. A. Thekdi, and J. H. Lambert, "Risk and safety program performance evaluation and business process modeling," *IEEE Trans. Syst. Man, Cybern. Part ASystems Humans*, vol. 42, no. 6, pp. 1504–1513, 2012.
[76] M. C. Hamilton, J. H. Lambert, and L. J. Valverde, "Climate and Related Uncertainties Influencing Research and Development Priorities," ASCE-ASME *J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.*, vol. 1, no. 2, p. 04015005, 2015.
[77] J. Xu and J. H. Lambert, "Distributed travel time savings of a multiscale transportation access management program," *Environ. Syst. Decis.*, vol. 33, no. 3, pp. 362–375, 2013.
[78] J. H. Lambert and T. Turley, "Priority setting for the distribution of localized hazard protection," *Risk Anal.*, vol. 25, no. 3, pp. 745–752, 2005.
[79] E. C. Rogerson, J. H. Lambert, and A. F. Johns, "Runway safety program evaluation with uncertainties of benefits and costs," *J. Risk Res.*, vol. 16, no. 5, pp. 523–539, 2013.
[80] M. Grant *et al.*, "Congestion Management Process: A Guidebook," 2011.
[81] R. Dowling, K. Parks, B. Nevers, J. Josselyn, and S. Gayle, "Incorporating Reliability into the Congestion Management Process : A Primer," 2015.
[82] S. Washburn, S. S. Washburn, and D. S. Kirschner, "Rural Freeway Level of Service Based on Traveler Perception Rural," *Transp. Res. Rec.*, vol. 1988, no. 1, pp. 31–37, 2006.
[83] National Academies of Sciences Engineering and Medicine, "Value of Travel Time Reliability in Transportation Decision Making: Proof of Concept Maryland," Washington, DC, 2014.
[84] University of Maryland Center for Advanced Transportation Technology Laboratory, "The RITIS Vehicle Probe Project Suite." [Online]. Available: https://pda.ritis.org/suite/. [Accessed: 11-Jan-2019].
[85] Transportation Research Board, "Traffic and Transportation Simulation," Washington DC, 2014.
[86] RStudio Team, "RStudio: Integrated Development Environment for R." RStudio, Inc., Boston, MA, 2018.
[87] M. Alsultan, J. Jun, and J. Lambert, "Systems Evaluation for Access Management of Multiscale Transportation Networks," in *2019 IEEE International Systems Conference (SysCon)*, 2019, pp. 1–8.
[88] Transportation Research Board, "Analytical Procedures for Determining the Impacts of Reliability Mitigation Strategies," Transportation Research Board, Washington DC, 2012.
[89] FHWA, "Crash Modification Factors Clearinghouse," Washington DC, 2017.

[90] J. H. Lambert, J. L. Tsang, and S. A. Thekdi, “Risk-Informed Investment for Tropical Cyclone Preparedness of Highway Signs, Signals, and Lights,” *J. Infrastruct. Syst.*, vol. 19, no. 4, pp. 384–394, 2012.
[91] J. H. Lambert, Y. Y. Haimes, D. Li, R. M. Schooff, and V. Tulsiani, “Identification, ranking, and management of risks in a major system acquisition,” *Reliab. Eng. Syst. Saf.*, vol. 72, no. 3, pp. 315–325, 2001.
[92] H. Thorisson *et al.*, “Addressing schedule disruptions in business processes of advanced logistics systems,” *Syst. Eng.*, vol. 22, no. 1, pp. 66–79, 2019.
[93] M. Rajabi-bahaabadi and A. Shariat-mohaymany, “Travel Time Reliability Measures Accommodating Scheduling Preferences of Travelers,” vol. 2673, no. 4, pp. 708–721, 2019.
[94] P. Ajinkya, Maine; Sriniva, “Effect of Land Devements on Travel Time Reliability,” in *International Conference on Transportation Development 2018*, 2018, pp. 39–47.
[95] B. W. Silverman, *Density Estimation for Statistics and Data Analysis*. London: Chapman and Hall, 1986.
[96] E. Kidando, R. Moses, T. Sando, and E. E. Ozguven, “Evaluating Recurring Traffic Congestion using Change Point Regression and Random Variation Markov Structured Model,” *Transp. Res. Rec.*, vol. 2672, no. 20, pp. 63–74, 2018.
[97] J. Ko and R. L. Guensler, “Characterization of Congestion Based on Speed Distribution : A Statistical Approach Using Gaussian Mixture Model,” *TRB Comm. Highw. Capacit. Qual. Serv. Div. A*, vol. 2278, 2004.
[98] E. Kidando, R. Moses, E. E. Ozguven, and T. Sando, “Evaluating Traffic Congestion Using the Traffic Occupancy and Speed Distribution Relationship : An Application of Bayesian Dirichlet Process Mixtures of Generalized Linear Model,” *J. Transp. Technol.*, vol. 7, pp. 318–335, 2017.
[99] K. Haynes, I. A. Eckley, and P. Fearnhead, “Efficient penalty search for multiple changepoint problems,” 2014, pp. 1–23.
[100] S. Kaplan and J. Garrick, “On the Quantitative Definition of Risk,” *Risk Anal.*, vol. 1, no. 1, pp. 1–24, 1981.
[101] Y. Y. Haimes, *Modeling and Managing Interdependent Complex Systems of Systems*. Hoboken, NJ: Wiley, 2019.
[102] J. Berman, *Maximizing Project Value*. New York: American Management Association, 2007.
[103] A. Kuang, Z. Tang, and L. Shan, “Road Network Capacity Reliability Considering Travel Time Reliability,” *Procedia - Soc. Behav. Sci.*, vol. 96, no. Cictp, pp. 1818–1827, 2013.
[104] S. Clark and D. Watling, “Modelling network travel time reliability under stochastic demand,” *Transp. Res. Part B Methodol.*, vol. 39, no. 2, pp. 119–140, 2005.
[105] A. Almotahari, M. A. Yazici, S. Mudigonda, and C. Kamga, “Analysis of Incident-Induced Capacity Reductions for Improved Delay Estimation,” vol. 145, no. 2, pp. 1–10, 2019.
[106] S. Sohrabi and A. Ermagun, “Optimum capacity of freeways: A stochastic approach,” *J. Transp. Eng. Part A Syst.*, vol. 144, no. 7, pp. 1–7, 2018.

[107] O. Cats, G. J. Koppenol, and M. Warnier, “Robustness assessment of link capacity reduction for complex networks: Application for public transport systems,” *Reliab. Eng. Syst. Saf.*, vol. 167, no. June, pp. 544–553, 2017.
[108] Z. Li and R. Laurence, “An analysis of four methodologies for estimating highway capacity from ITS data,” *J. Mod. Transp.*, vol. 23, no. 2, pp. 107–118, 2015.
[109] G. M. D’Este and M. a. P. Taylor, “Concepts of network vulnerability and applications to the identification of critical elements of transport infrastructure,” *26th Australas. Transp. Res. Forum Wellington, New Zeal.*, pp. 1–15, 2003.
[110] FHWA, “Considerations of Current and Emerging Transportation Management Center Data,” Washington, DC, 2019.
[111] B. S. Kerner, *Breakdown in Traffic Networks: Fundamentals of Transportation Science*. Berlin: Springer, 2017.
[112] AASHTO, A *Policy on Geometric Design of Highways and Streets, 6th Edition*. 2011.
[113] B. S. Kerner, *Introduction to Modern Traffic Flow Theory and Control*. Berlin: Springer, 2009.
[114] B. S. Kerner, “Statistical physics of synchronized traffic flow: Spatiotemporal competition between S→F and S→J instabilities,” *Phys. Rev. E*, vol. 100, no. 1, pp. 1–23, 2019.
[115] M. Börjesson and J. Eliasson, “On the use of average delay as a measure of train reliability,” *Transp. Res. Part* A, vol. 45, pp. 171–184, 2011.
[116] L. C. Edie, “Car-following and steady-state theory for noncongested traffic,” *Oper. Res.*, vol. 9, no. 66, 1961.
[117] F. V. W. H. Van Lint, “Genealogy of traffic flow models,” *EURO J. Transp. Logist.*, vol. 4, pp. 445–473, 2015.
[118] H. J. Payne and S. C. Tignor, “Freeway Incident-Detection Algorithms Based on Decision Trees With States.,” *Transp. Res. Rec.*, no. 682, pp. 30–37, 1978.
[119] J. Weng and Q. Meng, “Decision tree-based model for estimation of work zone capacity,” *Transp. Res. Rec.*, no. 2257, pp. 40–50, 2011.
[120] C. Truong, L. Oudre, and N. Vayatis, “Selective review of offline change point detection methods,” *Signal Processing*, vol. 167, 2020.
[121] G. Comert and A. Bezuglov, “An online change-point-based model for traffic parameter prediction,” *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 1360–1369, 2013.
[122] I. A. Eckley, P. Fearnhead, and R. Killick, “Analysis of changepoint models,” in *Bayesian Time Series Models*, Cambridge: Cambridge: Cambridge University Press, 2011, pp. 205–224.
[123] P. J. Ossenbruggen and E. M. Laflamme, “Time series analysis and models of freeway performance,” *J. Transp. Eng.*, vol. 138, no. 8, pp. 1030–1039, 2012.
[124] S. Hashimoto, S. Yoshiki, R. Saeki, Y. Mimura, R. Ando, and S. Nanba, “Development and application of traffic accident density estimation models using kernel density estimation,” *J. Traffic Transp. Eng. (English Ed.*, vol. 3, no. 3, pp. 262–270, 2016.

[125] Y. Cao, L. Zhang, and D. Sun, “An air traffic prediction model based on kernel density estimation,” *Proc. Am. Control Conf.*, pp. 6333–6338, 2013.
[126] R. Killick and I. A. Eckley, “changepoint: An R Package for Changepoint Analysis,” *J. Stat. Softw.*, vol. 58, no. 3, 2014.
[127] D. V Hinkley, “Inference About the Change-Point in a Sequence of Random Variables,” *Biometrika*, vol. 57, no. 1, pp. 1–17, 1970.
[128] M. Zhou and V. P. Sisiopiku, “Relationship between volume-to-capacity ratios and accident rates,” *Transp. Res. Rec.*, no. 1581, pp. 47–52, 1997.
[129] S. Aminikhanghahi and D. J. Cook, “A Survey of Methods for Time Series Change Point Detection,” *Knowl. Inf. Syst.*, vol. 176, no. 1, pp. 339–367, 2017.
[130] Science Applications International Corporation and American Transportation Research Institute, “Traffic Incident Management Handbook,” 2010.
[131] M. J. Schroeder, J. H. Lambert, M. J. Schroeder, and J. H. Lambert, “Scenario-based multiple criteria analysis for infrastructure policy impacts and planning,” *J. Risk Res.*, vol. 14, no. 2, pp. 191–214, 2011.
[132] S. Zhu, G. Jiang, and H. K. Lo, “Capturing value of reliability through road pricing in congested traffic under uncertainty,” *Transp. Res. Part C Emerg. Technol.*, vol. 94, pp. 236–249, 2018.
[133] S. Cheng, F. Lu, P. Peng, and S. Wu, “Short-term traffic forecasting: An adaptive ST-KNN model that considers spatial heterogeneity,” *Comput. Environ. Urban Syst.*, vol. 71, no. May, pp. 186–198, 2018.
[134] V. Prasannakumar, H. Vijith, R. Charutha, and N. Geetha, “Spatio-Temporal Clustering of Road Accidents : GIS Based Analysis and Assessment,” vol. 21, pp. 317–325, 2011.
[135] G. Schultz, K. Braley, and T. Boschert, “Prioritizing Access Management Implementation,” in *8th National Conference on Access Management*, 2008, no. August, pp. 2–16.
[136] J. Xu and J. H. Lambert, “Risk-Cost-Benefit Analysis for Transportation Corridors with Interval Uncertainties of Heterogeneous Data,” *Risk Anal.*, vol. 35, no. 4, pp. 624–641, 2015.
[137] S. Farrow, “Using Risk Assessment , Benefit-Cost Analysis , and Real Options to Implement a Precautionary Principle,” *Risk Anal.*, vol. 24, no. 3, pp. 727–735, 2004.
[138] N. Dutta, R. A. Boateng, and M. D. Fontaine, “Safety and operational effects of the interstate 66 active traffic management system,” *J. Transp. Eng. Part A Syst.*, vol. 145, no. 3, 2019.
[139] M. S. Dehghani, G. Flintsch, and S. McNeil, “Parametric analysis of roadway infrastructure vulnerability to disruptions,” *J. Infrastruct. Syst.*, vol. 23, no. 4, pp. 1–9, 2017.
[140] S. Turner and T. Qu, “Developing Twin Cities Arterial Mobility Performance Measures Using GPS Speed Data,” St. Paul, MN, 2013.
[141] C. W. Karvetski, J. H. Lambert, J. M. Keisler, and I. Linkov, “Integration of decision analysis and scenario planning for coastal engineering and climate change,” *IEEE Trans. Syst. Man, Cybern. Part ASystems Humans*, vol. 41, no. 1, pp. 63–73, 2011.

[142] P. Mackie and J. Preston, “Twenty-one sources of error and bias in transport project appraisal,” *Transp. Policy*, vol. 5, no. 1, pp. 1–7, 1998.
[143] F. Leite *et al.*, “Visualization, Information Modeling, and Simulation: Grand Challenges in the Construction Industry,” *J. Comput. Civ. Eng.*, vol. 30, no. 6, pp. 1–16, 2016.
[144] E. R. Tufte, *Visual Explanations*, 7th ed. Cheshire: Graphics Press LLC, 2005.
[145] Cambridge Systematics Inc, “An Initial Assessment of Freight Bottlenecks on Highways,” Cambridge, 2005.
[146] VDOT, “2018 Virginia Department of Transportation Jurisdiction Report Daily Traffic Volume Estimates Including Vehicle Classification Estimates,” Richmond, VA, 2018.
[147] VDOT, “VDOT Pathways for Planning,” 2019. [Online]. Available: https://vdotp4p.com/. [Accessed: 01-Dec-2019].
[148] FHWA, “The Urban Congestion Report (UCR): Documentation and Definitions,” 2019. [Online]. Available: https://ops.fhwa.dot.gov/perf_measurement/ucr/documentation.htm. [Accessed: 01-Nov-2019].
[149] E. B. Connelly, J. H. Lambert, and S. A. Thekdi, “Robust Investments in Humanitarian Logistics and Supply Chains for Disaster Resilience and Sustainable Communities,” *Nat. Hazards Rev.*, vol. 17, no. 1, p. 04015017, 2015.
[150] H. You, J. H. Lambert, A. F. Clarens, and B. J. McFarlane, “Quantifying the influence of climate change to priorities for infrastructure projects,” *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 44, no. 2, pp. 133–145, 2014.
[151] S. Kim and B. Coifman, “Comparing INRIX speed data against concurrent loop detector stations over several months,” *Transp. Res. Part C Emerg. Technol.*, vol. 49, no. 614, pp. 59–72, 2014.
[152] C. McIntyre and M. K. Parfitt, “Decision support system for residential land development site selection process,” *J. Archit. Eng.*, vol. 4, no. 4, pp. 125–131, 1998.
[153] J. Zak and S. Węgliński, “The selection of the logistics center location based on MCDM/A methodology,” *Transp. Res. Procedia*, vol. 3, no. July, pp. 555–564, 2014.
[154] S. A. Thekdi and J. H. Lambert, “Decision Analysis and Risk Models for Land Development Affecting Infrastructure Systems,” *Risk Anal.*, vol. 32, no. 7, 2012.
[155] North American Council for Freight Efficiency, “Regional Haul : An Opportunity for Trucking?,” 2019.
[156] US Census Bureau, “Vehicle Inventory and Use Survey: United States: 2002,” Washington DC, 2004.
[157] R. Guo, W. Guan, and W. Zhang, “Route design problem of customized buses: Mixed integer programming model and case study,” *J. Transp. Eng. Part A Syst.*, vol. 144, no. 11, 2018.
[158] Q. Hu and Z. Hu, “Resource Balancing in the Design of Hub-and-Spoke Network for LTL Logistics,” *J. Highw. Transp. Res. Dev. (English Ed.*, vol. 8, no. 1, pp. 101–110, 2014.
[159] H. Y. Mak and Z. J. M. Shen, *Integrated modeling for location analysis*. Hanover:

now Publishers Inc., 2016.
[160] C. Davidson, "Insights into the scenario planning methodology," 2014.
[161] H. Sadatsafavi, A. A. Kim, S. D. Anderson, and P. Bishop, "Scenario Planning Application in US Highway Transportation Industry," *J. Infrastruct. Syst.*, vol. 25, no. 2, p. 05019002, 2019.
[162] INRIX, "Transportation Agencies turn to INRIX to get more out of NPMRDS," 2018. [Online]. Available: http://inrix.com/blog/2018/08/transportation-agencies-use-npmrds/.
[163] VEDP, "Virginia Economic Development Partnership," 2020. [Online]. Available: https://www.vedp.org/about-vedp. [Accessed: 03-Jan-2020].
[164] H. Thorisson, D. C. Hendrickson, T. L. Polmateer, and J. H. Lambert, "Disaggregating Uncertainties in Operations Analysis of Intermodal Logistics Systems," *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.*, vol. 5, no. 1, 2019.
[165] H. Thorisson, C. A. Pennetti, D. J. Andrews, D. C. Hendrickson, T. L. Polmateer, and J. H. Lambert, "Systems modeling and optimization of container ship berthing with various enterprise risks," in *SysCon 2019 - 13th Annual IEEE International Systems Conference, Proceedings*, 2019.
[166] Federal Motor Carrier Safety Administration, "Interstate Truck Driver's Guide to Hours of Service," 2015.
[167] E. B. Connelly, L. M. Colosi, A. F. Clarens, and J. H. Lambert, "Risk Analysis of Biofuels Industry for Aviation with Scenario-Based Expert Elicitation," *Syst. Eng.*, vol. 18, no. 2, pp. 178–191, 2015.
[168] H. Thorisson, J. H. Lambert, J. J. Cardenas, and I. Linkov, "Resilience Analytics with Application to Power Grid of a Developing Region," *Risk Anal.*, vol. 37, no. 7, pp. 1268–1286, 2017.
[169] X. Wang and Z. Meng, "Study of the local-comparison change-point algorithm to analyze traffic flow breakdown," *Conf. Proc. - IEEE Int. Conf. Syst. Man Cybern.*, vol. 7, pp. 6186–6191, 2004.
[170] A. Getis, S. Diego, and S. Diego, *Spatial Association , Measures of*, Second Edi., vol. 23. Elsevier, 2015.
[171] A. Getis and J. K. Ord, "The Analysis of Spatial Association," *Geogr. Anal.*, vol. 24, no. 3, pp. 189–206, 1992.
[172] K. Zhang and S. Zhang, "Testing Simulated Positive Spatial Autocorrelation by Getis-Ord General G," in *2015 23rd International Conference on Geoinformatics*, 2015, no. 41174003, pp. 1–4.
[173] G. Mohler, M. D. Porter, J. Carter, and G. Lafree, "Learning to rank spatio-temporal event hotspots," in *The 7th International Workshop on Urban Computing (UrbComp 2018)*, 2018, pp. 1–9.
[174] Virginia Department of Transportation, "Highway Safety Improvement Program Implementation Guidelines," 2019.
[175] NOAA, "State Plane Coordinate System of 1983," no. January 1989, 1990.
[176] J. H. Lambert *et al.*, "Prioritizing Infrastructure Investments in Afghanistan with Multiagency Stakeholders and Deep Uncertainty of Emergent Conditions," *J. Infrastruct. Syst.*, vol. 18, no. 2, pp. 155–166, 2011.

[177] INCOSE, *Systems Engineering Handbook*. INCOSE, 2007.
[178] C. R. Allen *et al.*, "Tiered Approach to Resilience Assessment Tiered Approach to Resilience Assessment," *Risk Anal.*, vol. 38, no. 9, pp. 1772–1780, 2018.
[179] A. Siddiiqi, F. Ereiqat, and L. Diaz Anadon, "Model Based Systems Engineering with Department of Defense Architectural Framework," *Syst. Eng.*, vol. 14, no. 3, pp. 305–326, 2012.
[180] FHWA, "Advancement of Performance-Based Scenario Planning for Regional Planning and Decision-Making A Synthesis Report," 2017.
[181] A. Chakraborty and A. McMillan, "Scenario planning for urban planners: Toward a practitioner's guide," *J. Am. Plan. Assoc.*, vol. 81, no. 1, pp. 18–29, 2015.

APPENDIX

Appendix A.

Author's Biographical Sketch

Cody A. Pennetti is a licensed professional engineer (P.E.) who has served as a manager and design engineer for the last twelve years at a private architectural/engineering firm in the United States. His professional career has focused on infrastructure development for both public and private projects. Mr. Pennetti has managed, planned and designed a multitude of project types, including road networks, hospitals, retail centers, recreation facilities, neighborhoods, mixed-use development, major utility corridors, and a golf course. Throughout his career, Mr. Pennetti has earned awards in design, land conservation, and innovation. He served as Principal Editor and Writer for a civil engineering textbook, Land Development Handbook, published by McGraw Hill [15]. Mr. Pennetti was the managing editor of two additional books in the series: Construction Practices for Land Development and Development of the Built Environment. Mr. Pennetti earned a BS in Civil Engineering (University of Virginia, USA, 2007). During his professional career, he earned a Graduate Certification in Engineering and Technology Management (George Washington University, USA, 2011), and an MS in Systems Engineering (Virginia Tech, USA, 2015). Mr. Pennetti served as an Adjunct Professor at George Mason University (USA) and the University of Virginia (USA) where he developed and taught courses in infrastructure management and design.