Identifying Real-World Transportation Applications Using Artificial Intelligence (AI)

Real-World AI Scenarios in Transportation for Possible Deployment

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16. Abstract

Artificial Intelligence (AI) is revolutionizing every walk of life, allowing machines to learn from experience, adapt, and perform tasks that have historically required human cognition. The US government elevated AI as one of its key priority science and technology areas. In response, the ITS JPO established research in AI as a priority area to accelerate adoption of AI by state and local agencies for addressing transportation problems.

As the USDOT embarks on advancing AI in transportation, it is essential to focus on high-value scenarios that can be used to motivate and inform stakeholders, accelerate the impact of AI deployment, and form the basis for potential proof of concept tests, prototype demonstrations and deployments that illustrate the transformational power of AI. The purpose of this report is to identify practical real-world scenarios where AI offers the potential to address specific transportation needs. The potential AI applications are identified based on a review of literature and interviews of public and private sector deployers and researchers of AI applications.

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The authors would also like to thank the volunteer Expert Stakeholders (Table 1) who discussed their experience using AI to address transportation problems, including the AI applications employed, types of data used, benefits experienced, challenges faced, and lessons learned.

Finally, the authors would like to thank Aaron Sessions and Chris Bischak from Noblis for illustrating the concepts included in the report.

Table 1. Volunteer Expert Stakeholders

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4	Brian Park	University of Virginia
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7	Dan Lukasik	Parsons
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15	Larry Head	University of Arizona
16	Mark Taylor	Utah DOT
17	Nadereh Moini	NJ Sports & Exposition Authority
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Chapter 1. Introduction

Background

Artificial Intelligence (AI) is revolutionizing every walk of life, allowing machines to learn from experience, adapt, and perform tasks that have historically required human cognition. AI was first conceptualized more than 60 years ago, and interest in AI applications has risen and fallen. Several factors have contributed to a recent resurgence in AI over the last decade, including increased computing power, mass data storage, and innovations in AI algorithmic approaches (including in machine learning (ML), a sub-field of AI).

AI has been broadly embraced, with promises of considerable benefits in productivity, efficiency, and quality of life. AI plays a significant role in the banking and finance industry for fraud detection and high frequency stock trading. AI is used in national security for cybersecurity and object/threat identification. AI is used in health care to analyze medical data to help with diagnosis and to make predictions about effective treatment options for patients. The current generation of AI sub-fields and techniques is poised for expansion into the transportation ecosystem—with potentially transformative impacts.

The Intelligent Transportation Systems (ITS) Joint Program Office (JPO) and its modal partners have been leaders in tackling fundamental problems in mobility, safety, and equity leveraging emerging technologies such as connected vehicles (CV), automated vehicles (AV), shared mobility services, and accessible transportation capabilities. In the last few years, explorations into AI have grown tremendously within the United States Department of Transportation (USDOT) (Thompson, 2019). Some of the USDOT's modal administrations, including the Federal Highway Administration (FHWA), Federal Railroad Administration (FRA), and Federal Aviation Administration (FAA), have been at the forefront of adopting AI solutions for mission delivery. AI-based applications have been implemented for video analytics, anomaly detection, safety analysis, and data fusion. For example, FHWA's Exploratory Advanced Research Program funded the development of AI technologies for the collection of large amounts of traffic data, including safety data, to spot trends and identify relationships between seemingly disparate data streams, and for video analytics to help determine driver behavior in various driving scenarios (U.S. Department of Transportation, 2019). FHWA's Traffic Analysis Tools (TAT) Program is investigating the use of AI for developing prediction techniques and evaluation tools (FHWA ATDM, 2020). FHWA's Advanced Transportation and Congestion Management Technologies Deployment (ATCMTD) Program recently awarded more than $16 million in grants to develop AI powered solutions for multimodal transportation management (USDOT, 2020). FRA is developing a suite of technologies for predictive analytics and intruder detection using AI and unmanned aircraft systems (UAS) (Baillargeon, 2019). Other agencies, such as the Federal Transit Administration (FTA), the Federal Motor Carrier Safety Administration (FMCSA), and the Pipeline and Hazardous Materials Safety Administration (PHMSA), are exploring the promise that AI has to offer in citizen-facing services (Borener, 2019).

On February 11, 2019, the Executive Order 13859 on Maintaining American Leadership in Artificial Intelligence was signed to implement a government strategy to elevate AI as one of its key priority science and technology areas (White House, 2019). The USDOT Strategic Plan (2018-2022) identifies "Innovation: Lead in the Development and Deployment of Innovative Practices and Technologies that Improve the Safety and Performance of the Nation's Transportation System" as one of the four strategic goals (U.S. Department of Transportation, 2018). In conjunction with the USDOT's strategic goals and the Executive Order, the ITS JPO established research in AI as a priority area to accelerate adoption of AI by state and local agencies for addressing transportation problems. Towards this end, USDOT has identified two key ways in which it will engage with emerging AI applications for transportation: (i) **enabling** the integration of AI into safety-critical domains, and (ii) **adopting and deploying** AI-based tools to improve the delivery of enterprise functions (U.S. Department of Transportation, 2019).

As the USDOT embarks on advancing AI in transportation, it is essential to focus on high-value scenarios that can be used to motivate and inform stakeholders, accelerate the impact of AI deployment, and form a template for potential field tests and deployments that demonstrate the transformational power of AI. Otherwise, a scatter-shot approach may misinform stakeholders and unnecessarily demotivate deployment—simply because AI cannot be applied as a panacea with uniform results.

Purpose

The purpose of this report is to identify practical high-level real-world scenarios where AI offers the potential to address specific transportation needs.

The potential AI applications are identified based on a review of literature and interviews of public and private sector deployers and researchers of AI applications.

Organization

The report is organized as follows:

- Chapter 2 presents the approach used to identify the real-world scenarios and provides an overview of the five practical scenarios, including Urban Arterial Network, Urban Multimodal Corridor, Regional System Management, Rural Freeway Corridor, and Underserved Communities. These are high-level scenarios that can be defined by unique operational challenges (e.g., manage regional system), facility types (e.g., urban arterial, rural freeway), and user types (e.g., underserved communities, urban commuter, long-haul truck driver).
- Chapter 3 provides an overview of AI for ITS, including the definition of AI for ITS and barriers to adoption of AI for ITS that are cross-cutting across transportation systems, modes, and network types.
- Chapters 4 to 8 present summary descriptions of each of the five scenarios, including: Urban Arterial Network, Urban Multimodal Corridor, Regional System Management, Rural Freeway Corridor, and Underserved Communities. Each chapter that corresponds to a scenario, is organized as follows:
    - *Background:* This section includes a brief description of the scenario.
    - *Relevant Operational Challenges:* This section describes the operational challenges commonly seen for the scenario.

- *Potential AI Applications:* This section provides a summary description of potential applications that can be powered by AI to address the challenges seen for the scenario. Additionally, each discussion includes the specific system functions that are enabled by AI and the benefits that can potentially be realized through use of AI.
- *Concept Illustration:* This section provides a graphical illustration of how AI might be used to address specific challenges seen for the scenario.
- *Actors and Actor Profiles:* This section includes a summary of key actors and their profiles. Each discussion includes a goal-oriented set of interactions between external actors and the AI-enabled system. Actors are parties outside the system that interact with the system. An actor may be a class of users, roles users can play, or other systems.
- *Relevant Research, Tests and Case Studies:* This section includes a summary of research, tests and case studies on the use of AI to enhance or enable specific applications to address challenges relevant to the scenario. These were identified through either a review of literature or interviews of stakeholders.
- *Potential Benefits:* This section includes a summary of the potential benefits of using AI-powered applications to address challenges relevant to the scenario.
- *Potential Barriers to Adoption of AI for the Scenario:* This section summarizes the barriers to adoption of AI for addressing operational challenges specific to the scenario.
- *Potential Value to USDOT:* This section summarizes the value to USDOT of investing in AI-powered applications for the scenario.

- Chapter 9 presents the conclusions.

Chapter 2. Study Approach

This chapter provides the approach used in this study to identify practical real-world scenarios where AI offers the potential to address transportation needs. Figure 1 illustrates the five-step approach.

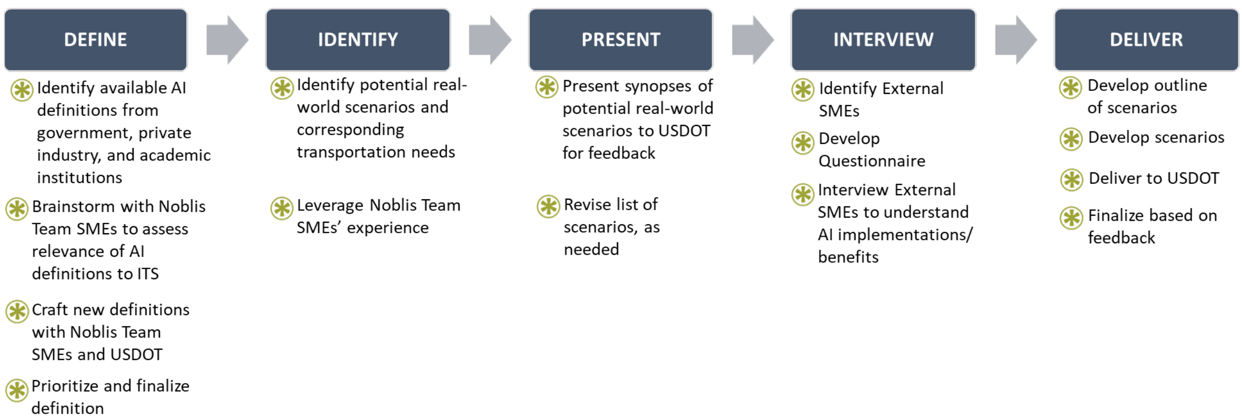

Figure 1. Approach for Identifying Practical Real-World AI Scenarios in Transportation.

Step 1. Define AI for ITS. As a first step, the research team reviewed existing definitions of AI offered or commonly used by government agencies, private industries, and academic institutions. The research team also considered new definitions crafted by the USDOT and subject matter experts (SMEs). The top 10 of the 17 definitions were shortlisted and prioritized based on four criteria, including relevance, clarity, inclusivity/delineation, and simplicity/conciseness (Dang, Townsend, & Vasudevan, 2019). The USDOT then selected the final definition of AI among the top 5 definitions, which is included in Chapter 3.

Step 2. Identify Potential Real-World Scenarios and Needs. Next, five practical real-world scenarios where AI could potentially be the most impactful in solving specific transportation problems were identified. These high-level scenarios were identified based on a review of existing applications of AI for addressing specific transportation problems, documented in the FHWA Report, "*Summary of Potential Application of AI in Transportation*" (Vasudevan, et al., 2020), as well as discussions with subject matter experts (SME) on the research team. The five scenarios were: (i) Urban Arterial Network, (ii) Urban Freeway Corridor, (iii) Regional/State-Wide System Management, (iv) Rural Freeway Corridor, and (v) Underserved Communities. The brainstorming discussions also included identifying potential AI applications under each scenario to address specific needs.

Step 3. Present Potential Real-World Scenarios of AI Applications. Next, the five potential scenarios and summary of example AI-applications were presented to the USDOT for feedback and consensus. The USDOT was also given the opportunity to replace or add new scenarios to the list. Based on feedback, the scenarios were further refined, and the final list included the following: (i) Urban Arterial Network, (ii) Urban Multimodal Corridor, (iii) Regional System Management, (iv) Rural Freeway Corridor, and (v) Underserved Communities.

- Urban Arterial Networks are low and medium speed mixed-use facilities that provide access to and from traffic generators and attractors, typically managed within jurisdictional boundaries by individual local agencies.
- Urban Multimodal Corridors are combinations of highways and arterial streets that serve as major regional travel routes, typically managed collaboratively by a group of state, regional, and local agencies.
- Regional System Management is the collaborative management by multiple agencies (often as a regional planning organization) to improve the performance of comprehensive, area-wide transportation systems.
- Rural Freeway Corridors are high-speed, limited-access divided facilities that run outside urbanized areas across multiple states and counties, typically managed by multiple agencies.
- Underserved Communities are those that do not have their transportation needs met by existing transportation services.

Step 4. Conduct Interviews of External SMEs. In this step, the research team worked with the USDOT to identify SMEs drawn from the public and private sectors and the academia with experience in implementing AI in transportation. Next, a questionnaire that captured the necessary information required for understanding the experts' implementations of AI was developed (see Appendix A). As the experts have limited resources to respond to the interview and requests for information, the questionnaire was sent ahead of the interviews to allow the expert the time to assemble the necessary information. The interviews lasted approximately 30 minutes. The discussions and feedback from the interviews were captured as part of the descriptions of the five scenarios.

Step 5. Deliver Summaries of Real-World AI Scenarios. In this step, first an outline was developed for feedback from the USDOT. Next, a draft report that documented the five scenarios was developed. Finally, the draft report was revised based on feedback from the USDOT and this final report was developed.

Chapter 3. AI for ITS

This chapter provides a definition of AI and identifies barriers to adoption of AI for ITS.

AI for ITS Definition

The research team worked with the USDOT to recommend a definition of AI with a focus on ITS. The recommended definition, as stated below, contextualizes AI for use in ITS, and is consistent with existing US government definitions of AI (Congress, 2017).

> Artificial Intelligence (AI) refers to processes that make it possible for systems to replace or augment routine human tasks or enable new capabilities that humans cannot perform. AI enables systems to: (1) sense and perceive the environment, (2) reason and analyze information, (3) learn from experience and adapt to new situations, potentially without human interaction, and (4) make decisions, communicate, and take actions.
>
> Examples of AI include machine learning, natural language processing, and object recognition. Machine learning (ML) is a broad subfield of AI in which computers learn from data, discover patterns and make decisions without human intervention. The ML field is broadly categorized into supervised, semi-supervised, unsupervised and reinforcement learning.
>
> In ITS, AI can be used to replace or augment actions of field, handheld and remote sensing devices, connected and automated vehicles, TMC operators, transit and freight operators, decision-makers, and travelers. For example, AI can be used to identify objects and images, recognize speech and audio, process large amounts of data to recognize patterns, learn from experience, and adapt to new environments to predict traffic phenomena, provide situational awareness, assist drivers with maneuvering, recognize unsafe driving conditions in real-time, identify or isolate malfunctioning or misbehaving system entities, improve cyber-security, operate infrastructure devices and vehicles, monitor pavement and support decision-making. AI can be embedded in any system entity (vehicle, mobile device, roadside infrastructure, or management center) or be distributed among many entities in the system.

This definition has three key components. First, it articulates AI's capacity to replace or augment human tasks and provides broad examples of AI. Second, it defines machine learning and mentions related concepts. Finally, it focuses on AI in ITS and provides example activities and applications in this domain. A detailed description of the approach and other definitions that were considered can be found in the USDOT *Memorandum on Documented Definition of AI with focus on ITS* (Dang, Townsend, & Vasudevan, 2019).

Figure 2 provides a list of the specific system functions, mentioned in the definition, that are enabled by AI-powered applications. Figure 3 provides examples of common AI sub-fields and techniques.

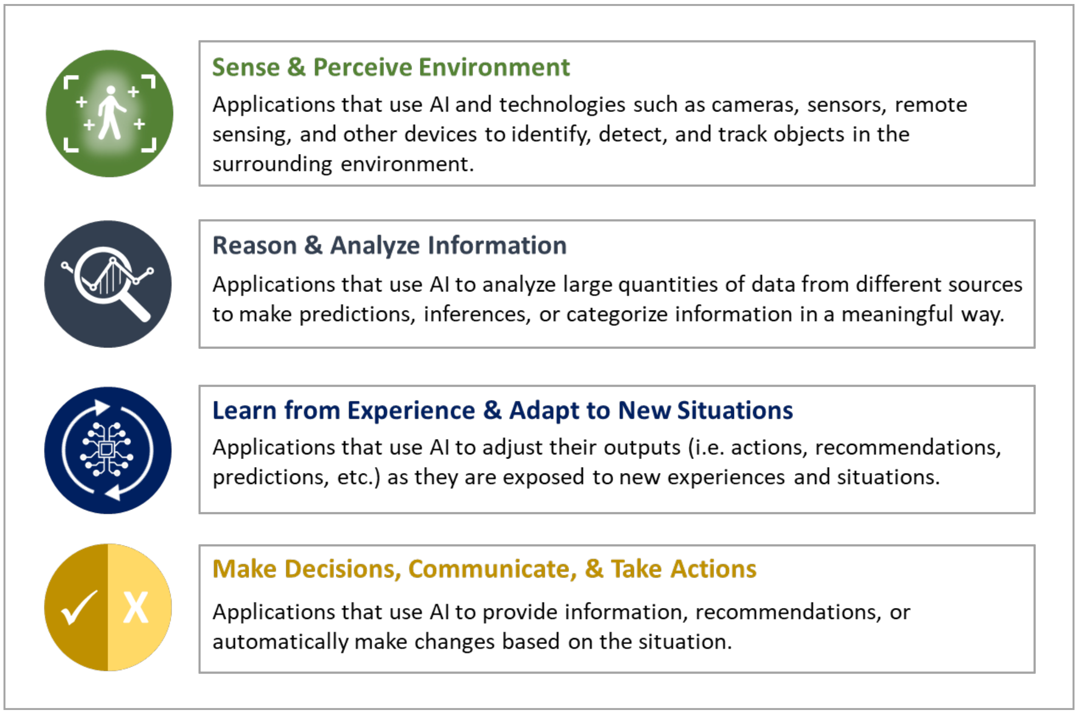

Figure 2. System Functions Enabled by AI.

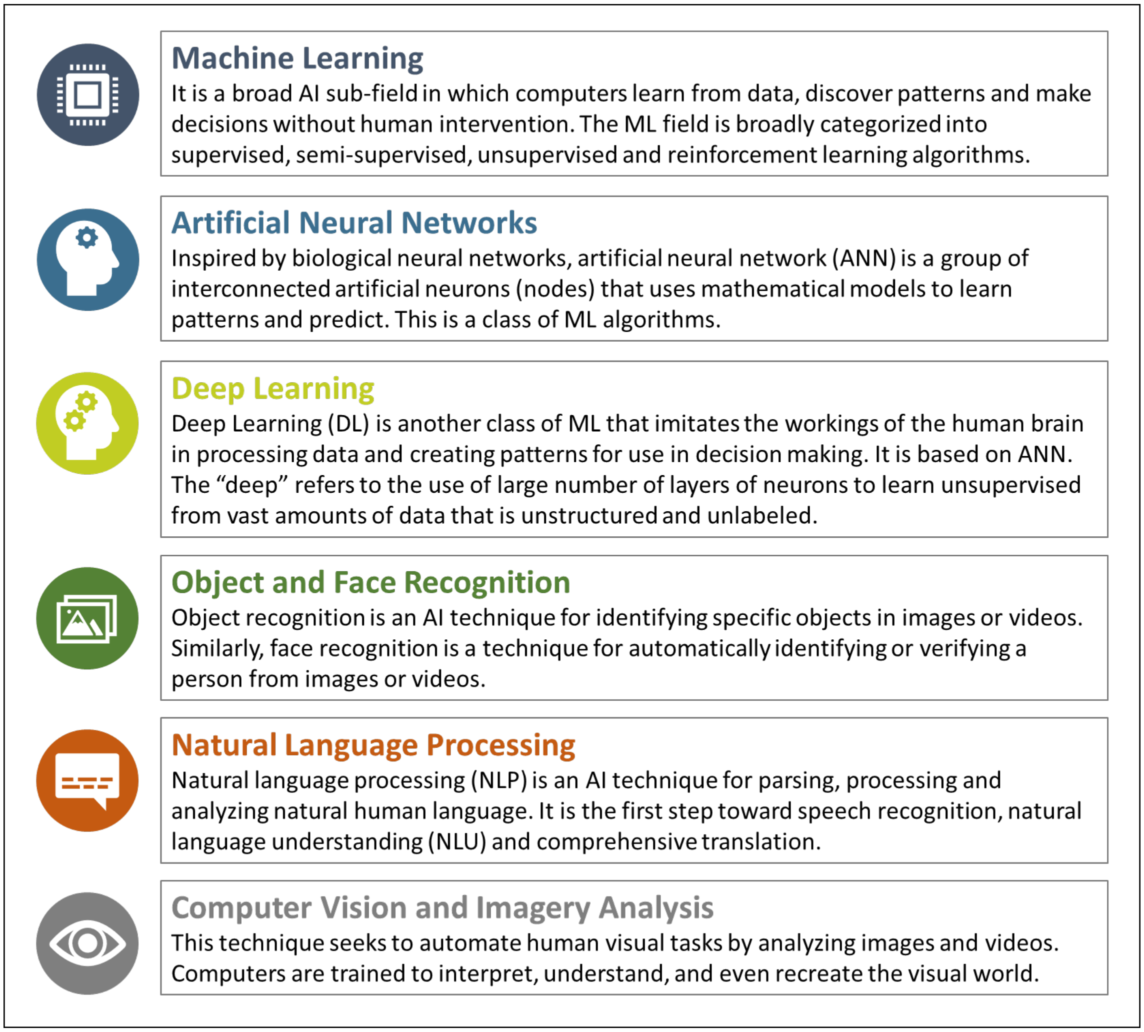

Figure 3. Examples of AI Sub-Fields and Techniques.

Potential Cross-Cutting Barriers to Adoption of AI

AI has many practical applications in the transportation domain. AI offers the promise to transform the transportation industry, by improving safety, mobility, accessibility, productivity, security and efficiency of transportation systems, users, or owners. However, there are significant challenges to adoption of AI. Given below are cross-cutting barriers faced by agencies interested in implementing AI-enabled solutions to address problems seen on their transportation networks, corridors, and systems.

- **Data**: Need for vast amount of high-quality data for application development, leading to lack of robust algorithms and limited implementations.

- **Computing Power:** Inability of many legacy systems/architectures to process large quantities of complex data, leading to possible latency, timeout, and storage issues, and voiding of safety-critical decisions.
- **Hardware**: Incompatibility of existing hardware/systems with AI-enabled sub-systems or components.
- **Bias:** Bias in application training data, leading to unethical and unfair consequences.
- **Generalizability:** Difficulty in developing applications that can generalize to new scenarios or locations leading to scalability and applicability issues.
- **Obsolescence:** Investment in long-term AI solutions undesirable due to the dynamism of the field.
- **Privacy:** Inability to protect privacy of individuals as AI applications are rooted in collecting and manipulating extensive personal data, tracking individuals and vehicles (e.g., speech/face recognition).
- **Ethics and Equity:** Misuse of AI applications for profiling and discriminating against individuals/populations based on unfair criteria.
- **Liability:** Liability unclear when a vehicle, device, equipment, or system that is enabled by an AI application is involved in a crash or is hacked.
- **Stakeholder Acceptance:** Mistrust among stakeholders as AI techniques are often seen as “black boxes.”
- **Talent/Workforce Availability:** Lack of staff trained in AI and advanced data analytics since AI is an emerging technology.
- **Risk Aversion:** Risk aversion and budgetary constraints limits inclination to experiment or deploy un-proven AI solutions.

Chapters 4 to 8 further discuss these barriers as they relate to the specific scenario.

Chapter 4. Urban Arterial Network

This chapter discusses how AI might potentially be used for addressing challenges relevant to the Urban Arterial Network scenario. This chapter provides a background of Urban Arterial Networks, an overview of the operational challenges relevant to the scenario, potential applications enabled by AI to address the challenges, a graphical illustration of the concept, actors or entities interacting with the AI-enabled systems, relevant research, tests and case studies, potential benefits, potential barriers to adoption of AI for the scenario, and potential value to USDOT of investing in AI-powered solutions for the scenario.

Background

The first scenario covered within this report is urban arterial networks. Arterial roadways are crucial to the transportation system as they provide mobility and access to homes, businesses, schools, and more. Within the United States, arterials account for more than one million lane miles of roadway and there are more than 330,000 traffic signals. Arterial roadways in the United States are managed by more than 3,000 state, regional, and local organizations (FHWA, 2020).

In the 2006 FHWA Coordinated Freeway and Arterial Operations Handbook, congestion was shown to be increasing substantially in metropolitan areas due to growing demand. The effects of congestion were observed to be multifaceted: increasing intensity (i.e., average delay), increasing extent (i.e., proportion of travel within the network experiencing delay), and increasing duration (i.e., peak periods). Delay resulting from congestion causes an overall loss in mobility and accessibility within urban networks, resulting in traveler frustration, loss productivity, and environmental degradation. Urban arterial networks are critical to the transportation of people and goods throughout our communities (Urbanik, Humphreys, Smith, & Levine, 2006). Further consequences of this severe congestion include:

- **Economic Growth**: "Efficient transportation access to employment and shopping sites is an important consideration to business and developers when considering expansion opportunities." (Urbanik, Humphreys, Smith, & Levine, 2006)
- **Quality-of-Life**: "Long, frustrating commutes are contributors to human stress. In addition, this stress can be heighted when dealing with traffic jams and delays within neighborhoods after a long commute home from work. Traffic problems and congestion are an important characteristic of quality of life to many people." (Urbanik, Humphreys, Smith, & Levine, 2006)
- **Environmental Quality**: "Congested road conditions can have a detrimental effect on the environment, in particular air quality. Making improvements to the transportation system or trying to change travel behavior has been an important objective of those wanting to improve environmental quality." (Urbanik, Humphreys, Smith, & Levine, 2006)

The FHWA Arterial Management program is intended to "advance the use of objectives and performance based approaches to traffic signal management, to improve design, operations and maintenance practices, resulting in increased safety, mobility and efficiency for all users" (FHWA, 2020). The specific focus areas within this program include: traffic signal program management, regional trafficsignal operations programs, traffic signal timing and operations strategies, and automated traffic signal performance measures. Thus, this first scenario evaluates how advances in AI could be applied to enhance current planning, operations, and maintenance strategies that benefit all road users within urban arterial networks.

Relevant Operational Challenges

Urban arterial networks and Infrastructure Owner/Operators (IOO) that manage them face numerous challenges. Many of these issues result from demands exceeding capacity, which causes large and often unpredictable delays. These delays not only reduce network mobility but also impact fuel consumption and air quality. Many arterial management IOOs have limited staffing and balance proactive management with reactive response to field issues. Major challenges related to urban arterial networks are listed below:

- **Traffic control devices (e.g., traffic signals) are often not optimized to maximize throughput.**
    - Poor signal progression results in unnecessary delays increasing lost time and fuel consumption.
    - Updating traffic signal coordination plans is time and resource intensive.
    - Additional factors impacting traffic signal coordination plan development include neighboring populations (i.e., elderly, school zones, and persons with disabilities).
    - Road closures and traffic control adjustments to accommodate collisions, utility work, and adverse weather conditions further impede the effectiveness of traffic signal coordination plans.
    - Transit signal priority and signal preemption strategies cause disruptions to the traffic operations controller which may adversely impact passenger vehicle progression.
    - Adaptive signal control frequently requires advanced hardware as well as supplemental software to manage and monitor the controller.
- **Urban arterial networks are complex making it difficult to model or predict traffic conditions on a network-wide level.**
    - Vehicle collisions can result in major network-wide delays.
    - Non-recurring road closures (e.g., caused by work zones) can result in large delays with high variability and unpredictability.
    - Technology and resource restraints limit the development of high-resolution network-wide models.
    - IOOs operating urban arterial networks regularly balance challenges related to access management.
- **There are numerous safety challenges in operating an urban arterial network.**
    - Urban arterial networks often experience oversaturated conditions resulting from high demand for travel throughout the network.
    - Incident risk is largely associated with the competing demands from many road users and transportation modes.

  - Additional factors influencing overall safety within urban arterial networks include: intersection spacing, driveway density, number of pedestrian crosswalks, availability of dedicated bicycle lanes, and roadway design (e.g., number of lanes, median type).
- **The interconnectivity between transportation modes (e.g., vehicles, transit, pedestrians, bicycles, and scooters) result in complex traffic control strategies.**
  - Legacy traffic signal logic has limited capabilities to account for numerous transportation modes and priorities.
  - Pedestrian, cyclist, micro-mobility, and other modal demands are difficult to quantify and accommodate in signal operations.
- **Urban arterial networks are often maintained by multiple stakeholders (e.g., state, county, and city agencies).**
  - Agencies regularly balance proactive planning with day-to-day operations.
  - Agency staff often have limited training or expertise focused specifically on traffic operations, particularly at smaller agencies where traffic operations staff may "wear many hats" as a city engineer.
  - In many cases, transit agencies operate separate from the DOT, requiring a significant amount of interagency coordination for effective transit deployment.
  - Emerging forms of ad-hoc micro-mobility require new strategies for coordinating with third-party companies operating such mobility solutions.
- **Dissemination of traveler information throughout an urban arterial network requires unique strategies compared to uninterrupted flow facilities.**
  - Travel time estimation accounting for control delay at traffic signals is challenging.
  - Notification of upcoming incidents and recommended diversion routes are often delivered to travelers by means of third-party navigation applications.

Potential AI Applications

Integration of AI could be used to address the complexities of urban arterial networks as a coherent system and begin using the multitudes of data available from network travelers to better optimize system mobility for all users.

Application #1: Traffic Signal Coordination Plan Optimization

Objective: Updating traffic signal coordination plans using AI

Summary: Urban arterial networks are composed of hundreds or thousands of traffic signals. In many jurisdictions, signal re-timing efforts occur on a limited, multi-year schedule (e.g., 3-5 years between signal re-timing). Advances in AI deep learning neural networks and ML (i.e., advanced training methods for neural networks) offer the potential to conduct signal re-timing efforts at a higher frequency using automated traffic signal performance measures (ATSPMs). This type of application ingests real-time traffic signal performance data to evaluate the operation of the existing signal timing plan and produce a recommended signal timing plan update, perhaps monthly, or even more frequently. This proactive approach to adapting signal timing based on recent operational data can be used to better accommodate seasonal changes in traffic demand due to school schedules or winter visitors and travel patterns due to land-use changes, such as new construction and re-development. This application uses AI for two system functions: reason & analyze and learn & adapt (see Figure 2). The power of AI techniques in this application include the capability to respond to the successes and failures from produced signal coordination plans, continually updating algorithm parameters to improve the quality of the next signal timing plan.

Application #2: Real-Time Traffic Signal Optimization

Objective: Adaptive signal control systems using AI

Summary: Advanced computing systems have been available for urban traffic signal control for many years. These adaptive traffic control systems (e.g., SCOOT, SCATS, Kadence, InSync, SynchroGreen, etc.) use infrastructure sensor-based traffic flow data (e.g., loop detectors, video detection) to optimize traffic signal operations, but do not typically learn from their past experience. These systems and new offerings are beginning to fuse additional sources of data such as infrastructure environmental sensor systems (e.g., precipitation sensors, ice detectors), third-party traffic information (e.g., Waze), third-party weather information, traffic incident reports, and Connected Vehicle messages (see #1 in illustration below). These additional data sources can improve the ability of adaptive traffic control systems to optimize operations for more objectives than reducing total travel time and vehicle delays. AI technologies in the form of deep learning neural networks can be used to improve existing adaptive traffic control systems by introducing outcome-based learning, where the system parameters are continually refined to maximize system benefits. Emerging AI systems are being developed and becoming increasingly available in the market to apply Imagery Analysis (i.e., using neural networks specifically trained for roadway scene analysis) to track vehicles and other system users (e.g., cyclists, scooters, pedestrians) using the video images captured by CCTV cameras. This can provide significant improvement to real-time signal control methods that currently use fixed detection zones or loops to measure traffic status. This application uses AI for three system functions: sense & perceive, reason & analyze, and learn & adapt (see Figure 2).

Application #3: Traffic Signal Decision Support Subsystem

Objective: AI-based Decision Support Systems (DSS) used to proactively respond to non-recurring congestion conditions at a network-level

Summary: AI techniques could provide means of advancing traditional decision support subsystems for urban arterial traffic signal control. The learning capabilities of AI could enable more intelligent and tailored responses to unpredictable events impacting all road users. Several decision support subsystems have already been used in Integrated Corridor Management (ICM) projects that integrate traffic prediction and on-line microsimulation to evaluate the potential benefits and disbenefits of response strategies (changes to signal timing parameters, DMS messages, and ATM lane-use display gantries) in near-real-time (SANDAG, 2020). Data used in such systems include real time and historic traffic data, event data, and possible response plans. In localities where this type of system has been deployed, the total travel time has been shown to decrease, as well as reductions in the variability of travel times (Lukasik D. , 2020). Future AI capabilities (i.e., deep learning neural networks) could enhance such algorithms to the extent in which they could operate at a network-level beyond a specific corridor by (a) reducing the significant level of effort required to build, maintain, and expand simulation models, (b) automatically updating parameters and rules based on outcomes, and (c) testing a wider range of potential responses through deeper exploration of the solution possibilities with smarter search methods. This application uses AI for decisions & actions system function (see Figure 2).

Application #4: Misbehavior Detection System

Objective: Connected Vehicle (CV) and field device misbehavior detection systems

Summary: AI could be used to improve the security of CV applications. Misbehavior detection systems could help protect users of ITS and CV applications from attacks by identifying anomalies in data communications. In this context, anomalies may include both malicious intent and device malfunctions, such as (a) false positioning information sent in CV Basic Safety Messages (BSM), (b) interruptions in the transmission of BSMs resulting in an incorrect perception of surrounding vehicles, (c) mismatch between signal status broadcast and actual signal indication displays, (d) urban canyon effects of GPS and dGPS reliability, and (e) GPS jamming or malicious denial of BSM transmission channels. Similarly, AI could be used to improve the maintenance of ITS field devices (traffic signals, detection systems, CCTV, DMS, etc.). Misbehavior detection systems could identify anomalies in data communications from TMC software to the field. In this context, anomalies may include both malicious intent and device malfunctions, such as (a) malicious control of ITS devices by bad actors, (b) anomalies in status responses and mismatch of current operation to historical data, (d) regional communication failures, due to wireless jamming or malicious denial of transmission channels. Misbehavior detection systems using streaming analytics with deep learning neural networks tailored for time-series analysis may provide advantages over traditional systems by reducing the level of effort to respond to new and novel anomalies by extracting patterns automatically rather than defining patterns in advance. Traditional misbehavior detection systems require manually written algorithms used to detect specific known and expected misbehaviors. This application uses AI for two system functions: reason and analyze and learn and adapt (see Figure 2).

Application #5: Comprehensive Traffic Modeling

Objective: Comprehensive urban network traffic modeling

Summary: Traditional traffic flow models on urban arterial networks are typically constrained to small study areas due to the resource and time intensive development of high-resolution models. AI applications using neural networks tailored for traffic network state representation could offer the potential to develop larger and more flexible models using the vast amount of data available by network users. This application could include the development of massive scale models to understand and forecast travel patterns, traffic operations, and traffic safety in large regions perhaps at a lower level of effort that is typically required to build and maintain a high-resolution microsimulation model. This application uses AI for the reason and analyze system function (see Figure 2).

Application #6: Crash and Incident Detection

Objective: Urban network crash and incident detection and incident management

Summary: AI could be used to improve the detection of crashes and arterial anomalies by monitoring feeds from arterial surveillance and traffic signal operation CCTVs. Agencies responsible for arterial management may experience challenges in monitoring and responding to crashes and incidents in a timely manner. Video analytics using neural networks specifically trained to recognize roadway scenes could improve the agency's ability to dispatch the necessary resources (emergency medical, hazmat, etc.) faster and more reliably. Many AI-enabled commercial products are emerging and will continue to evolve, including incident management support with automated aerial drones. CCTVs and video detection are relatively ubiquitous, but have a wide range of aspect angles, resolution, occlusion, and many can be remotely adjusted to different pointing directions and zoom levels. This creates some challenges for video analytics. Aerial views using drones can be more easily standardized for zoom level, aspect angle and so on for incident surveillance and post-crash data collection. This application uses AI for three system functions: sense & perceive, reason & analyze, and learn & adapt (see Figure 2).

Application #7: Pedestrian, Cyclist, and Micro-mobility Detection

Objective: Detection of pedestrian, cyclist, micro-mobility, and other modes

Summary: Traditional traffic control has limited ability to manage demand of pedestrian, cyclist, micro-mobility, and modes of travel other than vehicles and transit. AI-enabled video analytics using neural networks specifically trained to recognize roadway scenes could improve the ability of traffic controllers to manage pedestrian crossing times, minimum green times, priority service, and even basic detection of alternate modes. Many AI-enabled commercial products are emerging and will continue to evolve. This application uses AI for the sense & perceive system function (see Figure 2).

Application #8: Safety Metrics Assessment

Objective: Predict safety metrics of Automated Driving Systems (ADS) interacting with human-driven vehicles in mixed traffic streams

Summary: This application involves the use of AI (i.e., deep learning neural networks) to evaluate traffic network safety under different traffic conditions, including varying penetrations of connected vehicles and Automated Driving Systems. AI algorithms are currently being developed to integrate these different data sources to predict safety condition patterns in future scenarios. This application requires a variety of data sources for successful implementation. While significant penetration of highly automated vehicles is likely years away, this information may be useful to IOOs for understanding projected impacts on their urban arterial networks and evaluate whether safety risks could be mitigated with updates to network infrastructure or control strategies. This application uses AI for the reason & analyze system function (see Figure 2).

Application #9: Transit Signal Priority (TSP) Optimization

Objective: Real-time optimization of TSP using AI techniques

Summary: TSP is a critical strategy for minimizing the travel time of transit-vehicles to provide riders schedule adherence reliability and support mode shift campaigns. Existing TSP solutions have multiple parameters that influence operational effectiveness. In most deployments, these parameters are configured at the start of a project and updated infrequently. TSP systems could be upgraded with AI-based algorithms to improve the adaptability of the system by introducing learning capabilities that would produce more tailored responses based on prevailing network-wide traffic conditions and transit schedule adherence. These systems may also improve system-response to unique traffic and environmental conditions. This application uses AI for two system functions: reason & analyze and learn & adapt (see Figure 2).

Application #10: Demand Response Transit Network Optimization

Objective: Improve network-wide transit service with an AI-based system that actively manages transit demand and capacity

Summary: This application builds on planning efforts undergone by transit agencies to match route capacities with ridership demand. Due to resource constraints, transit agencies do not typically operate demand-response services. The challenge with this approach is that ridership demand in some urban arterial networks fluctuates day-by-day and season-by-season. In response, the proposed demand responsive transit network optimization system would identify and respond to instances where transit demand exceeds the capacity or where capacity exceeds the demand. In real-time, this system would be designed to adjust transit vehicle headways to better align capacity with demand. The incorporation of AI technologies would enable outcome-based learning, where the system would ingest the outcome of each proposed response and learn from the successes and failures to adapt the underlying algorithm parameters and improve the next response. In this way, the system would continuously evolve and adapt to current conditions for optimal transit response. This application uses AI for two system functions: reason & analyze and learn & adapt (see Figure 2).

Application #11: Identification of Unauthorized Bus Lane Usage

Objective: Identify and improve enforcement of unauthorized bus lane use to improve transit schedule adherence and travel time reliability

Summary: Bus travel lanes have been designed in large urban arterial networks to improve bus travel time, reliability, and schedule adherence. Some of these bus lanes are dedicated facilities, whereas others are peak-hour facilities with off-peak general-purpose or parking options. However, the effectiveness of these dedicated lane facilities is significantly impacted by compliance. The purpose of this application is to use AI techniques to process CCTV imagery (i.e., located at fixed locations or on buses) to identify violations and enforce lane restrictions. This system has the potential to reduce unauthorized use of bus lanes resulting in improved bus operations throughout the urban arterial network. This application uses AI for two system functions: sense & perceive and reason & analyze (see Figure 2).

Concept Illustration

Figure 4 shows *performance-driven* examples of how AI can potentially be used in an urban arterial network scenario to make multimodal travel more accessible, reliable, efficient, and secure. For example, agencies can detect vehicle crashes and road closures to proactively respond to non-recurrent congestion (**#1**). Multimodal transportation network users can be detected and considered in signal timing strategies, and smart infrastructure can be used to collect and identify misbehaviors in Connected Vehicle (CV) and Intelligent Transportation System (ITS) device data. Additionally, enforcement of unauthorized bus lane usage can be conducted to improve transit reliability (**#2**). Advanced computational capacity in AI systems enables larger and more comprehensive urban network modeling for Decision Support Subsystems (DSS) and corridor-wide signal timing optimization (**#3**). Improved understanding of mixed traffic streams (i.e., non-automated driving intermixed with varying levels of automated driving systems) can be achieved and safety metrics can be predicted. Demand-responsive headway adjustments for transit operations throughout the corridor can improve transit reliability and encourage further mode shift (**#4**).

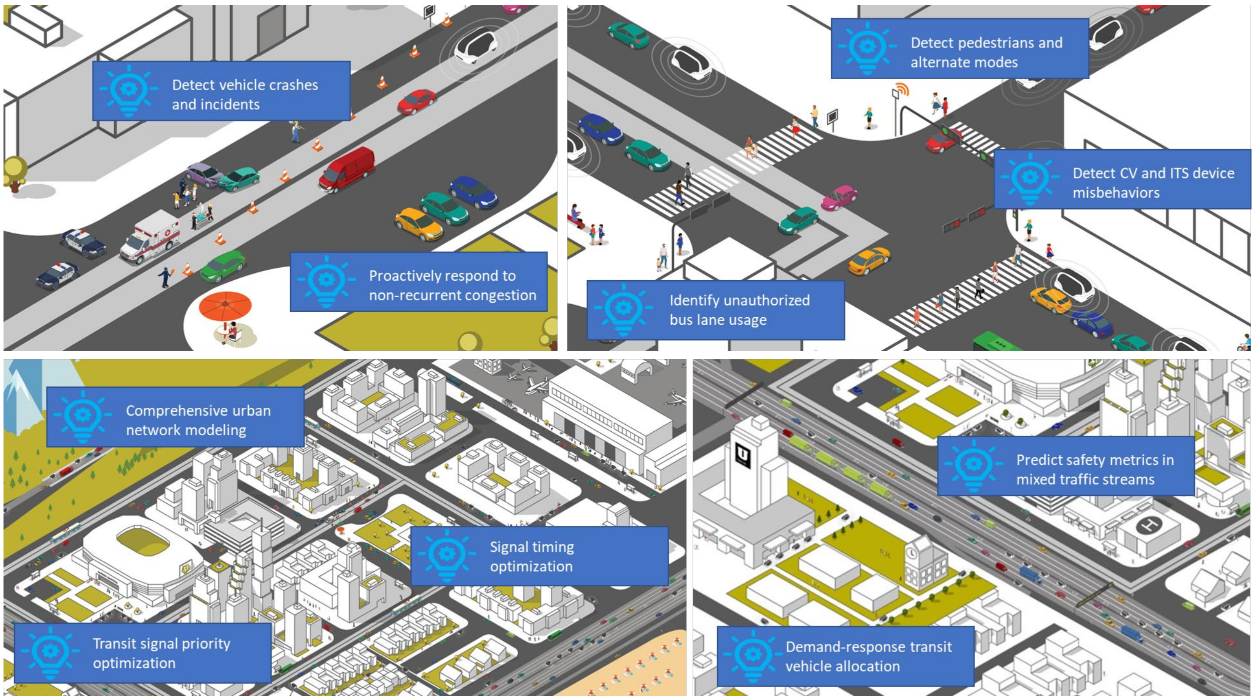

Figure 4. Graphical Illustration of Potential AI Applications for an Urban Arterial Network.

Actors and Actor Profiles

Actor #1: Transportation Management System (TMS) Operator

Stephen is a TMS Operator in a large metropolitan city. On Thursday at 3:00 PM, he receives notification that a collision involving multiple trucks has occurred on a heavily traveled commuter route. The AI-enabled decision support subsystem is already analyzing alternative response plans and predicting expected outcomes. Stephen approves the suggested response plan that reduces total network delay and successfully mitigates the negative effects of the collision.

Actor #2: Commuter

Amy is a doctor in a large metropolitan area, and she commutes to the hospital she works at during off-peak hours. In the past, Amy would often experience a significant amount of delay waiting at traffic signals for the light to turn green, even when no vehicles were present at conflicting movements. However, her city just started implementing an AI-based signal re-timing effort that recommends signal timing plan adjustments based on observed traffic conditions. Amy notices that the updated off-peak signal timing plan resulted in reduced delay for her daily commute.

Actor #3: Policy Maker

Linda is the Secretary of Transportation responsible for guiding statewide transportation policy. Linda's department recently hired a team of practitioners and researchers to develop and validate an AI-based application to predict the impact of automated driving systems in the state's capitol city. This application provides estimates of network safety and performance at varying penetration rates of automated driving systems. These results suggest automated driving systems are promising for improving travel safety, and Linda uses these findings to secure funding and support for further research and deployment.

Actor #4: Systems Engineer

Alex is a systems engineer working for a large urban municipality. His agency is currently rolling out a series of new ITS capabilities. Alex works directly with the communication securities team and developed a misbehavior detector system with AI components intended to identify potentially erroneous or malicious data communicated to the ITS devices. This system is expected to improve the reliability of ITS applications communications to prevent misleading information from being communicated to travelers.

Actor #5: City Engineer

Peter is the city engineer for an IOO with broad responsibilities that include traffic and signal management. His organization is understaffed and reactive to field device failures and equipment malfunctions. In a recent collaboration, Peter's organization partnered with IOOs from neighboring jurisdictions to implement an anomaly detection system using streaming analytics with neural networks that alerts the organizations to malfunctions and suspected misbehaviors that are precursors to device failures (e.g., traffic controllers, MMUs, detectors) at high volume intersections throughout the urban arterial network. Using this system, Peter is better able to pro-actively address issues before they are reported by the public. In addition, this AI-enabled traffic control system responds to fluctuations in demand and arterial incidents automatically, reducing his need for signal re-timing studies. The benefits of this system have improved traffic conditions within Peter's jurisdiction as well as within those of partner IOOs.

Relevant Research, Tests, and Case Studies

Real-Time Traffic Signal Optimization

The Utah Department of Transportation (UDOT) operates over 1,200 traffic signals throughout the state. Traditional traffic signal re-timing efforts occur every five-years. However, with emerging technology—specifically AI—UDOT is exploring the possibility of conducting traffic signal re-timing efforts at a much higher frequency. On December 31, 2019, UDOT entered a one-year contract with Flow Artificial Intelligence, Inc. to develop this system. The system will leverage AI based on neural networks and ML technologies to optimize signal timing using UDOT's Automated Traffic Signal Performance Measures (ATSPM) data source. This contract includes the optimization of 48 UDOT traffic signals along 5 distinct corridors throughout the state over a 12-month period. UDOT will be provided with timing plans for all 48 signals on a monthly basis alongside performance predictions and performance outcome reports. The impact of these signal timing adjustments will be evaluated over the course of the year using HERE travel time data (Taylor, 2020).

Safety Metrics Assessment

The University of Arizona is working on a project through the Institute of Automated Mobility (IAM)—a program initiated by the governor of Arizona—to identify safety metrics that can be computed from automated vehicles. This project is evaluating a mixed traffic stream (i.e., traffic with both automated driving systems and human driving systems) to evaluate the safety of the full network. As part of this project, a variety of data sources are being collected: (1) State Farm user data, (2) Connected Vehicle (CV) on-board devices (OBUs), (3) surrogate Basic Safety Message (BSM) data, (4) cameras on vehicles and infrastructure, and (5) lidar from vehicles and infrastructure. AI algorithms based on neural networks are being used to integrate these largely different data sources to uncover patterns enabling us to better understand safety conditions of the network (Head, 2020).

Misbehavior Detection

Qualcomm uses AI to secure CV and ITS applications. Qualcomm is working with OEMs to begin developing manufacturer-specific security misbehavior detection systems; however, uncertainties in regulation and standardization are anticipated to slow progress but increase transparency of security systems between manufacturers. Misbehavior detection algorithms are being developed generically, such that they may be applied to numerous applications (e.g., vehicle to vehicle and vehicle to infrastructure communications). However, experience dictates some security protocols are more or less relevant based on the intended application; therefore, as applications mature and prepare for deployment, the AI algorithms based on streaming analytics of time-series data using neural networks for different security protocols will be narrowed down to focus on the independent needs of each application (Petit, 2020).

Unauthorized Bus Lane Use Enforcement

New York City's Metropolitan Transit Administration (MTA) implemented an automated bus lane enforcement program to reduce unauthorized use of dedicated bus facilities that contributes to bus delay. The intention was to clear bus lanes, speed up rides, and prioritize transit on high-volume corridors. The system uses cameras mounted directly on the buses. As buses travel on their typical routes, vehicle obstructing lanes are recorded, and a violation is issued. As of February 2020, MTA reported bus speeds have risen 55 percent since December 2018 (i.e., an average of 5.8 mph) and 9,700 tickets have been issued. The city's 2020-2024 Capital Plan includes $85 million for further expansion of this program, as well as additional strategies to improve transit throughput including transit signal priority (Spencer & Hill, 2020).

Incident Detection

Both Nevada and Florida departments of transportation (DOT) use a proprietary software as a supplement for incident detection. The AI system fuses information from a variety of sources to detect and report suspected incidents. In addition to the traditional sources which include radar and loop detectors, the AI system processes feeds from existing Nevada DOT (NDOT) and Florida DOT (FDOT) closed-circuit television (CCTV) cameras to identify incidents using AI (neural networks). This neural network is trained to recognize scenes that are “incidents” and “not incidents,” as well as “incident may be likely to occur.” In both cases, the application software was deployed in areas with good existing coverage of cameras and traditional point detection. Both NDOT and FDOT have reported improvements in incident detection times by the AI system of up to 12 minutes faster than other input streams and reducing crashes by 17 percent by positioning highway patrol assets accordingly and providing advanced warning of downstream congested areas on dynamic message signs (Zamsky, 2018).

Iowa DOT has partnered with Iowa State University to develop an incident detection system that relies on AI (neural networks). Similar to the goals of NDOT and FDOT, Iowa’s system is focused on improving incident detection time, particularly in rural areas where camera surveillance may be available, but highway patrol notifications may take an extended period to be received. Iowa DOT has named this system Traffic Incident Management Enabled by Large-data Innovations (TIMELI) (Sharma & Hawkins, 2017). TIMELI uses NVIDIA Titan X graphics processing units and the open-source TensorFlow deep learning system to classify images from traffic surveillance cameras in near real time. The Iowa DOT TIMELI system monitors cameras from across the entire State and includes other data feeds such as incident reports and traffic congestion level. The research project is being piloted now.

Digital Assistants

For many years, 511 systems have used natural language processing (NLP) to understand a user’s requested route. These systems historically have been limited in both their technical capability (e.g., understanding user phrases with background noise while driving) and the phraseology expected from the user (e.g., bus stop identification numbers, freeway names and sections). Significant enhancements of NLP capabilities in digital assistants should be available in coming years. Metropolitan Transportation Commission (MTC) Bay Area 511 now has an Alexa skill to pass through requests for 511 information for the same phraseology that works with their interactive voice response (IVR) module (Amazon, 2020). Alexa skills are becoming popular with cities as part of 311 and community service information systems, one of many examples in John’s Creek, GA, a suburb of Atlanta (Hutmacher, 2018).

Recently, the Virginia Department of Transportation (VDOT) held a “hackathon” with more than 50 volunteer developers to leverage the VDOT open data application programming interfaces (API) for a variety of quick demonstration projects. One of the winners (“Talk DOT”) was an Alexa skill to allow users to ask questions of the VDOT database as if they were manipulating the VDOT Web interface (Chandran & Kumar, 2018). Additional functions of AI-based assistants, such as smart home technology can easily be extended to TMC operations, such as voice-activated video wall configuration and other enhancements to traditional operations.

In 2018, the City of Surprise, AZ (a suburb of the Phoenix metro area) developed a Google Assistant interface to their adaptive traffic control system (Gettman D. , 2018). The chatbot system allows the traffic engineer to query status data using voice commands through a Google Home speaker, Google Mini, as well as Google Assistant on any phone or computer. The system is implemented using Google’s DialogFlow, Actions console, Firebase, and Microsoft Azure.

Decision Support Subsystem

Delaware DOT (DelDOT) recently received a $5 million grant from the Advanced Transportation and Congestion Management Technologies Deployment (ATCMTD) program of United States Department of Transportation (USDOT) to develop an AI TMS as part of the Advanced Transportation and Congestion Management Technologies Deployment Program (Singer N. , 2019). While much of the funding will go towards upgrading infrastructure including cameras and traffic controllers, a significant portion will fund the development of AI technologies for traffic prediction, incident detection, and automated traveler information dissemination. In partnership with FHWA Turner-Fairbank Highway Research Center, DelDOT has piloted several AI methods in advance of the grant award. One component of the DelDOT AI strategy is to use reinforcement learning to train neural networks to manage traffic control systems as a “game” (e.g., chess) by predicting the impacts of certain traffic control actions and selecting the most effective control strategies.

Potential Benefits

In urban arterial networks, AI may not be anticipated to replace classic problem solving and conventional traffic management solutions. Rather, these classic systems are anticipated to provide a foundation for integrating AI-techniques to further improve existing systems. AI is also anticipated to introduce new ways to solve urban challenges that have been previously unsolvable using conventional methods. AI offers the opportunity to widen the scope and evaluate larger traffic control networks, rather than largely localized control strategies, and ask bigger picture questions that could result in solutions that address multiple issues simultaneously. Systems incorporating AI introduce the concept of outcome-based learning to traditionally static applications. When a system can learn from its successes and failures and continually refine algorithm parameters to produce better results, the system may become more adaptable and produce greater benefits. A list of potential benefits of AI-enabled systems in the context of an urban arterial network are provided below:

- **Decision-Making**: Intelligent decision support sub-systems that can inform the selection of response plans to non-recurring congestion caused by crashes and road closures.
- **User Satisfaction**: Integration of AI into existing and new urban arterial network management systems has the potential to increase the satisfaction of all road users.
    - **Vehicles**: Optimization of signal timing coordination plans and adaptive signal controllers may reduce overall delay and improve travel time reliability.
    - **Transit**: Optimization of transit signal priority strategies, real-time demand response based on prevailing ridership, and enforcement of dedicated transit facilities may improve the experience of existing transit riders and support a greater mode shift from personal-vehicle travel to reliable transit alternatives.
    - **Micro-mobility**: Improved detection of pedestrians, cyclists, scooter-riders, and other non-motorized road users would improve the ability of traffic controllers to manage necessary crossing times to serve these road-users more effectively.
- **Network-Wide Planning**: A challenge faced by large urban metropolitan areas is simply the size of the network. In forecasting demand and planning for future operational challenges, existing systems are limited in their capacity to account for the full urban arterial network as a whole. AI offers the

potential for new models and decisions support subsystems to be developed that could better analyze the network comprehensively. This would result in improved understanding of the inter-related elements of the urban arterial network (e.g., infrastructure elements, modes) and may lead to improved planning and operational decisions.

  - **Connected and Automated Vehicles**: Connected vehicles and Automated Driving Systems are anticipated to make a significant impact on traffic flow at varying penetration rates in urban arterial networks. AI-based models enable IOOs to examine the forecasted impacts and identify proactive solutions that may reduce risk as adoption of these technologies arise.

- **Adaptability**: AI systems offer adaptability that static systems are not able to offer. These systems would enable operational adjustments based on time-of-day, day-of-week, seasons, special events, and other unpredictable unique situations.
  - **Signal Operation**: Improved frequency in which traffic signal coordination plans are updated would allow for the urban arterial network to more readily respond to seasonal changes, new developments, and other factors impacting signal operation effectiveness. Similarly, integration of AI-based adaptive signal controllers offers increased potential for adapting to real-time situations as they occur in the urban network.
  - **Transit Operation**: Similarly, increases to the agility of transit operations would enable real-time adjustments to accommodate stark changes in ridership demand occurring in real-time throughout the urban network.
- **Environmental**: Upgraded and new systems incorporating AI have the potential to reduce the negative impact of transportation on the environment.
  - **Vehicles**: Optimization of signal timing coordination plans and adaptive signal controllers that reduce delay may result in reduced fuel consumption.
  - **Transit and Micro-mobility**: Improving user-experience on transit and non-motorized travel modes has the potential to further benefit the environment by reducing the number of personal-vehicles on the road.
- **Security**: AI systems are critical to the system security across dozens of industries. Within transportation, the learning capabilities of AI-based security systems are anticipated to fill an essential need for securing data communications between connected and cooperative vehicles and ITS field devices.
- **Big Data**: There is a significant amount of data coming out of urban arterial networks. These data streams are stemming from infrastructure sensors (e.g., traffic counts, ATSPMs), fleet travel companies (e.g., Uber, Lyft, Door Dash), mobile device-based travel patterns data (e.g., INRIX, HERE), transit farecard readers, and scooter/bicycle renting applications, to name only a few. The scalability of AI applications offers novel opportunities to leverage these old and new sources of data to provide further benefits within the urban arterial network.

Potential Barriers to Adoption of AI for Urban Arterial Networks

Integrating AI-based algorithms and techniques into urban arterial network planning and operational strategies offers a gamut of benefits. However, there are a number of potential challenges associated with these innovative AI solutions as well. The list below summarizes key barriers to integrating AI in urban arterial networks.

- **Workforce Capacity:**
  - Transportation engineers operating and maintaining urban transportation networks typically come from a traditional civil engineering background with limited awareness of AI applications.
  - Data scientists and those trained to develop AI applications do not traditionally have a background in urban arterial management and necessary applications.
  - Development of new AI systems will require workforce training for developers, operators, and engineers.
- **Data Availability and Quality:**
  - AI applications are constrained by the data available for analysis; until more data become available, implementation of AI solutions will be limited.
  - Data quality challenges the development of robust AI algorithms.
- **Hardware Constraints:**
  - AI-enabled signal optimization may be constrained by the capabilities or compatibility of signal controllers.
  - Computational requirements for AI algorithms are typically extensive and often beyond the available technology at urban traffic control centers.
- **Institutional and Financial Challenges:**
  - Institutional challenges related to policy, regulation, personally identifiable information (PII), and funding.
  - Public agencies are responsible for spending public funding responsibly; however, there is certain risk of the unknown when developing innovative solutions that have not been tried before.
  - The cost of implementation for certain AI-based applications may prove to be significantly higher than the cost of a conventional system that provides adequate performance.

Potential Value to USDOT

Urban arterial networks are a key area where the benefit of AI solutions can be widely explored. Improved signal control, network-wide model development, connected vehicle applications, and safety assessments of complex traffic conditions are a few use cases that address problems that conventional solutions may not be able to. Local jurisdictions operating the majority of urban arterial networks are challenged to adopt innovative solutions, such as AI applications, without precedence of their successful implementation in research or test beds. The USDOT could spur the adoption of these AI solutions by providing additional funding for related research to generate application-specific evidence of network performance differences with and without AI solutions. The findings and lessons learned from these studies can then be used by local agencies to prioritize innovative applications to adopt based on their unique needs.

Additionally, successful and efficient deployment of AI applications in urban arterial networks will require consistency among jurisdictions in different cities and states across the United States. The USDOT has the opportunity to continue developing education, guidance, recommendations, and standards as AI applications are tested and deployed in urban settings.

Chapter 5. Urban Multimodal Corridor

This chapter discusses how AI might potentially be used for addressing challenges relevant to the Urban Multimodal Corridor scenario. This chapter provides a background of Urban Multimodal Corridors, an overview of the operational challenges relevant to the scenario, potential applications enabled by AI to address the challenges, a graphical illustration of the concept, actors or entities interacting with the AI-enabled systems, relevant research, tests and case studies, potential benefits, potential barriers to adoption of AI for the scenario, and potential value to USDOT of investing in AI-powered solutions for the scenario.

Background

Operations in today's urban transportation corridors are largely handled independently by each transportation network operator within the corridor. While the transportation network operators may collaborate or interact to some extent to deal with incidents, or pre-planned events occurring within the corridor, transportation network operators handle most day-to-day operations independently, without much communication between operators. As congestion becomes heavier, this independent operation of multiple agencies has become less effective in meeting the transportation needs of the corridor and the businesses and people within it and using it. However, coordination of operations of all involved agencies in multimodal urban corridors present a high level of complexity that requires the use of novel approaches, because a failure (Event) in one of the modes such as rail or subway can affect other interacting modes, often in disproportionate ways. Impacts from disruptions in one mode cascade, creating hyper congestion and increasing other externalities such as emissions, safety, and noise due to unexpected demand shifts to other modes that are already operating at or above capacity.

In the light of the problems described above, the USDOT set up the Integrated Corridor Management (ICM) initiative to help agencies manage their assets in a unified way so that corrective actions can be taken to benefit the *entire* transportation system, and not just parts of it through institutional, operational, and technical integration (Hardesty & Hatcher, 2019). The USDOT launched the Active Transportation and Demand Management (ATDM) program to enable agencies to proactively and holistically manage the entire trip chain by integrating traffic, demand, and parking management operational strategies to achieve established performance objectives in trip reliability, mobility, and safety (Lukasik, et al., 2020). Figure 5 shows the ICM and ATDM concepts.

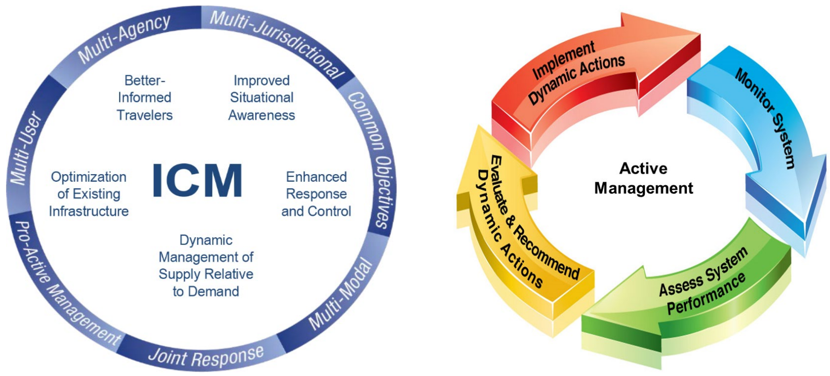

Figure 5. Integrated Corridor Management (ICM) and Active Transportation and Demand Management Program Concepts (Source: Federal Highway Administration).

Managing a corridor in an integrated fashion requires corridor network operators to develop strategies in four areas, including:

- Demand Management
- Load Balancing
- Event Response
- Capital Improvement

Within the first three strategic areas (demand management, load balancing, and event response), corridor operators can develop control strategies (tactics or actions) and procedures for implementing those strategies. In contrast, the capital improvement area focuses on the development of recommendations for capital expenditures for technological and infrastructure improvements. The focus of AI-based solutions will be on the first three strategic areas. However, there are opportunities for the use of AI in the last category to develop long-term capital plans that will minimize costs and risks while maximizing benefits.

Relevant Operational Challenges

Integrated multimodal systems face several challenges including effective interagency communication and collaboration as well as development and real-time deployment of alternative scenario-specific corridor-wide operations. Moreover, even if some proactive response plans can be deployed, disseminating this information to travelers in a timely and efficient manner can be extremely challenging. Finally, identification, procurement, deployment, and maintenance of advanced technology solutions required to solve the above problems can pose additional long-term challenges in terms of agency priorities and budgets. AI-based approaches and other time-tested traditional ones can provide effective tools to address some of these challenges.

Key operational challenges for urban multimodal corridors include:

- **Integrated day-to-day Multimodal Corridor Management**

  - Complex systems due to the interaction of different modes and agencies serving commuters with different travel needs.
  - Involvement of multiple agencies makes it challenging to deploy alternative corridor-wide operating scenarios.
- **Integrated Multimodal Corridor-wide Incident Management**
  - Certain failures in one mode, can affect other interacting modes, often in disproportionate or unexpected ways.
  - Incident management and interagency coordination across different modes in real-time can be difficult and lead to increased emissions and reduced safety.
- **Real-time Multimodal Travel Information Generation/Dissemination**
  - Not being able to generate coordinated multimodal delay and diversion information can cause additional delays.
  - Even if proactive response plans for certain modes can be deployed, disseminating this information to multimodal travelers can be challenging.
- **Long-term Transportation System Management**
  - Under funded and/or under-staffed modes can suffer from longer delays, lower reliability and safety related issues reducing their mode-share in the long-run.
  - Implementing novel sensor and technology solutions can be costly and sometimes infeasible due to differences in funding and staffing differences among agencies.

Potential AI Applications

Application #1: Interagency Collaboration

Objective: Real-time interagency collaboration using Decision Support Systems and Knowledge Based Expert System (KBES)

Summary: Effective multimodal corridor-wide transportation system management requires collaboration among all agencies involved. A KBES can be developed to facilitate this type of interagency coordination in terms of identifying which agencies should be involved and what they should do to minimize system-wide impacts. In each agency as well as in some regional multiagency centers, there are highly skilled and experienced professionals with a vast knowledge of the system they are managing. Their experience can be acquired and elucidated to capture and represent this specific domain knowledge that can be used to build a KBES that can support decision making for: a) sharing computational resources; b) revising train/subway/bus schedules; c) deciding optimal actions to remove accidents or to fix certain kinds of mechanical and /or computer related failures. For example, if re-scheduling a bus or rail service must be performed in real time, genetic algorithms or simulated annealing techniques can be used to reduce computation times that can be otherwise prohibitive for real-time applications. As another example, if there is a major failure of the suburban train service serving commuters traveling to the city, then pre-scheduled work zones that are on the major freeways and arterials that can serve as alternatives for commuters shifting from rail to car can be postponed using an expert system coupled with AI-based predictive approaches. Moreover, real-time heuristics and reinforcement learning methods can be used to optimize signals along the affected arterials to ensure that they can accommodate additional demand. This application uses AI for three system functions: reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Benefits of such an application include, improved throughput, reduced delays, emissions, and energy consumption across modes, and reduced risk of incidents and resulting impacts, including secondary incidents.

Application #2: Detection of Multimodal Failures and Incidents

Objective: Real-time detection of multimodal failures and incidents using AI techniques

Summary: Unlike highway-based systems where traffic information from infrastructure sensors and third-party traffic information providers (e.g., Waze) can provide relatively reliable and timely information, in a multimodal setting, system-wide information can be derived from more heterogenous sources such as transit agency's in-house monitoring system, electronic ticketing data, in-vehicle or mobile cameras, and social media in addition to these traditional sensors. AI can be used to achieve a more reliable and real-time fusion of data from heterogeneous sources mentioned above. For example, Bayesian Learning can be used to identify errors and uncertainties in certain data sets before it is fused with others. In the case of multimodal corridors, it is highly likely that more than one failure might occur at any given time. AI can be trained to recognize these different types of failures for different modes, including freeways, arterials, bus lanes, commuter train lines, subway, and ferry service. This can be done using anomaly detection algorithms that can identify the existence and severity of disruptions using historical data. These can be based on unsupervised learning methods that will reduce time and effort needed to continuously train the ML algorithms because they do not require the development of a training set by manually labeling events and/or objects. In the case of subway or commuter train, information from social media and commuters can also be very valuable sources of data because travelers tend to react to unexpected delays faster than agencies. Neural Networks can be trained to recognize the existence and significance of delays using social media and commuter data to identify exact location, type and duration of delays. In-vehicle cameras installed in both public and private vehicle fleets can also be used to collect street level and pedestrian data that can be processed by image recognition algorithms to improve real-time safety of pedestrians and other users. There are several private companies that have already deployed in-vehicle cameras in either individual vehicles or commercial vehicle fleets with the goal of collecting this type of video data. These companies have also developed solutions to acquire, store and process this massive video data. AI is used in processing these images and recognizing "events" of interest both on-line and off-line. Recent developments in the use of Convolutional Neural Networks for image processing have made it possible to improve both the accuracy and speed of these image recognition tasks. Infrastructure cameras that are deployed and maintained by transportation agencies can be another source of information for the detection of mode specific failures, especially the ones that occur in terminals or closed areas where public vehicles do not have access to. This application uses AI for three system functions: sense & perceive, reason & analyze, and learn & adapt (see Figure 2).

The benefits of this application include reduced incident detection time, which will in turn improve overall corridor performance. By providing information to travelers on mode-specific failures, travelers will be able to make pre-trip and en route mode switch decisions and avoid delays.

Application #3: Prediction of Multimodal Corridor Delays

Objective: Real-time prediction of the multimodal delays using AI techniques

Summary: Once the existence of one or more delay causing events are identified at a relatively high level of confidence, their impact can be predicted using ML and AI methods mentioned in Application #2. Deep Learning Neural Networks that can be trained using historical travel time and event data are a natural candidate. Again, it is highly desirable to work with unsupervised learning methods given the complexity of multimodal transportation networks and problems that would be encountered for the labeling events/objects required by supervised methods. An important aspect of multimodal transportation networks is the possible interaction among modes. For example, if the commuter rail experiences expected or planned disruptions (e.g., repair work) during the morning rush hour, then AI-based prediction algorithms can be used to estimate the shift to other modes such as bus and car as well as reductions in overall travel demand. Then, given these predictions, possible delays in terms of travel times can be estimated using neural networks. Another important aspect of multimodal systems is the extent of the impact of a given disruption. For example, if a section of a subway line is closed due to emergency repairs then certain parts of the system will be affected. This impact can be predicted using spatio-temporal clustering methods that can divide the system into clusters that will in fact act as relatively independent sub-systems. This application uses AI for two system functions: reason & analyze and learn & adapt (see Figure 2).

The benefits of this application include, reduced congestion, emissions, and energy consumption, and connection protection for multimodal travelers. Additionally, the predicted delay information can help Commercial Vehicle Operators that depend on timely deliveries, thus minimizing the cost of operations for an industry that already operates at very low profit margins.

Application #4: Personalized Dissemination of Multimodal Travel Information

Objective: AI-based Decision Support Systems (DSS) to generate personalized real-time multimodal travel information

Summary: Commuters in an urban multimodal corridor can greatly benefit from the provision of real-time, up-to-date and actionable information that is customized to their personal travel needs. However, this kind of highly personalized travel information is not available due to complex data and algorithmic requirements. This application will require the fusion of information from different modes and generating a combined advisory in a timely manner. For example, if commuter trains are delayed along a certain line due to bad weather conditions, commuters should not only receive this information, but they should also be given alternative multimodal options along with expected delays. AI can be used to build shortest “multimodal” path information specifically designed for each commuter. A commuter who tries to minimize their out of pocket cost and does not own a car does not need to know highway travel times. His personalized advisory can focus on transit and train-based routes. On the other hand, for a commuter who is on a business trip with a greater travel budget flexibility, it is possible to generate a travel time along a shortest path that incorporates the use of for-hire vehicles. Thus, AI can provide highly personalized travel time information that combines multiple modes. In doing so, information from heterogenous sources can be processed using neural networks and generate in real-time time-dependent stochastic shortest paths for every origin-destination pair. Graph Neural Networks (GNN) have been increasingly used in the context of dynamic networks because they are shown to effectively capture spatio-temporal characteristics of complex networks such as transportation networks. Since GNN's are also capable of learning patterns that are key in solving dynamic network problems such as time-dependent shortest paths, its predictions will become better with time. They can even be tailored to the actual choices and changing needs of each traveler using more than one mode. A natural extension of this application is to provide this kind of highly customized information to commercial vehicle operators. Accurate and timely travel time predictions can be used by commercial vehicle operators to revise their schedule or re-configure their pre-determined routes to minimize overall delays and operating costs. At the agency level, AI based methods can be used to identify key operational staff from each agency and send them travel time advisory information for better coordination and decision making. This can be achieved through a relatively simple expert system developed using past practices and expert knowledge. This application uses AI for three system functions: reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

The benefits of this application include:

- Improved traveler experience and safety by providing real-time predictive, personalized travel information.
- Inclusion of less commonly used modes (e.g., pedestrians, bicyclists, and other forms of micro-mobility) that will have the least impact on congestion, emissions, and energy consumption.
- Introduction of maximum flexibility through the use of emerging strategies such as incentives, mode-specific pricing, etc.

Application #5: Multimodal Corridor Demand Management

Objective: Proactively select and implement personal and commercial demand management strategies using AI-based DSS and ML techniques to reduce the impacts of planned and unplanned events

Summary: AI-based DSS and ML techniques can be used to proactively select and implement personal and commercial demand management strategies to reduce the impacts of planned and unplanned events. AI can help determine the best demand management strategies in response to major events. The most powerful tool in the toolbox to influence behavior is through the provision of traveler information, and a great opportunity for AI to play a role in by:

- Selecting specific multimodal messages, travel times, and other information to be disseminated.
- Predicting disaggregate (and aggregate) responses to the information provision nuanced by content, target audience, urgency indicators, timing, implementation horizon, and other factors.

For example, many urban areas in the eastern seaboard experience congestion during the summer season due to increased beach traffic. AI can be used to develop a system based on historical system-wide traffic data. This system can be used to adjust tolls, fares, and incentives to reduce demand for a specific mode with the overall objective of shifting demand to other less crowded modes and facilities. This problem can be formulated as a large-scale optimization problem that can be solved using Genetic Algorithms (GA). GA can solve complex problems that are not solvable by traditional solution approaches. Moreover, ML can be used to filter and process system-wide data that can then be fed into this optimization algorithm with the goal of updating its model parameters to better reflect prevailing system conditions. A transit agency can also use AI-based based methods such as Learning Decision Trees and

State Vector Machines (SVR) to change the frequency of its service to better serve its customers and shift demand from other modes.

There are also opportunities specific to CVO in managing truck demand during an event that causes major congestion along a major freeway in a multimodal urban corridor. Using predictive information generated by Neural Networks, trucks headed towards the incident area can be re-routed to rest areas or alternative routes. This will reduce additional congestion and the likelihood of secondary incidents due to the trucks. Also, it will reduce operational costs of trucks. Some cities might even provide incentives for off-hour deliveries during these major events. Classification algorithms can be used to determine optimal clusters of receivers that are in the database of partners for off-hour deliveries in an urban area given the location and severity of the traffic incident. This will be a highly challenging implementation that will require optimal matching of trucks and receivers using methods such as K-means clustering or Hierarchical Agglomerative Clustering. This application uses AI for two system functions: reason & analyze and learn & adapt (see Figure 2).

The benefits of this application include:

- Reduced congestion/emissions/energy consumption.
- Improved safety by minimizing the likelihood of secondary incidents.
- Improved and efficient use of alternative modes with available capacity.

Application #6: Integrated Payment for Multimodal Corridor

Objective: Integrated and secure electronic payment for fares, tolls, road use, parking, ride-sharing and other areas requiring electronic payments for travel on multimodal corridors

Summary: Integrated and secure electronic payment for fares, tolls, road use, parking, ride-sharing and other areas requiring electronic payments for travel on multimodal corridors can be implemented by using some of the AI and ML methods described in previous applications. AI can be used to improve coordination of multimodal payments which will involve several private and public transportation service providers. For example, an AI-based payment system that can learn from past data to reduce conflicts among different payment methods and implement incentives to reduce congestion. The Learning Decision Trees method can be used for such a system. As a result of the proliferation of micro-mobility options operated by private companies, such a recommender system that can integrate payments in a seamless manner over public and private payment systems can be expected to improve overall performance of a multimodal system under all types of operational conditions. In this context, AI and ML methods could be used to:

- Ensure seamless integration of multimodal payments through emerging application technologies without interruption and loss of revenue (off-line).
- Provide advisory to facilitate integration of new players when they become available (off-line).
- Calculate trip fares by resolving conflicts and optimizing fares across multiple private and public modes with and without disruptions (on-line).
- Decide combination of optimal payments for a multimodal trip with and without disruptions (on-line).

- Recommend lowest cost, shortest time, safest route, or a certain weighted combination of all these given the available modes with and without disruptions (on-line).
- Detect anomalies and problems related to payments in real-time (on-line).

AI can also be used to ensure privacy and security of these highly integrated transactions. Privacy and security related issues that can be addressed using AI and various ML methods include:

- Compromised personal mobility and financial information.
- Sharing private information with parties that are not privy to obtain such information.
- Malicious attacks to agency systems through such electronic payment methods (on-line).

This application uses AI for three system functions: reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Benefits of such an application include:

- Minimizing mode specific conflicts in terms of payment and reimbursement of service providers.
- Enabling the addition of dynamic incentive methods that reduce congestion.
- Preventing malicious attacks/loss of private data, revenue, and service disruption.

Application #7: Real-Time Demand Responsive Traffic Management and Control

Objective: Enable real-time demand responsive traffic management and control

Summary: An urban multimodal corridor includes different types of facilities and modes. As a result, demand responsive real-time traffic management along an urban multimodal corridor requires an integrated approach that considers interaction among different facilities and modes. For example, traffic signals along an arterial network and an interacting ramp metering system regulating inflow to a parallel freeway need to be coordinated to avoid queue spillbacks and system-wide congestion. Interactions between modes (e.g., bus, cars) operating along the arterial network need to be coordinated to minimize delays to the modes. Large scale complex traffic simulation or dynamic traffic assignment models have been used for traffic management in urban multimodal corridors. However, these approaches have several well-known problems that can be addressed by AI. First, real-time demand responsive traffic management requires the use of real-time data from the multimodal network. With the advent of connected vehicles, the task of acquiring and processing data from multiple sources has become even more crucial. This data is initially used to decide whether to update traffic management plans (e.g., dynamic speed limits, dynamic pricing), ramp metering rates, and traveler information. Typically, data are processed to be used as input to a traffic simulation model for decision-making. AI can be used to combine the data from different sources for determining optimal traffic management and control strategies for prevailing or predicted traffic conditions. For example, neural networks can be used to provide estimates of missing input data (Yang, Yang, Han, Liu, & Pu, 2018) (Wang & Kockelman, 2009). Graph Neural Networks can be used to predict dynamic Origin-Destination (OD) matrices that are the main input into traffic simulation or Dynamic Traffic Assignment (DTA) models (Xiong, Ozbay, Jin, & Feng, 2020). Second, simulation-based optimization approaches for traffic control have high computation times that are not always suitable for real-time applications. The highly stochastic nature of traffic further complicates this issue by requiring multiple runs. Genetic Algorithms are extensively used to reduce optimization times of complex DTA and simulation models. Third, simulation-based model needs to be periodically re-calibrated due to the time-dependent changes in the system. Machine learning techniques can be used for the continuous calibration of simulation models. Finally, converting simulation outputs into actionable and robust traffic management plans in real-time is in itself a very challenging task. AI can be used to post-process simulation outputs and convert it into actionable control strategies in real-time.

Machine learning techniques can also be used for the continuous calibration of traffic control algorithms. Reinforcement Learning (RL) based approaches can be used to perform integrated traffic control for multimodal urban corridors. Both traffic signals plans and interacting ramp metering rates can be jointly optimized using RL methods (Wen, Qu, & Zhang, 2009) (Choy, Cheu, Srinivasan, & Logi, 2003). There is extensive research on combining traditional feedback control methods with AI algorithms (Kachroo & Ozbay, 2003) (Kachroo & Ozbay, Feedback Control Theory for Dynamic Traffic Assignment, 2018). In this context, neural networks can be used as function approximators (Zhang, Ritchie, & Lo, 1997) that are integrated into ramp metering algorithms (Zhang & Ritchie, 1997) or DTA models.

This application uses AI for three system functions: reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Concept Illustration

Figure 6 shows a graphic illustration of how an AI-powered real-time decision support system operates as a closed loop system where detection, prediction, coordination and information dissemination occurs in real-time to reflect actual conditions and to provide all stakeholders most up-to-date information. The illustration is for a commuter train derailment.

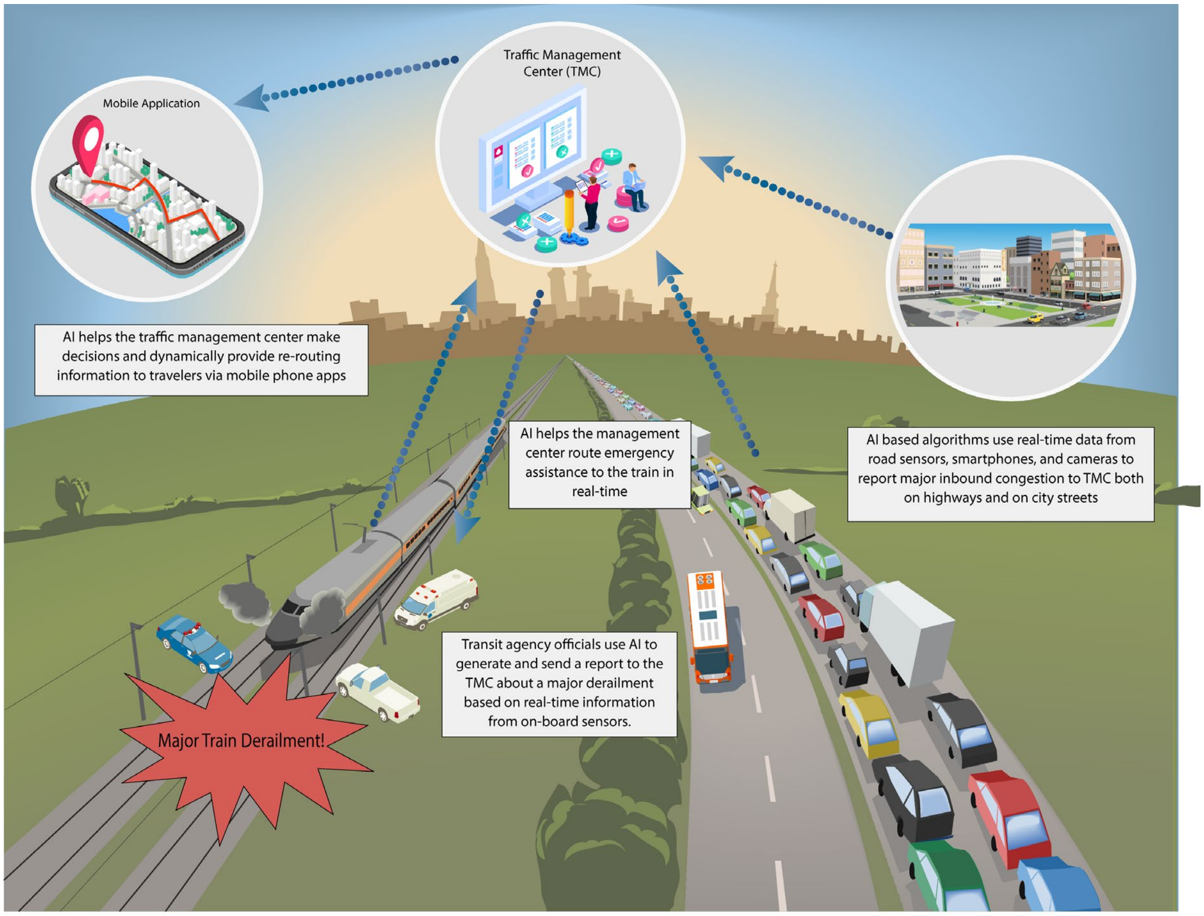

Figure 6. Graphical Illustration of Potential AI Applications for an Urban Mutlimodal Corridor.

Actors and Actor Profiles

One morning, there is a commuter train derailment on a line that runs between the suburbs and the City. Commuters need to be re-routed and provided with real-time information including alternate modes to allow mode shift; the multimodal corridor needs to be re-configured (e.g., re-optimize signals on adjacent arterials, postpone pre-scheduled work zones, revise transit schedules and frequencies) and the derailment problem needs to be fixed by mobilizing appropriate resources in a timely manner to resume rail operations. Given below are descriptions of key actors and how they interact with the AI-powered system on this particular morning.

Actor #1: Director of Regional Traffic Management Center

Leila is the TMC director and becomes aware of a commuter train derailment during the morning peak hour on a line between suburbs and the City. AI-based multimodal decision support system (MMDSS) is accessible through the internet by all the agencies in region. MMDSS provides her direct access to the train information and warns her about the possible system-wide impact of this major incident. She is worried that train commuters will decide to drive into the city. AI-enabled decision support system also warns her about a pre-scheduled work zone and suggests her to postpone it until the rail derailment problem is resolved and the traffic demand becomes normal. She uses the MDSSS to quickly analyze alternative incident response plans which include the pre-scheduled work zone and to predict expected outcomes. Leila also identifies affected agencies using the using the same AI-enabled system to share the suggested response plan that reduces total network delay to successfully mitigates the negative effects of the train derailment. When she hears a positive response from other agencies, she approves the plan and proceeds with its implementation.

Actor #2: Manager of State Highway Agency

Harjit is the manager of the State highway agency and works with the TMC director to re-optimize signals and postpone work zones until the problem is resolved. Harjit uses an AI-based signal re-optimization algorithm that is capable of adopting to the changing traffic levels in real-time. He also activates AI-based bus priority algorithm to provide additional capacity to transit buses that are going to carry some of the travelers who are expected to shift from train to bus to avoid the delays caused by derailment.

Actor #3: Manager of State Transit Agency

Jack is the manager of the agency and needs to make sure that transit riders who cannot drive to their work because they do not own a car can be served by for-hire services or on-demand bus service. He uses an AI-enabled Knowledge Based Expert System (KBES) to plan and coordinate on-demand and FHV (For-Hire Vehicle) services for providing the last mile/first mile service for his customers. This KBES obtains real-time spatio-temporal supply and demand information and determines best matches in terms of minimizing waiting times and maximizing connections to alternative modes. Its AI-based matching algorithm capable of learning from experience can run in real-time and provides system-wide updates to individual travelers and service providers.

Actor #4: Commuter (Car)

Sammy is about to leave home to drop his daughter to day care and then drive to the City but he hears about the train derailment problem and wants to know if it is better for him to work from home after dropping his daughter at the day care. AI-based recommender system coordinated with real-time information from agencies determines the best trip plan based on his past preferences and experiences as well as prevailing conditions. This recommender system provides Sammy with an incentive to leave later than his usual departure time in terms of reduced tolls for using the tolled tunnel into the city. Sammy calls his work and tells that he will arrive two hours later than usual due to a major disruption and asks permission for working from home during these two hours. While driving her daughter to the day care, he notices that AI-enabled traffic responsive algorithms have re-configured *both* traffic signals and ramp metering plans to avoid congestion to increased car demand.

Actor #5: Commuter (Transit)

Eric does not own a car and needs to use the train to visit his doctor in the City. He cannot cancel his appointment, but he knows the train service is suspended. He decides to use mobility service provider such as Uber, Lyft or bus transit but needs to find the optimal solution about his multimodal route that will reduce his travel time and trip cost. Eric's smart phone app which uses AI based trip planning algorithm obtains crowd source data from social media and real-time predicted delay data provided by agencies. The same app then checks the availability and price of available mobility services in his area and gives him top three alternatives to choose from. He chooses the bus which stops at a location that less than a mile away from his house and while traveling to his doctor appointment in the bus, he notices that traffic signals are re-programmed by AI to give priority to his bus by reducing overall bus travel time by 25%.

Actor #6: Rail Technician

Jennifer is a rail technician for State Train Tracks company and is taking the day off to attend a one-day training workshop. AI-based resource management system determines that she is the best expert for fixing rail tracks and identifies her whereabouts and availability. The system then contacts Jennifer about the train derailment problem and calls her to duty to work on this emergency. Before she leaves for the accident site, Jennifer receives a remote diagnosis of the rail derailment accident from an AI-based video analytics software which determines that special repair equipment is needed. She uses the same AI-based resource management software to request this equipment from her company. Finally, she acknowledges the receipt of her emergency assignment and travels to the incident site immediately.

Actor #7: Manager of State Train Tracks Company

Julio is one of the top managers of the State Train Tracks company and he is tasked with coordinating the response to the train derailment problem. He has to first coordinate with his engineers responding to the problem. He uses the AI resource management system to see that the system has already contacted the best rail technician for the problem at hand and that she is on her way to the incident site. Julio also receives a request for special equipment and asks AI to locate and dispatch this equipment to the incident site immediately. He uses MMDSS to provide information to other agencies, system users, general public and press among others. The use of two different AI-based systems enables of him to effectively deal with the monumental task at hand and significantly reduces possible delays in mobilizing engineers, technicians, and equipment to solve the problem.

Actor #8: Truck Driver (Fleet vehicle)

Sue is a driver of a commercial truck instrumented with a camera and tracking system. She is stuck at the train crossing where the derailment happened. She has already communicated with her boss and the on-board camera in her truck continuously sends anonymized streams of video of the accident to the cloud. This anonymized information is processed and shared using AI-based image recognition algorithms with authorities. This information also used by the AI-based remote diagnosis software that provided accident specific diagnosis to the State Train Tracks Company. Based on the delay predictions done by AI-based algorithms at the Traffic Management Center, it becomes evident that she will experience several hours of delay in traffic if she does not change her current plans. She receives a message from the TMC to re-consider her trip plan and exit at the next rest area until the incident is cleared. She sees a similar recommendation on a VMS while traveling towards the exit to the next rest area. She decides to get her break at the closest rest area.

Relevant Research, Tests and Case Studies

Traffic Prediction

In academia, there has been extensive work in using AI for traffic prediction. Researchers at the Old Dominion University used dynamic neural networks for short-term traffic predictions (5-15 minutes) as well as for traffic volume forecasting. For travel time prediction, they used extreme gradient boosting methods with BSM data from the Safety Pilot Model Deployment conducted in Ann Arbor, MI (Ishak, 2020). Researchers at Texas A&M used fuzzy logic for short-term traffic flow forecasting (Zhang Y. , 2020). However, there is limited real-world implementation of such methods. Thus, there is an opportunity to use this relatively extensive body of work using AI for traffic prediction and create real-world implementations.

Real-Time Traffic Signal System Optimization

Many transportation agencies have implemented traffic adaptive signals. According to a review of the state-of-the-art and interviews of agency representatives such as Solomon Caviness of Middlesex County Planning Authority, NJ and Nadereh Moini of New Jersey Sports and Exposition Authority as well as academicians like Professor Yunlong Zhang of Texas A&M and others,

AI can be used to improve performance of existing adaptive traffic signal systems in real-time (Caviness, 2020; Moini, 2020; Zhang Y. , 2020). For example, there are numerous research papers on using reinforcement learning for optimizing signal timings in real-time. On the other hand, real-world implementations of these methods are not available. These are likely due to issues with deployment efficiency and safety. Thus, case studies are mainly based on simulation studies. Clearly, there is a need to work closely with vendors and consultants who are developing and deploying these signal optimization algorithms in close collaboration with State and City transportation agencies to incorporate the large body of research results related to AI and signal optimization. This kind of effort will move AI-based signal optimization approaches from lab to the field.

Pedestrian and Vehicle Detection

Researchers at Carnegie Mellon University (CMU) rely on off-the-shelf video cameras or radar for detecting and counting pedestrians waiting at an intersection (Smith, 2020). This type of pedestrian detection and counting using images from cameras can be achieved using AI-based image processing techniques that are now widely used by some commercial products as well emerging autonomous vehicles tested by several companies. The work done by CMU has made signal crossing safer for pedestrians with disabilities. Initially, they did not have the ability to detect pedestrians and did not synchronize with the pedestrian walk signals, and hence, pedestrians crossing time was set to the minimum times. By fixing this aspect, they reported that “they increased the amount of pedestrian walk time in Pittsburgh by 50%.” This type of technology combining AI-based pedestrian and vehicle detection not only at traffic intersections but also at rail crossings can improve the safety and operations for normal and accident conditions like the one described in the urban multimodal scenario.

Real-Time Routing

The private sector (Sinagra & Davies, 2020) has been focusing on AI-related solutions for accessible transportation for individuals with cognitive disabilities. There are several algorithms to help individuals with cognitive disabilities to make the right decisions and interact with the app. According to Sinagra and Davies, there is great potential for using AI to integrate the best routes identified through machine learning and how a user rates a route after completion of a trip. As more people rate different routes, AI can improve its learning, and base the next route off of a combination of the existing algorithm and user preferences. This approach is also relevant for real-time routing of traffic. As another example of AI applied to real-time dynamic routing is the work of Kachroo and Ozbay (Kachroo & Ozbay, Feedback Control Theory for Dynamic Traffic Assignment, 2018), who proposed the use of fuzzy logic to implement real-time traffic routing in the presence of traffic accidents.

Decision Support Systems

One of the earliest efforts for using expert systems for real-time decision making under non-recurrent traffic condition dates back to 1990s (Ozbay & Kachroo, 1999). Researchers at Virginia Tech worked on the development of decision support systems that made use of expert systems that capture expert knowledge of engineers at the TMC. The same group from Virginia Tech, later in collaboration with Rutgers University researchers, has introduced AI methods such as fuzzy logic to control diversion of traffic under non-recurrent traffic conditions. Like most of the AI-related work, this research has not yet been implemented by agencies, but due to the advances in communications and computation there is increasing possibility to operationalize these ideas involving AI-based techniques.

The ATCMTD Program awarded several grants in 2019 for developing AI-powered decision support tools for integrated corridor management (USDOT, 2020). Tennessee DOT received a grant for $2.6 million from the ATCMTD Program for developing AI-Powered Decision Support Tools for Integrated Corridor Management. The project will use AI to advance a comprehensive ICM system – part of the multiphase, 28-mile-long I-24 Smart Corridor project along that interstate and connecting highways and state routes. AI solutions will specifically address challenges related to increased congestion, high incident rates and limited real-time performance monitoring. Virginia DOT received a grant for $4.35 million from the ATCMTD Program for expanding two important programs that are part of the Northern Virginia Regional Multi-Modal Mobility Program using AI. The first project will deploy predictive parking availability information using AI to the planned on-street value-pricing parking project in Arlington and the commuter parking project at lots operated by the Virginia Railway Express around Fredericksburg. The second project will expand the decision support system to Fredericksburg, employing advanced machine-learning techniques and AI to generate incident and congestion management responses based on real-time conditions. Washington DOT received a grant of $3.4 million to develop AI solutions for multi-agency, multimodal integrated corridor management to coordinate responses to clear roadway incidents quickly and reduce congestion.

Potential Benefits

As mentioned in Chapter 4, AI may not be anticipated to replace classic problem solving and conventional traffic management solutions. Rather, these classic systems are anticipated to provide a foundation for integrating AI-techniques to further improve existing systems. AI is also anticipated to introduce new ways to solve urban multimodal corridor challenges that have been previously unsolvable using conventional methods. The use of AI techniques for urban multimodal corridor could potentially improve inter-agency coordination and decision-making, incident response, safety, user satisfaction and experience, and result in cost-savings as described below.

- **Inter-agency coordination and decision-making:** AI can help agencies to better communicate, share and deploy resources and thus improve their collective multimodal decision-making process.
- **Multimodal system performance:** AI can help agencies develop data-driven real-time management algorithms that can reduce overall regional travel times and improve travel reliability in the presence of major non-recurrent events.
- **User satisfaction and experience:** AI can help improve user satisfaction and experience in different ways.
  - **Transfer delays:** AI techniques can be used to provide real-time routing information that can be used to protect multimodal travelers' transfers and thus reduce overall trip delays for multimodal travelers.
  - **Transit and highway systems:** AI can help reduce crowding and wait times at transit vehicles and stations as well as for other transportation systems.
- **Safety:** AI can be used to improve the safety of vehicles, pedestrians and other system users, especially during incidents. Secondary incidents can be avoided by AI-based solutions that can be used to alert drivers and pedestrians, provide warnings, and modify traffic control and management systems accordingly.
- **Payment:** AI can be used to enable agencies to deploy integrated payment systems that can provide various advantages mentioned below.
  - **Seamless payment:** Travelers can make payments that are seamless to them without being penalized for changing modes due to unexpected events.
  - **Incentives:** Agencies can provide real-time incentives (disincentives) to optimize overall system performance.

Potential Barriers to Adoption of AI for Urban Multimodal Corridors

As with any new and potentially revolutionary technology, development and deployment of AI technologies in a real-world multimodal urban environment will present several barriers and challenges. Most of these barriers are also common to the other scenarios discussed in this report.

- **Institutional Issues:** Multi-agency hardware and software integration required to make AI systems work in real-time can be very challenging due to institutional issues that will need to be resolved prior to any system-wide deployment.
- **Legacy Systems**: Integrating legacy systems of multiple agencies in one combined decision support system can be technically and financially very challenging.
- **Data Availability:** Real-time availability of data to be used with AI might not be reliable or might not have sufficient coverage.

- **Training Data:** Extensive data required for training Neural Networks and other machine learning methods might not be readily available.
- **Model Validity:** There might be major problems in acquiring expert knowledge for the development of Knowledge Based Expert Systems which might in-turn reduce model validity.
- **Speed of Change:** AI methods such as Deep Learning are changing very fast and there is a danger of obsolescence due to the dynamism of the field.
- **Agency Acceptance and Adoption:** Decision makers / agencies might not be comfortable with the predictions and recommendations generated by AI and might not use them if the real-world validation results are not convincing and /or intuitive.
- **Transparency:** Most of the AI methods such as Neural Networks are black boxes and the lack of understanding of how the results / predictions are generated can slow down the adoption of these methods by practitioners.
- **Justifying ROI:** Cost for implementation and maintenance can be too high with unproven benefits.
- **Private sector:** Private sector plays a leading role in certain aspects emerging technologies such as AI. One interviewee mentioned the need to better define the role of private sector when discussing the use of AI for multimodal routing of travelers. Thus, establishment of long-term and mutually beneficial public private partnerships required to make AI systems successful can be a challenge.

Potential Value to USDOT

The USDOT by providing the leadership and funding for building a highly complex urban multimodal AI based decision support system that can operate in real-time can encourage multi-agency coordination and thus help create a much better integrated urban transportation system.

- **Coverage:** This scenario covers all possible transportation modes in an urban corridor setting. AI helps to achieve operational efficiencies not possible with facilities or modes of one type.This wide scale coverage brings the opportunity to experiment with a large number of AI and machine learning solutions that can address both traditional (incident detection; signal optimization; information dissemination) and relatively novel problems (resource identification, allocation and deployment; incentive-based routing of travelers).
- **Cost savings:** There are various ways costs savings can be realized.
    - **Externalities:** AI based technologies can reduce externalities such as congestion, safety, and emission costs. This can be a way to promote environmentally friendly transportation modes.
    - **Out-of-Pocket Costs (Agency)**: AI could potentially reduce agency costs by reducing staffing needs, and additional infrastructure costs needed to add more capacity to mitigate impact of scenarios such as this one. AI provides the opportunity to proactively improve and maximize the performance of the transportation system by serving as an alternate to traditional major infrastructure investments which may be more expensive or constrained by environmental issues.
    - **Out-of-Pocket-Costs (Traveler)**: AI could potentially reduce travelers' costs by reducing their energy consumption and avoiding vehicle damages and injuries due to secondary accidents.

- **Opportunities:** There are many opportunities along the lines of benefits cited above. However, several more long-term opportunities also exist.
    - **Technological Leadership**: AI based multimodal corridor management systems present an unprecedented opportunity to develop and test new and revolutionary technologies that can be deployed throughout the world in the next couple of decades.
    - **Mobility**: With the emergence of several new micro-mobility systems and improvements of existing modes, AI can assist DOT to work with local agencies to maximize their long-term benefits. AI techniques can help advance existing ICM approaches to achieve a more appropriate supply/demand balance.
    - **Safety**: AI-based systems will reduce primary and secondary impacts of incidents which will save many lives and reduce severe injuries. Pedestrians and people with disabilities can benefit the most from the use of AI-based safety solutions.

Chapter 6. Regional System Management

This chapter discusses how AI might potentially be used for addressing challenges relevant to the Regional System Management scenario. This chapter provides a background of Regional System Management, an overview of the operational challenges relevant to the scenario, potential applications enabled by AI to address the challenges, a graphical illustration of the concept, actors or entities interacting with the AI-enabled systems, relevant research, tests and case studies, potential benefits, potential barriers to adoption of AI for the scenario, and potential value to USDOT of investing in AI-powered solutions for the scenario.

Background

A regional system is one that is managed collaboratively by multiple agencies, often as a regional planning organization. Cross-boundary coordination allows partners to be fully responsive to the travel activity in a regional area. While transportation assets are usually managed at the state and local levels, these assets are part of larger systems that connect across jurisdictions. For example, a work zone in one area could lead to bottleneck trouble down the road in a different area. Additionally, a major hurricane evacuation requires coordination across state boundaries to be effective.

Given the interconnected nature of transportation systems, several regions in the United States have found it useful to develop a plan focused on transportation systems management and operations (TSMO) in the region. The plans are often then used as either an addendum to the metropolitan transportation plan (MTP) or provide input to the overall plan in terms of operations goals, objectives, performance measures, strategies, and projects or programs (FHWA, 2020).

The New York Metropolitan Transportation Council (NYMTC) and the San Diego Association of Governments (SANDAG) are two example regional planning organizations. Created in 1982 as the MPO for New York City, Long Island, and the lower Hudson Valley, the New York Metropolitan Transportation Council (NYMTC) provides a collaborative planning forum to address transportation planning activities from a regional perspective; undertakes studies for transportation improvements; forecasts future conditions and needs; pools the resources and expertise of its member agencies to plan for transportation and development in the region; and makes decisions on the use of federal transportation funds (https://www.nymtc.org/REGIONAL-PLANNING-ACTIVITIES). Working effectively across the boundaries which separate planning regions is of paramount importance to NYMTC and its members, who must also address working with local municipalities within the NYMTC planning area. Partnerships that cross jurisdictional lines are essential if transportation planning is to be fully responsive to the travel activity in a regional area. These partnerships also cross functional boundaries so that the development of the transportation system is better integrated with land-use planning, economic development, goods movement, waste disposal, and other related infrastructure (https://www.nymtc.org/Regional-Planning-Activities/Mega-Regional-Planning).

Similarly, SANDAG serves as the forum for regional decision-making for the San Diego region. SANDAG builds consensus; makes strategic plans; obtains and allocates resources; plans, engineers, and builds public transportation, and provides information on a broad range of topics pertinent to the region's quality of life.

While these examples and other existing regional planning organizations focus on large urban and suburban areas, the regional system management idea could expand to rural areas as well. Chapter 4 and Chapter 5 focus on urban scenarios for AI in ITS, but this scenario focuses on opportunities for AI in regional system management focused on coordination across large, less dense territories predominantly in rural areas.

Relevant Operational Challenges

Regional System Management faces a variety of unique challenges that AI could help mitigate. For example, frequent snow falls during the winter season are increasingly costly while maintenance budgets continue to shrink. Additionally, identifying and classifying pavement issues before they become critical without significant increases in operating costs is challenge ripe for technological solutions. Finally, unpredictable congestion during summer months due to concurrent roadwork and tourism leaves travelers frustrated (https://www.its.dot.gov/pilots/pdf/Pilot_District13.pdf). AI has the potential to address these and other challenges for regional system management. Transportation problems in this scenario center around asset management, weather response, emergency response, and work zone management. In this case, asset management refers to both routine and emergency situations. Some of the major transportation challenges include:

- **Data Fusion at TMCs**
  - Data coming into the TMC from multiple, disparate sources can be difficult to manage and create a single coherent view of the situation.
  - Lack of timely coordination among the multiple agencies and jurisdictions responsible for the region, which may span multiple counties and states, can lead to poor management of resources and demand.
- **Assets/Infrastructure**
  - Impaired assets endanger travelers, can lead to crashes and costly repairs.
  - Inadequate or insufficient asset condition data can lead to high demand for human surveyor time.
  - Asset inspections, such as bridge inspections, can be risky for inspectors and travelers.
- **Weather**
  - Unsafe infrastructure due to severe weather, such as slippery pavement, can lead to fatal crashes, secondary incidents, property damage, and deterioration of roadway assets.
  - Uncertain and changing weather conditions can make it difficult to determine which surface treatments to use.

- **Incidents/Emergencies**
  - Uncoordinated agency responses to emergencies, such as hurricane evacuations, can lead to dangerous bottlenecks and stranded vehicles.
  - Uninformed travelers during incidents and emergencies can lead to panic and dangerous behaviors.
  - Delays in detection of crashes and major incidents due to sparse sensor deployment and limited cellular coverage can lead to increased fatalities and secondary incidents.
  - Failing to identify where emergency road repair work is needed can endanger travelers.
- **Work Zones**
  - Lack of traveler information on work zones can leave travelers uninformed and frustrated.
  - Ineffective work zone planning can lead to reduced safety and productivity, increased emissions, fuel consumption, and costs.
- **Port Operations**
  - Unexpected failures in critical port equipment can cause major delays.
  - Uncertain truck arrival windows at ports can lead to queues and underutilized equipment.

Potential AI Applications

AI applications can help enhance asset, weather, emergency, and work zone management, which are all critical components of regional and statewide system management.

Application #1: AI for Asset Condition Monitoring

Objective: Identify asset conditions, monitor pavement, inspect bridges, and inform infrastructure maintenance decision-making

Summary: AI can assist with a variety of asset management tasks including pavement monitoring, bridge inspection, and infrastructure maintenance. For example, AI can monitor pavement from sensor data and detect hazards and obstructions, such as potholes. AI can then alert drivers and maintenance crews to these issues before they cause major vehicle or personal damage. AI could also extract asset condition information, such as road curvature and sign status. Clustering algorithms could identify distinct sections on a roadway and estimate detailed horizontal curvature and corresponding crash modification factors (CMFs). Additionally, virtual reality (VR) and AI can assist in bridge safety inspections by detecting small cracks from images. Furthermore, assistive robotics applications, such as drones and land robots, can help with infrastructure maintenance. For example, with remote sensing via drones, AI can identify and record signage locations and states (e.g., obscured or damaged). Asset managers can use this information to make more informed and rapid decisions on where to dispatch maintenance crews. Using AI minimizes the need for field data collection and saves time, staff, and other resources.

This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #2: AI for Weather Prediction and Response

Objective: Enhance weather management and response by predicting road surface conditions before they become dangerous and responding accordingly

Summary: AI can help predict road surface conditions from weather, sensor, vehicle, and historical data. By predicting high-risk areas before adverse weather strikes, management can deploy and concentrate preventative resources (such as salt or sandbags) along the most dangerous segments. In addition to using AI for preventative measures, AI can also help with weather detection and response. For example, in the winter, AI could detect snow drifts in the road and alert winter response teams and snowplow drivers. In the summer, AI could detect areas of flooding and notify maintenance crews to close certain road segments. This application uses AI for two system functions: reason & analyze and learn & adapt (see Figure 2).

Application #3: AI for Incident Detection and Response

Objective: Detect incidents, predict their impacts, and respond in real-time

Summary: Combining infrastructural health information, weather, alert, and social media data, AI could rapidly detect emergency incidents and predict impacts. Additionally, AI could aid in incident response by assisting first responders. For example, AI could learn to predict the best routes for EMS under different weather and traffic flow conditions and route them effectively. AI can support emergency response decision makers in other ways as well. For example, machine learning can predict incident outcomes by learning from historical data. It could also predict visibility, rain drainage and other environmental conditions important for traveler safety. Finally, decision makers can use decision trees and other algorithms to estimate evacuation zones.

This application uses AI for three system functions: reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #4: AI for Work Zone Safety and Information Dissemination

Objective: Share work zone traveler information, detect hazards, and support construction planning

Summary: Drones, sensors, and automated vehicles could collect data on work zones. AI could use these data to a variety of work zone-related activities. For example, using drones and aerial imagery, AI could automatically create a schematic of a work zone's configuration. This could be communicated through an API to popular navigation applications to give drivers a heads-up of upcoming deviations from normal traffic patterns. Looking further into the future, ADS developers are interested in having this kind of information to supplement their onboard high definition (HD) maps and sensing. In addition to sharing information on work zone geographies and traffic patterns, AI could also share information on potential hazards detected to travelers and construction staff. For example, AI could flag an area where a series of cones have been run over by a vehicle. Maintenance managers could then quickly alert their crews to this situation, minimizing the hazardous time window. Additionally, this information could be shared with upstream drivers via advisory signs or app alerts. This information could also be ingested into AI-enabled traffic prediction applications, alerting users to work zone-related delays in real-time. Finally, AI-enhanced planning tools could use streamed data to predict how many hours of work the crew can successfully finish that day given anticipated weather and traffic.

This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #5: AI for Data Fusion in Transportation Management Centers

Objective: Improve situational awareness by fusing data from multiple sources

Summary: AI can be used to fuse and make sense of disparate historical and real-time data, including in-vehicle, infrastructure-based sensor, Bluetooth reader, license-plate reader, closed-circuit television (CCTV) camera, road weather, traffic incident, traveler information, crowdsourced and social media data. AI algorithmic approaches have the potential to enable robust data fusion in real-time and enable system-wide, proactive management of the multi-modal transportation system on a regional scale. With this more complete picture, TMC operators can proactively manage emerging events and situations, rather than simply react to them. This application uses AI for two system functions: sense & perceive and reason & analyze (see Figure 2).

Application #6: AI for Port Operations and Planning

Objective: Predict arrival and wait times, future equipment and maintenance needs, and utilization at ports to support planning efforts

Summary: Currently, AI is being leveraged in automated loading cranes at ports and for predictive maintenance of port equipment. In the future, AI is expected to help motor carriers gather and apply data for container deliveries more efficiently, creating a central portal of information (https://www.ttnews.com/articles/smart-ports-when-ai-takes-over-shipping). Having learned from historical freight and cargo movement “successes” at ports, AI could optimize cargo movement within ports given a variety of real-time, dynamic data inputs. Additionally, AI could predict equipment failures and suggest maintenance. This application uses AI for three system functions: reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Concept Illustration

Figure 7 shows six examples of how AI could potentially be used in the regional system management scenario with one example for each of the following: asset management, weather response, emergency response, work zone management, and data fusion at the TMC. For example, AI can be used to fuse data of multiple types from disparate sources into a central data warehouse, providing better situational awareness to regional managers (**#1**). For asset management, AI could determine pavement status from vehicle sensors and send that information to the TMC (**#2**). For weather management, snowplows could use an AI-enabled app to determine how much salt to lay on certain stretches of the roadway given historical drift patterns and expected weather (**#3**). During an evacuation, drivers could receive AI-enabled responsive traveler information telling them to avoid certain areas due to fallen trees or flooding (**#4**). AI could alert a construction manager to misplaced or distorted cones from drone-collected images (**#5**). Finally, AI could be used to predict freight arrival and wait times at ports, vehicle maintenance needs, and equipment utilization to support port operations planning (**#6**).

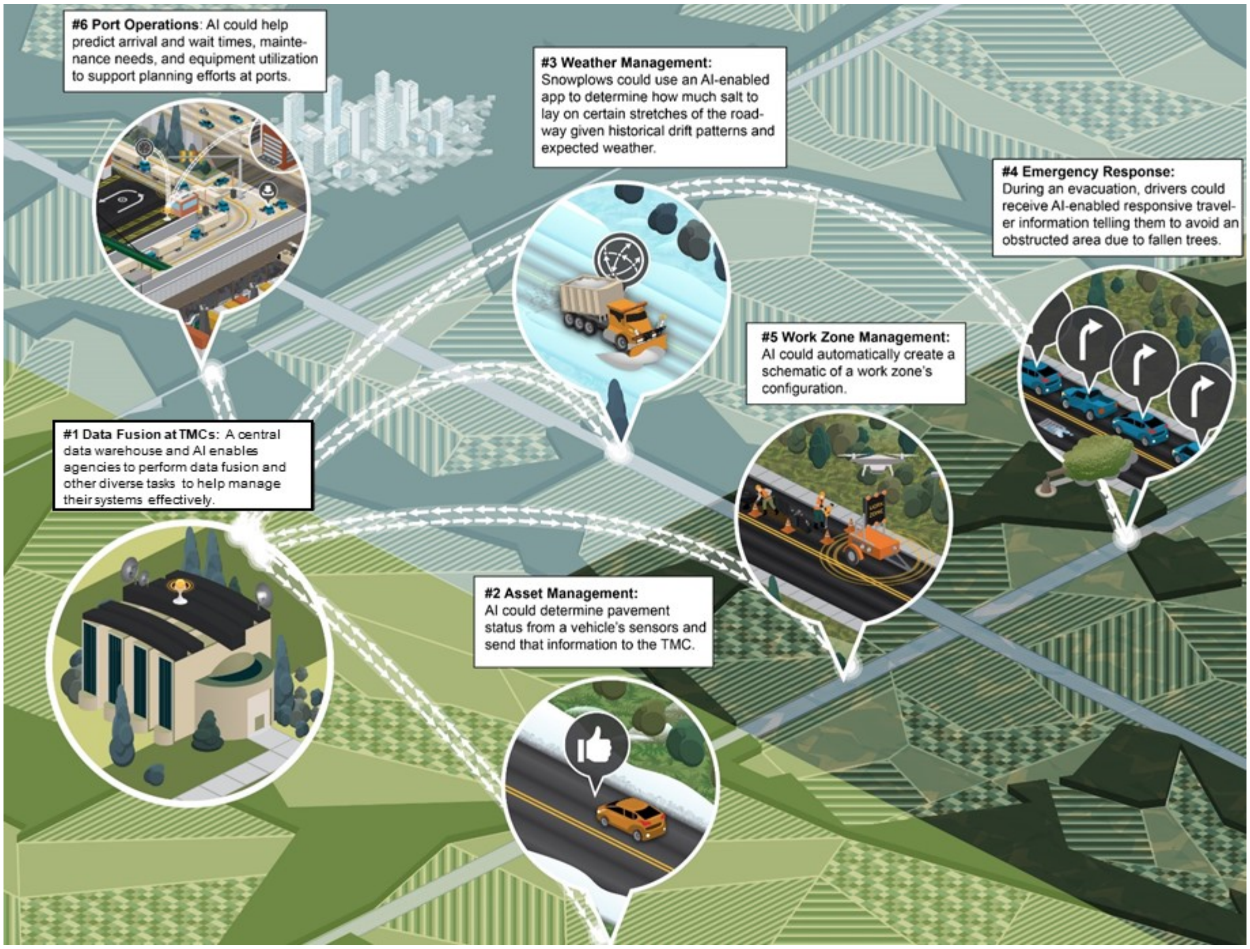

Figure 7. Graphical Illustration of Potential AI Applications for Regional System Management.

Actors and Actor Profiles

A large port sits near the juncture of three southeastern states, State A, State B, and State C. These three states share multiple borders, rivers, mountains, and major thoroughfares. The Blue Rock River is the largest river and flows from the port into State A and State B. State B and State C share a coastline along the Atlantic Ocean. Areas of these states, particularly along the coast, are subject to hurricane-force winds and flash flooding in the early summer months.

Given below are descriptions of key actors and how they interact with the AI-powered system one Monday morning in June, after a weekend of dangerously high winds and torrential rains. The last two actors, actor #7 and actor #8, are interacting with the AI-powered system on a Monday morning in late January after an overnight snowstorm.

Actor #1: Director of State DOT

Leslie is the Director of State DOT A. The state has two major cities at opposite ends of its borders but is otherwise fairly rural with many bridges over rivers. Remote sensing via cameras and drones allows for consistent data collection across rural areas of the state. Her office's AI-enabled decision support system provides her with key insights regarding the status of bridges. For example, the system can predict when and where a catastrophic malfunction is likely to occur. She and her management team use this information to plan short- and long-term investments in repairs. Given the harsh weather over the weekend, Leslie receives an alert from the system warning her that one of the main bridges over the Blue Rock River, the Washington Bridge, needs immediate inspection. She conveys this alert to her infrastructure team right away and works with her planning team Monday afternoon to reevaluate maintenance spending for the quarter.

Actor #2: Bridge Inspector

Taylor is a certified bridge inspector who has been directed to a particular portion of the Washington Bridge over the Blue Rock River. Her maintenance manager shows her the high-risk areas of the bridge from the AI-enabled mapping software at the office. She uses this information to quickly locate the damaged areas during her inspection. She confirms that five out of the six AI-flagged areas need immediate repair.

Actor #3: Emergency Medical Dispatcher (EMD)

Ricardo and Daniel are the lead Emergency Medical Dispatchers working out of the emergency dispatch center in State B's capital city and State C's largest coastal city, respectively. Ricardo and Daniel receive an AI-generated alert that flooding is likely to overwhelm residents predominantly along State C shores of the Atlantic Ocean near State B within the next 3 to 6 hours given current water levels, expected rainfall Monday night, and previous trends. Daniel informs his team of this impending disaster, and they immediately take steps to help evacuate the elderly and other residents incapable of traveling without assistance. Meanwhile, Ricardo's team helps by laying sandbags near the predicted problem area and closing one side of the major highway in State B so that evacuees from State C can use it.

Actor #4: Traveler Information User

Noah drives to work downtown every day. His commute is highly variable due to unexpected road closures due to work zones and bridge closures. Recently, he has been using his new AI-enabled smartphone app that sends him road closure alerts along his usual route. On Monday morning on his normal commute, Noah receives a safety alert advising him to avoid the rightmost lane on an approaching quarter mile stretch of I-13. A tractor trailer accidentally ran over a series of orange barrels in that area 5 minutes prior due to minor flooding, leaving the construction staff exposed.

Actor #5: Road Construction Manager

Matt is a Road Construction Manager working on a 3 mile stretch of I-13. Every Monday morning, he consults his AI-enabled project planning tool to decide when and where to direct workers for the week. The tool combines weather, standards, staffing, traffic, and scheduling information to make recommendations on the best times and spots to complete certain tasks. For example, the tool suggests postponing asphalt paving for 24 hours due to minor flooding, expected rain on Monday night, many sick workers, and a major sporting event likely to lead to higher-than-normal congestion levels. Additionally, the tool reviews work plans Brenda, the project's Traffic Manager, inputs into the system. It recently flagged a section unlikely to conform to FHWA standards for construction. It also predicts when Brenda will need a variance plan three days prior to the deadline for state DOT approval.

Actor #6: Lead Port Planner

Maria is the Lead Planner at the main port in the area. She uses her AI-enabled system to monitor and predict freight flows. Due to weather-related morning delays, queues and wait times are likely to be higher than normal in the afternoon. Based on its knowledge of similar historical events, the system recommends slightly revised cargo movements to optimize throughput.

Actor #7: Director of Winter Weather Management

Angela is State A's Director of Winter Weather Management housed in the Department of Emergency Management. A large snowstorm is expected to hit the northeast region of the state in the coming days. Her and her team use their AI-enabled dashboard to see where snow drifts are likely to obfuscate certain road segments. The AI system integrates weather, road surface, and historic snow drift data, including data from adjacent State B and State C, to predict areas of high risk. With this information, she instructs her team to set up snow fences and lay salt in those areas.

Actor #8: Snowplow Driver

While on his normal route, one of Angela's snowplow drivers, Liam, is re-routed ten miles away to the small town of Middleburg in State C on the border between State A and State C. Many commuters live in Middleburg but commute to a nearby big city in State A for work. Middleburg's main snowplow driver was in the midst a family emergency and could not complete his route. The backend AI-enhanced routing system gathered this information and reallocated the team's plowing resources in real-time to the areas of greatest need so morning commuters could still get to work on time safely.

Relevant Research, Tests and Case Studies

None of the interviewees had implemented AI solutions for this scenario. However, a few mentioned conceptual possibilities and relevant research where AI has the potential to improve or assist ITS. Therefore, this section presents four broad examples for asset management, weather response, emergency response, and work zone management.

Predicting Asset Failure and Obsolescence

AI could be used to detect pavement hazards, such as potholes, and alert drivers and maintenance crews to these issues before they cause major vehicle damage (Hoang, 2018). Beyond classifying hazards in real time, deep learning algorithms could predict what kind of maintenance a road requires from evaluating cracks, fractures and other road damage (AI Task 3 report, RCM-01, "Pavement Monitoring and Predictive Road Maintenance").

According to one interviewee, there is an opportunity to utilize AI for predictive decision-making regarding asset failures and obsolescence. He said current methods for predicting asset failure include visually inspecting the asset and using the manufacturer's estimated system life. He thinks it could be a good question to ask how AI could be applied to risk-based Transportation Asset Management Plans (TAMPs), which must be updated every 4 years according to the Moving Ahead for Progress in the 21st Century Act (MAP-21). While some agencies are looking at asset management for ITS, they face a few challenges. Developing management system software is one major challenge. Additionally, large vendors are not currently familiar with the requirements for ITS management. These vendors are focused on pavement and bridges, so they are not yet on board with ITS.

Another interviewee mentioned upcoming AI efforts for safety and resilience. Specifically, she mentioned efforts to protect infrastructure in high crash locations. AI could be used to assess the grade and curvature on approaches.

Assessing Infrastructure Under Severe Weather Conditions

Machine learning can be used for road weather pavement condition sensing and prediction. This information can be used by traffic managers to re-route snowplows, dispatch maintenance crews, re-route traffic, etc. (AI Task 3 report, RCM-01, "Pavement Monitoring and Predictive Road Maintenance").

AI could automatically detect and label road surface conditions in real-time from photo and video data including anonymous user-submitted data collected from smart phones. For example, a machine learning algorithm can be trained to detect subtle differences in road surface conditions such as accumulated snow, packed snow, slush and dry road. By differentiating these subtle yet important differences in road surface condition (such as snow types), crews can more effectively respond to dynamic conditions (Task 3 report, RCM-05, "AI-Enabled Road Management Support System").

In addition to automatically assessing pavement and road surface conditions, the AI-enabled application could also assess traffic signs and weather conditions. With this information, the app could alert crews to downed, damaged, or visually obscured signs. Additionally, using color grading, AI could derive air and road temperatures and road roughness information. Overall, applications like these could be useful tools for TMCs, road maintenance crews, emergency personnel, and others in transportation planning and maintenance, specifically in response to severe weather (AI Task 3 report, TSM-13, "Video Analytics for Planning and Maintenance").

Predicting Emergency Impacts and Evacuation Zones

AI could predict impacts to transportation networks, identify transportation lifelines, and support decision making for EMS deployment following hazards and disasters. Furthermore, AI can classify transportation safety risks in different geographical areas from anticipated weather events (National Aeronautics and Space Administration, 2019) (Task 3 report, RS-05 "AI for Safety Hazards and Disaster Assessment").

Predetermined evacuation zones can be used to estimate the demand of evacuees, which is helpful in assessing the resilience of transportation systems in the presence of natural disasters. Evacuation zones will need to be able to adapt to changing road networks, environmental and demo-economic characteristics, climate change, and sea level impacts, especially for areas at risk of hurricanes. Traditional methods for predicting future evacuation zones rely heavily on storm surge models, which are often time-consuming and costly to use. A grid cell–based data-driven method can predict future evacuation zones under climate change without running expensive storm surge models. Machine learning algorithms are used to establish the relationship between current predetermined evacuation zones and hurricane-related factors and then predict how those zones should be updated as those hurricane-related factors change in the future. The proposed method can support decision-making in evacuation planning and management of emergency resources. (Xie Kun, Kaan Ozbay, et.al. “Evacuation Zone Modeling under Climate Change: A Data-Driven Method” DOI: 10.1061/(ASCE)IS.1943-555X.0000369 (2017)).

Predicting Capacity Under Uncertain Conditions

A recent study developed a neural network model to predict work zone capacity including various uncertainties stemming from traffic and operational conditions. The neural network model is formulated in terms of the number of total lanes, number of open lanes, heavy vehicle percentage, work intensity, and work duration. The model provides predicted work zone capacity distribution and predictiotn intervals, whereas traditional models only provide a single estimate. (Zilin Bian and Kaan Ozbay (2019), “Estimating Uncertainty of Work Zone Capacity using Neural Network Models.” https://doi.org/10.1177/0361198118825136).

Overall, AI has the potential to be useful for management and decision support. For example, according to one interviewee, AI could help with financial planning, risk analysis, lifecycle cost analysis, and other analyses that are data sensitive. This could be particularly helpful with respect to work zone planning and management.

Freight Advanced Traveler Information System (FRATIS)

The Freight Advanced Traveler Information System (FRATIS) is a bundle of applications that provides freight-specific dynamic travel planning and performance information and optimizes drayage operations so that load movements are coordinated between freight facilities to reduce empty-load trips. FRATIS seeks to improve the efficiency of freight operations by using several levels of real-time information to guide adaptive and effective decision-making. FRATIS builds upon a previous research effort, the Cross-Town Improvement Project (C-TIP). C-TIP was a 2009-2010 prototype of a system and algorithm that sought to demonstrate the benefits of travel demand management, dynamic routing, and drayage optimization for the Kansas City inland port. FRATIS is being piloted in a few cities. For example, the Los Angeles-Gateway Region site is developing the FRATIS applications to address the dynamic travel planning algorithm around the marine terminals and queues to move cargo out of the port more efficiently. (https://www.its.dot.gov/research_archives/dma/bundle/fratis_plan.htm). According to one interviewee, FRATIS is primarily used to optimize cargo movement within ports and monitor queue and wait times.

Potential Benefits

Using AI techniques for regional system management could bring many potential decision-making, satisfaction, safety, response, and cost-savings benefits, including:

- **Decision-making:** AI could help managers make more informed decisions including where and when to dispatch emergency personnel. It could also improve decision-making for travelers.

- **Management:** By helping managers make faster and better decisions, AI could improve overall system management. For example, emergency response could be better coordinated, targeting areas of expected need before conditions deteriorate.
- **User Satisfaction:** Better decisions could improve satisfaction for a variety of system users, including travelers and managers.
  - **Closures**: AI could help reduce the frequency and/or length of road closures.
  - **Awareness**: AI could also increase the number of travelers aware of closures.
- **Safety:** AI could improve infrastructure and roadway safety in many ways, two of which are mentioned below.
  - **Crashes**: AI could help reduce the number of crashes and fatalities due to severe weather.
  - **Stranded vehicles**: AI could reduce the number of stranded vehicles in severe weather.
- **Evacuation response:** AI could improve evacuation planning and response in a variety of ways, a few of which are mentioned here.
  - **Time to clear**: AI could help reduce the time it takes to clear a roadway in an evacuation. It could also reduce the time it takes evacuees to leave an area and find refuge. Overall, AI could help get people out and get response personnel into evacuation areas.
  - **Preparation**: Number of pre-positioned vehicles after a hurricane has passed (time, volume metrics).
  - **Fuel consumption**: AI could reduce the total fuel consumption to clear a roadway.
- **Weather response:** AI could better inform weather fleet management in winter. For example, AI could predict the amount of materials needed for preventative winter weather management on road surfaces. For example, it could inform fleets how many pounds of salt to lay in certain high-risk areas. This could improve safety and save money by better allocating scare resources, such as road salt.
- **System availability:** AI could help increase the number of days of infrastructure operation and availability.
- **Vehicle damage:** AI could help reduce the number and severity of vehicle damages due to impaired infrastructure. For example, by detecting large potholes early, managers can fix them before they cause major damage. Therefore, AI could reduce the overall number of disabled vehicles from blown tires due to pavement issues. This would also save repair costs.
- **Big data:** AI and machine learning methods can handle big data where traditional methods cannot. Additionally, machine learning methods can handle highly nonlinear relationships in data.

Potential Barriers to Adoption of AI for Regional System Management

While there are many potential benefits of using AI for regional system management, there are many obstacles as well. Interviewees mentioned a wide variety of existing and potential barriers to adoption of AI for this space, some of which include:

- **Vendor focus:** Currently, vendors focus on pavement and bridges for asset management. They are not on board yet for management software to support decision support systems (DSS).
- **Proprietary software:** Existing AI software generally resides in the private sector. It must be purchased from vendors.
- **Procurement:** It remains an active question of how to include AI and machine learning in procurement. Attribution for a model's poor performance is unclear which could result in potential lawsuits.
- **User acceptance and adoption:** User acceptance is a major obstacle to AI adoption. In many cases, interviewees mentioned the difficulty in convincing people to use their system. Many agencies were reluctant to change their existing processes. Additionally, AI is considered a "black box" by many, leading many to distrust it. According to one interviewee, commercial tools claim to use machine learning algorithms, but it is impossible to know if or how they are using them.
- **Software complexity:** AI and machine learning are often embedded in highly complex software, contributing to the "black box" perception of AI.
- **Data volume:** The volume of data needed to run machine learning algorithms brings a few challenges. Many developers do not have access to enough data for AI tasks. Even if big data are available, quality control becomes difficult. Additionally, legacy computing resources struggle to handle big data. Additionally, availability of non-proprietary freight data for port operations can be challenging.
- **AI maturity:** Generally, AI-enabled technologies are still in the research and development stages. Additionally, assessing AI maturity is very difficult. One interviewee mentioned the desire for an AI technological maturity scale.
- **Measuring ROI:** Many pilot projects do not measure return on investment (ROI) for AI projects in part because the cost of AI is very difficult to estimate.
- **Data quality and precision:** Data accuracy from roadside sensors is a major issue. Additionally, coverage is often sparse. One interviewee mentioned that high quality weather data does not exist right now for urban areas; it is not precise enough.
- **Ethics and equity:** If AI is used for workforce scheduling, it will need to be equitable. For example, one interviewee mentioned the challenge of ensuring drivers receive equivalent amounts of work with respect to freight dispatching. Additionally, another interviewee expressed his concern regarding underlying prejudices in data leaving algorithms with only negative options to choose from.
- **Speed of change:** The data landscape is changing very rapidly. One interviewee mentioned that what was available 2 years ago is already obsolete. Investing in long-term AI solutions could be challenging giving their rapid evolution.
- **Inconsistent outcomes:** AI results are non-deterministic, meaning the algorithms present different outcomes and inconsistent behavior. This can be frustrating to users.
- **Supervision:** According to a few interviewees, AI automated networks and systems require some form of supervision.
- **Real-time AI:** Current AI research predominantly uses historic rather than real-time data.
- **Generalizability:** Many AI-enabled applications struggle to generalize to new scenarios or locations. Vendor products are not necessarily designed to work everywhere. This leads to issues for scalability.

- **Workforce preparation:** Transportation engineers typically come from civil engineering backgrounds. Even as AI is becoming more prominent in many fields of study, civil engineering degree programs have not started including basic AI concepts.

Potential Value to USDOT

This scenario can offer value to the USDOT in many ways. Since it is on a large scale, it has the potential to help many users, especially those in non-urban areas. Additionally, data availability is less of a concern in this scenario. Safety, weather, pavement, and evacuation data are available.

- **Scale:** This scenario offers the opportunity for greater scale and potential impact than some of the others. This scenario casts a wide net which is beneficial for AI and machine learning algorithms.
- **Data availability:** There may be enough data in these areas to get started right away. Specific opportunities are mentioned below.
- **Cost savings:** Using AI for regional system management could save public sector agencies and system users significant funds.
    - **Hard costs**: AI could reduce a measurable amount of hard costs, such as the number or time required for snowplows. Additionally, the cost of infrastructure failure (such as a bridge collapse) could be catastrophic. Repairs are likely to cost far less than a major failure.
    - **Soft costs**: AI could also reduce soft costs such as the cost per minute it takes to evacuate an area.
- **Opportunities:** There are many great and feasible opportunities for investment in this scenario. Specifically, in these four areas:
    - **Safety**: The greatest opportunity and likelihood of adoption lies with safety applications. This was emphasized by many interviewees.
    - **Weather**: Winter weather management and response could be a good place to start. There is a significant amount of weather data currently available. Additionally, the road weather management program has done work in this area, so the work would not start from scratch.
    - **Pavement**: Data are also available on pavement condition. Pavement monitoring is a major task for agencies, offering great potential for AI assistance.
    - **Evacuations**: Data are available on evacuations. Models have been developed in this area and could be leveraged for new cases.

Chapter 7. Rural Freeway Corridor

This chapter discusses how AI might potentially be used for addressing challenges relevant to the Rural Freeway Corridor scenario. This chapter provides a background of Rural Freeway Corridors, an overview of the operational challenges relevant to the scenario, potential applications enabled by AI to address the challenges, a graphical illustration of the concept, actors or entities interacting with the AI-enabled systems, relevant research, tests and case studies, potential benefits, potential barriers to adoption of AI for the scenario, and potential value to USDOT of investing in AI-powered solutions for the scenario.

Background

Rural Freeway Corridors are high-speed, limited-access divided facilities that run outside urbanized areas. Approximately 56% of the freeway system is rural (FHWA Highway Policy Information, 2018). These highways serve to provide long-distance travel, connecting major urban areas and ports. Rural Interstate Highways frequently serve as freight corridors. This results in a mix of vehicle types, including passenger cars, single unit trucks (e.g., recreational vehicles, concrete mixers), single-trailer trucks, multi-trailer trucks, etc., traveling at high speeds through uneven terrain.

Safety is a major concern for rural freeway corridors since the majority of the highway fatalities take place on rural roads. "In 2012, 19 percent of the US population lived in rural areas, but rural road fatalities accounted for 54 percent of all fatalities. Even with reductions in the number of fatalities on the roadways, fatality rate in rural areas is 2.4 times higher than the fatality rate in urban areas" (Federal Highway Administration, 2018). The relatively high vehicle speeds, freight volumes, and extreme weather events contribute to severe rural crashes and high fatality rates. Sparse sensor deployment and limited cellular coverage make early detection of crashes and incidents challenging. Even with the emergence of connected and automated vehicles, low traffic volumes can create challenges in acquiring sufficient data. Agencies are constrained by their ability to take timely actions. First-responders take longer to arrive at the scene of a rural crash, leaving victims waiting longer for medical attention. Rural freeways have limited alternate routes, making travel information a critical need. Information on crashes and closures may need to be disseminated several miles upstream of the problem area.

Proactively implementing relevant safety countermeasures, road-weather treatments, and repairing highway/roadway assets can reduce the likelihood of incidents. Coordinating responses among agencies responsible for the rural freeway and disseminating timely information on crashes and closures can potentially reduce secondary incidents and improve reliability, on time goods delivery, and traveler experience.

This chapter focuses on how AI techniques could be applied to improve the safety of travelers, and enhance the management, operations, and maintenance of rural freeway corridors to benefit users, operators, and other stakeholders of rural freeway corridors.

Relevant Operational Challenges

Rural roads have unique safety challenges. Some key contributing factors to rural freeway crashes include inconsistent and outdated design elements, driver fatigue and in-attention, inclement weather, excessive speeds, the presence of wildlife, and roadside hazards (e.g, utility poles, sharp-edged pavement drop-offs, trees close to the roadway). Agencies often do not have the resources needed to adequately and proactively address safety problems on the roads they own and operate. Major challenges related to rural freeway corridors are identified below.

- **Safety Management**
    - Delays in detection of crashes and major incidents due to sparse sensor deployment and limited cellular coverage can lead to increased fatalities and secondary incidents.
    - Presence of wildlife on the rural freeway when combined with high vehicle speeds can endanger the lives of the driver as well as the animal and cause property damage.
- **Road Weather Management**
    - Adverse weather, ponding/flooding, and slippery pavements/icy patches can lead to fatal crashes, secondary incidents, property damage, and deterioration of roadway assets.
- **Asset Management**
    - Delays in identifying where emergency asset repair work is needed can lead to crashes and delays.
    - Risky asset inspections due to high vehicle speeds and necessary lane closures can endanger the lives of maintenance crews as well as travelers.
    - Failing assets (e.g., distressed bridges) can further deteriorate and lead to crashes, and costly repairs.
- **Work Zone Management**
    - Stopped vehicles and shockwaves at work zones can lead to crashes and delays, due to high vehicle speeds.
    - Ineffective work zone planning can lead to reduced safety and productivity, increased emissions, fuel consumption, and costs.
- **Commercial Vehicle and Freight Operations**
    - Drowsy and distracted driving due to long stretches of time on the road can lead to fatal crashes.
    - Inability to plan for parking at designated truck stops can lead to fatigue-related crashes.
    - Unreliable freight travel time due to weather and incidents can lead to missed deliveries and loss in productivity.
- **Integrated Management**
    - Lack of timely coordination and collaboration among the multiple agencies and jurisdictions responsible for a rural freeway, which may span multiple counties and states, can lead to poor management of resources and demand.

Potential AI Applications

AI techniques can potentially enhance the effectiveness of safety countermeasures, asset management, road weather management, commercial vehicle and freight operations, and work zone management for rural freeway corridors, especially due to limited resources available to agencies. This section includes potential applications where AI may be used to address the challenges listed in the previous section.

Application #1: AI for Crash and Emergency Detection

Objective: Rapidly detect crashes, incidents, and disasters, and identify response plan using AI techniques

Summary: AI can be used to rapidly detect crashes and emergencies (e.g., HAZMAT spills, vehicle in sinkhole) from sensor data, weather data, social media data, connected vehicle messages, and high-resolution images captured by drones. Data can be fused from multiple sources using machine learning (ML) techniques such as anomaly detection, clustering, neural networks to detect crashes and emergencies. Once an emergency is detected, agencies can potentially dispatch drones to capture accurate images safely and rapidly about the nature and extent of the emergency (e.g., 10-vehicle crash, 3 fatalities, vehicle in sinkhole, HAZMAT spill). This is especially beneficial for rural roads where sensors are more widely spaced. Image recognition (IR) can be used to analyze images captured by drones. Machine learning models using neural networks or decision trees can be built to predict the impact and identify the type of responses needed by learning from historical data. For example, the ML model can be trained to predict the best routes for EMS under different weather and traffic flow conditions. This information along with the recorded images can be shared in real-time with first responders and maintenance personnel, allowing them to respond quickly and effectively. First responders and maintenance personnel can communicate with an emergency center on the nature and extent of the crash using AI-enabled chatbots. Agencies can also disseminate the incident information through a traveler information system and/or dynamic message signs to travelers and fleet providers. Connected and automated vehicles can also be warned of the presence of a crash, first responder or maintenance personnel. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

The benefits of such an application include: rapid detection of crashes and emergencies, even with sparse sensor deployment; safe confirmation of crashes and emergencies, with drones and image recognition; effective response actions, with prediction; improved safety of EMS personnel; and decreased fatalities, cost, time, and other resources.

Application #2: AI for Wildlife Detection

Objective: Detect the presence of wildlife and warn drivers to minimize collisions

Summary: According to an article by the Center for Large Landscape Conservation, “reported collisions between motorists and wildlife cause more than 200 human fatalities and over 26,000 injuries each year, at an annual cost to Americans of more than $8 billion in vehicle repair, medical costs, towing, and other expenses. The average cost of a vehicle colliding with a moose exceeds $44,000 in 2018 dollars.” (Skroch, 2020). AI techniques can be used to detect the presence of wildlife on or near the road from animal detection systems, connected and automated vehicles, and high-resolution images captured by cameras mounted at wildlife crossings or drones. For example, image recognition can be used to analyze images captured by the cameras and machine learning techniques such as Random Forest can be used to classify if the image is an animal or not. Using image recognition and machine learning techniques can minimize false alarms typically seen with conventional laser or radar-based animal detection systems (Antônio, Silva, Miani, & Souza, 2019). Once an animal is detected, the information can be used to alert drivers as well as post speed reduction advisories on message signs upstream of the impacted segment. This information can also be shared with connected and automated vehicles and in-vehicle systems. Lowering the speed and alerting drivers can potentially either prevent a collision or reduce the severity of a collision. Additionally, ML models can be trained to predict wildlife crossings based on historical data allowing for more proactive implementations of speed advisories. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #3: AI for Emergency Planning

Objective: Improve emergency planning by identifying high-risk crash locations, identifying populations vulnerable to natural calamities, and planning for evacuation needs of specific population groups using AI

Summar: AI can be used by agencies to improve their emergency and evacuation plans. For example, ML models can be trained to predict high-risk locations, severity, and types of crashes based on historical data. Agencies can use the predicted information to implement countermeasures to reduce the crash risk. If resources are limited, agencies can potentially use the predictions to focus on locations with high potential for severe crashes or specific crash types. As crashes are rare events, agencies may want to explore AI techniques that address the issue of small data sets. For example, agencies may want to explore ensemble learning, which is a machine learning technique where multiple models are trained to solve the same problem and combined to get better results. Bagging and boosting are two commonly used ensemble techniques. In the bagging technique, several new training sets are created from the original training set using sampling with replacement. Each new training set is used to train a model. The average of all predictions leads to more accurate and robust prediction. Boosting does not resample the data, instead it combines a number of weak learners into a single weighted model. Ensemble techniques can be used for both small data sets as well as data imbalance (i.e., classes or types of data are not equally represented in the data set).

AI can also be used by agencies to identify evacuation zones and develop plans. For example, an ML model can be trained to identify areas that are susceptible to natural calamities, predict high-risk localities, and potential severity of impact. These predictions can be used to identify vulnerable populations and develop specific plans for evacuating people who require assistance during local or multi-jurisdictional emergency evacuation (i.e., people with disabilities, people with medical conditions, the aging population, people with no access to transportation, and people with pets).

This application uses AI for three system functions: reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #4: AI for Road-Weather Management

Objective: Detect and predict where weather-related road surface treatments or preventative measures are needed

Summary: AI can help detect as well as predict road surface conditions from weather, sensor, connected vehicle messages, and/or images recorded by drones. As with the other applications, ML techniques such as clustering, classification, nearest neighbor, etc., can be used for data fusion. Next, ML techniques such as clustering, neural networks, etc., can be trained to rapidly detect weather events such as icy patches, snow drifts, ponding or flooding on roads. ML models can be trained to predict the most optimal response plans. Agencies can use this information to alert weather response teams and dispatch snowplows to specific segments or maintenance crews to repair or close flooded road segments. This information can also be disseminated through a traveler information system and/or dynamic message signs to travelers and fleet providers for route diversion and trip planning. Agencies can also use the information to post timely weather-based speed advisories on dynamic message signs upstream of the impacted segments to enable slowing down of vehicles and minimize crashes.

ML models can also be trained to predict high-risk areas and intensity of impact before conditions deteriorate or adverse weather strikes. Agencies can accordingly deploy and concentrate preventative weather surface treatments along the most dangerous segments.

This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Using AI for timely detection as well as prediction of where weather-related treatments are needed can potentially reduce crashes, secondary incidents, and deterioration of roadway assets, and save lives, cost, time, and other resources.

Application #5: AI for Safe Asset Health Inspections

Objective: Safely and reliably identify emergency repair work by assessing conditions of highway/roadway assets

Summary: AI can potentially be used by agencies to rapidly assess the health and condition of their highway/roadway assets and determine a cost-effective approach for timely repair. ML techniques can be applied to assess pavement, bridge, culvert, signs, gantries, and other highway/roadway asset conditions using multi-source/multi-sensor data fusion. Drones can be especially useful for asset inspections that are risky and dangerous (e.g., unstable bridges and other structures), for frequent data collection and for providing a more accurate view of the health of the asset in real-time. Classificiation techniques such as Decision Trees and Random Forest can be used to classify the asset conditions rapidly. For example, it can classify the asset condition as an existing hazard (e.g., potholes, cracks, fractures), imminent hazard, or a less-time sensitive need (e.g., maintenance, repair, or replacement needs). ML models using decision trees or neural networks can be trained to identify the type of response actions required. For example, the information can be used by agencies to direct maintenance crews to areas in need of emergency repair to prevent crashes, major vehicle or infrastructure damage, or personal injuries. Connected and automated vehicles can be warned of the presence of the hazard and maintenance personnel. Additionally, this information can be disseminated through a traveler information system, dynamic message signs, mobile apps, and in-vehicle systems to travelers and fleet providers for route diversion and trip planning.

This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

The benefits of such an application include the safe inspections of assets with drones and image recognition; rapid detection of existing hazards; and effective response actions, with prediction. Using AI for timely detection of asset repair and maintenance needs, can reduce crashes, and secondary incidents, and save lives, cost, time, and other resources.

Application #6: AI for Predictive Asset Maintenance

Objective: Predict future maintenance needs by assessing conditions of highway/roadway assets and enable effective investment and risk analysis

Summary: AI can potentially be used by agencies to assess the health and condition of their highway/roadway assets and plan for cost-effective approaches for timely maintenance, repair, rehabilitation, and replacement of their assets.

AI can be applied to assess real-time as well as historical data on the conditions of highway/roadway assets. Agencies can potentially fuse multi-sensor/multi-source data using ML techniques and data analytics. ML models can be trained to predict future maintenance, repair, rehabilitation, and replacement needs, and identify response actions, based on the data (Morales, Reyes, Caceres, Romero, & Benitez, 2018). Agencies can prioritize their response actions based on available resources to sustain a desired state for their assets. These long-term plans may also be relayed to the traveling public through traveler information systems and message signs for trip and route planning (e.g., one lane closed in July for bridge maintenance, take alternate routes to avoid delays).

This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

The benefits of such an application include, prediction of future maintenance needs enabling effective investment decisions; prevention of deterioration of assets and resulting crashes; and decrease in asset repair costs due to timely detection.

Application #7: AI for Work Zone Management

Objective: Detect and predict queues and shockwaves to harmonize speeds for reducing work zone crashes and delays

Summary: Historical and real-time multi-source/multi-sensor data (e.g., connected vehicle messages, weather data, sensor data, real-time aerial imagery captured by UAS/drones) can be fused by ML techniques such as anomaly detection, classification, clustering, etc. ML models can be trained to detect as well as predict queues and shockwaves at work zones using the fused data. ML models can also be trained to identify effective speed advisories for specific queues and propagation speeds. This information can be used by TMC managers responsible for the corridor to post timely speed advisories on dynamic message signs upstream of the impacted segments to enable slowing down of vehicles and harmonize speeds. Speed advisories can also be shared with vehicles through in-vehicle warnings. This information can potentially reduce crashes, improve throughput, and reduce delays. Connected and automated vehicles can also be warned of the presence of construction or maintenance personnel.

Additionally, ML techniques can be used to predict the safety, mobility, and environmental impacts of planned work zones. This can be used by agencies to determine the most effective work zone plans (e.g., duration and length of work zones, number and timing of lane closures), schedule and costs. Using AI for prediction of impacts of work zones can potentially improve work zone management, and save time, cost, and other resources. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #8: AI for Smart Truck Parking Information Systems

Objective: Predict parking availability at truck stops to expedite search for parking

Summary: AI can be used to predict future availability of safe parking at public rest stops and private truck stops along the rural freeway corridor using historical and current data (e.g., sensors, video images) (Lamb, 2017). Video analytics be used to detect empty spaces. ML models can be trained to predict future parking availability based on empty and used parking spaces and truck demand. This information can be relayed to truck drivers through their in-cab systems and mobile applications. Predictions of future parking availability can be used by drivers to estimate and make targeted truck stops due to fatigue, inclement weather, or road closures. This in turn can help reduce crashes. Another advantage is reduced emissions and fuel consumption due to idling by truck drivers to keep their cabins warm if they are forced to park away from amenities. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #9: AI for Distracted Driver Behavior Detection

Objective: Detect unsafe and distracted driver behaviors

Summary: AI can potentially be used to recognize if a driver is having problems based on their driving behaviors. Image recognition techniques can be used to detect drowsy or inattentive drivers of vehicles equipped with cameras. ML models can be trained to detect unsafe driving based on steering, lanekeeping performance, and speeds. This information can be used to alert drivers in real-time and possibly be used by fleet providers for remedial coaching. Similar AI applications can also be used to alert drivers of light duty vehicles. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Using AI for detecting unsafe and distracted driving behaviors can reduce driver fatigue-related crashes.

Application #10: AI for Freight Traveler Information

Objective: Provide real-time traveler information for freight-specific needs

Summary: AI can be used for predictive traveler information and route planning by freight managers. As with the other applications, ML techniques such as clustering, classification, nearest neighbor, etc., can be used for rapid fusion of multi-sensor/multi-source data such as wait times at intermodal facilities, traffic conditions, crashes, weather, road closures, work zones, pavement conditions, route restrictions (e.g., hazardous materials, oversize/overweight trucks), and truck parking availability. ML models can be trained to predict route travel times and expected time of arrivals based on historical and real-time data. These can be used for pre-trip as well as en route travel planning and routing. The real-time travel information, parking, and routing can be disseminated to drayage companies, drivers, and intermodal facilities.

This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Using AI for predicting travel times for real-time freight traveler information can faciliate reliable travel planning, improve on-time delivery of goods, and save costs.

Application #11: AI for Decision Support System

Objective: Facilitate coordinated decision-making among multiple agencies and jurisdictions

Summary: AI can be used to enable the deployment of a real-time decision support system (DSS) for integrated management of rural freeway corridors. This application encompasses the previous 10 applications powered by AI. For example, ML techniques can be used for data fusion from multiple sensors and multiple sources (e.g., weather, sensor, connected vehicles, high-resolution images recorded by drones). Agencies can use ML techniques to detect and predict the health of the highway/roadway assets, isolate where weather-related road surface treatments or preventative measues are needed, identify high-risk crash locations and their impacts, determine the best routes for emergency response and evacuations. Based on the detected and predicted information, the real-time DSS can identify optimal response actions based on business rules agreed upon by agencies responsible for the rural freeway. The necessary response actions can be communicated to various agencies responsible for the corridor for coordinated actions. Agencies can also communicate with each other and interact with the data management systems using AI-powered chatbots (using ML and Natural Language Processing).

This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

The advantages of such an application include, improved timeliness of decision-making, improved staff's ease of use of data management systems, increased efficiency of communication between staff, and reduced costs.

Concept Illustration

Figure 8 shows performance-driven examples of how AI could potentially be used for operations and maintenance of Rural Freeway corridors to make travel safer, and more reliable and efficient. For example, agencies could use AI coupled with drones for rapid incident detection, safe and cost-effective incident verification, and efficient incident response planning (**#1**). AI could be used to detect the presence of wildlife, a common problem on rural freeways, and warn drivers to minimize collisions (**#2**). AI could be used to rapidly detect ponding, flooding, black ice or other weather-related conditions and alert maintenance crews (**#3**). AI could be used to predict deterioration of assets and dispatch drones for confirmation, especially for inspections that are risky or dangerous (**#4**). AI could be used to predict impacts of work zones on delays to enable effective work zone management and planning (**#5**). AI could be used to detect unsafe and distracted behaviors of truck drivers and predict parking availability at truck stops to expedite search for parking (**#6**). AI could be used to drive DSS for proactive and coordinated decision-making (**#7**).

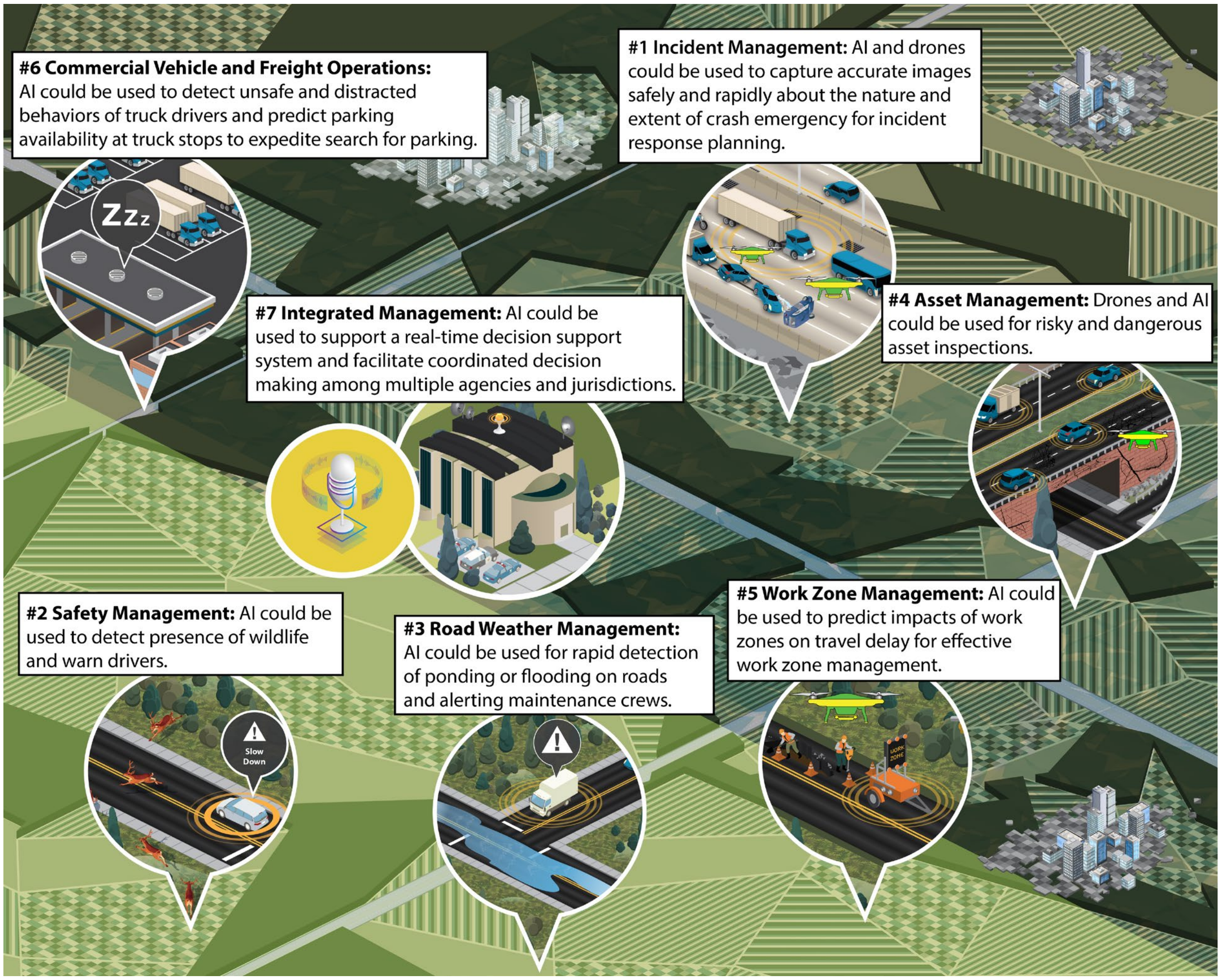

Figure 8. Graphical Illustration of Potential AI Applications for a Rural Freeway Corridor.

Actors and Actor Profiles

A major portion of a transcontinental freight corridor runs through rural areas of multiple states, including a large Midwestern state. Long stretches of the rural freeway are extremely flat, causing driver drowsiness. Portions of the rural freeway run through mountainous terrain with wildlife frequently crossing the road. A few underpasses have been built for safe crossing; however, these are insufficient. The corridor also faces severe inclement weather. In the winter months, the corridor experiences several inches of snowfall and in the summer months, there are frequent ponding and flooding due to overrunning of streams.

Given below are descriptions of key actors and how they interact with the AI-powered system one Monday morning in June, after a week of torrential rains.

Actor #1: ITS Manager of State DOT

Ronan is the ITS Manager at the Midwestern state DOT. He is responsible for the operations and maintenance of the rural freeway corridor that runs through his state. As he has limited funding, he has investigated the benefits of emerging technologies and techniques in managing the rural freeway corridor smartly and efficiently. His team recently developed a DSS enabled by AI, and AI-powered chatbots for communicating with staff and with other agencies responsible for the corridor. In addition, he was able to procure a few drones outfitted with high-resolution video cameras.

At 6:05 AM, Pinar, a TMC Operator, notifies Ronan that the AI-powered DSS has flagged the formation of a traffic shockwave. Ronan uses a chatbot to pull up the information on his computer. At 6:10 AM, the DSS alerts the possibility of multi-vehicle pileup. At 6:20 AM, Ronan receives confirmation of the crash from Thao, a Highway Patrol Officer. He also receives images captured by a drone dispatched by Thao to investigate the crash scene. Ronan uses the DSS to determine the best response plan to re-route traffic. He directs Pinar to enact the plan.

Actor #2: Maintenance Manager

Mason is the Maintenance Manager for the rural freeway corridor that runs through the state. At 7:30 AM, the AI-powered DSS flags a few problem areas requiring immediate repair. One of the flagged assets is an aging bridge. Mason decides to confirm the urgency and assess the extent of damage by dispatching a drone. Upon receiving video images captured by the drone, Mason determines that the bridge is an existing hazard requiring urgent repair. He uses an AI-powered chatbot to communicate with and dispatch his maintenance crew to repair the bridge to prevent crashes and personal injuries. He also communicates his response plan with Ronan, the ITS Manager, and the TMC staff using an AI-powered chatbot.

At 8:30 AM, the AI-powered DSS flags several Forward Collision Warning (FCW) and Emergency Electronic Brake Light (EEBL) messages at a location close to a stream. Mason realizes that the rains the previous week may have caused the stream to overrun. He uses a chatbot to dispatch a maintenance crew to clear the water and fix the drainage. He also communicates his response plan with Ronan, the ITS Manager, and the TMC staff using a chatbot.

Actor #3: TMC Operator

Pinar is a TMC Operator and reports to Ronan. She is responsible for monitoring the AI-powered DSS. The AI-powered DSS continuously pulls in data from sensors, RWIS, and CV, cleans the data, and fuses them to synthensize information.

At 6:05 AM, the AI-powered DSS flags the formation of a shockwave. Pinar immediately notifies Ronan of impending problems.

At 7:55 AM, Pinar receives Mason’s response plan for emergency repair of the bridge. Pinar follows the standard operating procedure (SOP) established for their TMC to update the traveler information system with lane closures. She also updates the message on a dynamic message sign (DMS) that is 2 miles upstream of the bridge. The DMS informs drivers of the lane closure ahead.

At 8:35 AM, Pinar receives Mason's response plan for clearing water off the road. She updates the traveler information system with the ponding message and lane closures.

Actor #4: Highway Patrol Officer

Thao is a Highway Patrol Officer. At 6:10 AM, the AI-powered DSS alerts the possibility of multi-vehicle pileup. There are no cameras at the potential crash site for confirmation. Driving to the crash site and taking photographs to assess the crash scene could put Thao and other officers at risk. So, Thao immediately dispatches a drone to take photographs and videos of the crash and vehicle backups. Upon receiving images of the crash scene, she assesses the nature and extent of the crash, and uses an AI-driven model to determine the type of response needed. Thao communicates the response plan with the emergency services and Ronan. Emergency services are dispatched, and the incident is cleared rapidly.

Actor #5: Truck Driver

Leonard is a long-haul Truck Driver. After a strenuous drive through the mountainous terrain under heavy rains, he is happy to be on a flat stretch. His joy is short lived as he is beginning to feel drowsy. Luckily, his truck is equipped with a camera and image recognition software. Upon detecting that Leonard is drowsy, the AI system predicts and informs him of the availability of safe parking at the next truck stop. Leonard is glad to take the exit to take a much-needed break.

Actor #6: Commuter

Maya is a commuter who takes the rural freeway every Monday and Friday to get to work in the next town. Although her drive is through a scenic stretch of the rural freeway, she is worried about hitting deer and other wildlife, especially during the dawn and dusk hours. She is happy to learn that the state DOT has implemented a system that uses AI to alert drivers when wildlife is detected. She decides to sign up for the service.

One Monday morning, on her way to work, her car issues an alert to slow down as wildlife has been detected. She immediately slows down and is able to avoid hitting a large moose.

Relevant Research, Tests and Case Studies

This section discusses example real-world case studies of AI applications for rural freeways. For additional case studies, please refer the FHWA report, "*Raising Awareness of Artificial Intelligence for Transportation Systems Management and Operations,*" which presents several real-world applications of AI for TMC operations that are relevant to rural freeways, including incident detection, traffic prediction, traveler information, chatbots for interfacing with TMC systems, and unmanned aerial systems (UAS/drones) for asset inspections and crash reconstruction (Gettman D. , 2019).

Safety Management

Drones and AI are being used by public safety agencies for crash reconstruction and investigation. Many states, including Oregon and Massachusetts have begun using drones for crash scene reconstruction (Drones For Good: Saving Time And Lives With Faster Crash Scene Reconstruction, 2019).

A vendor for ADAS and Automated Vehicles is using AI to detect the presence of wildlife under a range of weather and visibility conditions. This system is being deployed in China and Europe. Another vendor in Brazil is using AI, robotics, and thermal imaging to detect the presence of wildlife.

Incident Detection and Prediction

Nevada DOT, Florida DOT, and Iowa DOT use AI techniques to fuse data from multiple sources, including radar and loop detectors and closed-circuit television (CCTV) cameras, to identify incidents (Gettman D. , 2019). A neural network model is trained to recognize scenes as “incidents,” “not incidents,” and “incident may be likely to occur.” Neither agency has used traditional software incident detection methods as highway patrol incident warnings have tended to outperform software detection methods in recent years. With the new AI system, both agencies have seen reductions in incident detection times and crashes. The system has been especially useful where traditional detection infrastructure is lacking.

Road Weather Management

Wyoming DOT is working with the University of Wyoming to develop an automated image-based weather detection system using machine vision and AI. The proposed application will make use of video images captured by webcams installed throughout the corridor as well as cameras installed on snowplows and maintenance vehicles. Most weather detection systems rely on data from Road Weather Information System (RWIS), which typically do not capture the weather at the road surface level and are location specific. For example, RWIS stations may fail to accurately represent poor visibility observed only at the road surface level (e.g., poor visibility due to blowing snow). Webcams and in-vehicle cameras are cost-effective alternatives to RWIS stations that can provide a more comprehensive view of the corridor. The WYDOT AI system will be trained to detect different weather conditions in real-time using processed images (Wyoming DOT, 2019).

Utah DOT is using drones to measure snow and other elements to keep them from blocking roads or other infrastructure. Drones are being used to capture video images to predict avalanches, water runoffs as snow melts and mudslides.

Asset Management

AI has been applied for safe, reliable, and cost-effective detection and prediction of asset failures and obsolescence. Machine learning and image recognition is being used by a Carnegie Mellon University (CMU) spinoff company to process roadway images captured by smartphones mounted on vehicles’ windshields and detect pavement conditions, including potholes, patches and sealed cracks, fatigue cracks, longitudinal and transverse cracks, pavement distortions and surface deterioration (Westrope, 2020). The application has been applied by several municipalities and cities such as Pittsburgh, PA, Bethel Park, PA, Savannah, GA, South Bend, IA, and Detroit, MI.

Drones are being used in over 30 states for various purposes, with 10 of the states using them for bridge inspections and 6 for pavement inspections (American Association of State Highway and Transportation Officials (AASHTO), 2018). Michigan DOT has successfully conducted field tests and demonstrations using drones with a combination of high-resolution optical, thermal, and lidar sensors for pavement and bridge inspections (Brooks, et al., May 2018). Use of drones for asset inspections can improve safety, save time and cost, and reduce congestion. Michigan DOT estimates that a traditional manual bridge inspection can take eight hours to complete and involve closure of two lanes of traffic for an approximate cost of $4,600. A similar inspection using a drone would take roughly two hours, no closures, and cost approximately $250 (AASHTO, 2018).

Commercial Vehicle and Freight Operations

AI is widely used by fleet managers for route planning, asset tracking, drayage optimization, and freight-specific traveler information. AI is also being used to detect unsafe driving behaviors. Remedial coaching is then provided to drivers who exhibit unsafe driving behaviors (Marsh, 2019).

Potential Benefits

AI offers the opportunity to operate and manage rural freeways more cost-effectively while reducing crashes and secondary incidents, improving the safety of EMS and maintenance personnel, facilitating ontime delivery of goods, and saving lives, time, and other resources. As indicated previously in Chapter 4, AI is not expected to replace classic problem solving and conventional traffic management solutions. Instead, AI affords the capability to enhance these systems. Additionally, as seen for the other scenarios, AI is expected to introduce new capabilities to address challenges seen with the operations and maintenance of rural freeway corridors. These new functionalities can be improved over time as the AI-enabled applications continually learn from the successes and failures and adapt to new situations. A few potential benefits of AI-enabled systems are:

- **Improved decision-making:** AI can help agencies responsible for the rural freeway make rapid, coordinated, and more informed decisions with respect to safety management, work zone management, asset management, and road weather management. Additionally, staff can interact with the TMC and data management systems and agencies can communicate with each other easily and efficiently using AI-powered chatbots.
- **Improved safety of EMS and maintenance personnel:** Use of drones for asset inspections, identification of construction and maintenance personnel at work zones, and verification of nature and extent of crashes and disasters can improve the safety of personnel.
- **Reduced crashes and secondary incidents:** AI can rapidly detect and predict crashes and their impacts. This information can be used to implement relevant countermeasures. AI can detect the presence of wildlife and unsafe driving behaviors (e.g., drowsy drivers, excessive speeding), which can be used to alert drivers and post speed advisories.
- **Reduced crashes due to adverse weather:** AI can isolate where weather-related road surface treatments or preventative measues are needed, which can potentially reduce crashes, secondary incidents, and deterioration of roadway assets.
- **Reduced asset repair costs and resulting crashes:** AI can rapidly, safely and reliably assess the health and condition of highway/roadway assets enabling agencies to plan and implement cost-effective approaches for timely maintenance, repair, rehabilitation, and replacement of the assets. These corrective actions can reduce crashes due to asset failures (e.g., cracked bridges or gantries, potholes).

- **Reduced work zone crashes and delays:** AI can detect and predict imminent queues and shockwaves at work zones, which can be used to warn drivers of reduced speeds. This can potentially reduce crashes, secondary incidents, and delays.
- **Improved emergency and evacuation planning:** Agencies can improve their emergency plans by using AI to identify high-risk crash locations and developing suitable countermeasures. Agencies can improve their evacuation plans by using AI to identify populations vulnerable to natural calamities, determine the best routes for emergency response and evacuations, and planning for evacuation needs of specific population groups.
- **Improved truck driver safety:** AI can detect and alert truck drivers of unsafe and distracted driving behaviors. AI can predict and inform truck drivers of parking availability at truck stops, which can help reduce fatigue-related crashes.
- **Ontime goods delivery:** Fleet managers can optimize routes and fulfill ontime delivery requirements through predictive traveler information for freight.

Potential Barriers to Adoption of AI for Rural Freeway Corridors

The adoption of AI solutions for the operations and maintenance of Rural Freeway Corridors must contend with a wide range of barriers, including:

- **Stakeholder Acceptance:** AI techniques are often seen as "black boxes." This can lead to mistrust among stakeholders, which can be a major barrier to adoption. This mistrust may be allayed by sharing with stakeholders the benefits of using AI. These may be from proof of concept tests or real-world implementations of AI. Even when agencies are open to exploring AI solutions, they are often concerned with how quickly technology becomes obsolete leading to the perception of wasted invesments. This frustration may be reduced through knowledge and technology transfer of AI-related best practices, including the need for continuous training of AI models.
- **Talent/Workforce Availability:** As AI is an emerging technology, the workforce will need to be trained in AI and advanced data analytics. Personnel will need to be trained on the safe use of drones and UAS devices.
- **Data:** AI techniques require vast amount of accurate data. Agencies will need to continually collect high quality data to train the AI algorithms. This can be a challenge, especially on rural freeways where sensors are widely spaced. With the increase in connected and automated vehicles, and probe data, the data coverage issue may decrease. But until then, since budget is typically imited, agencies may want to start small and focus on applications with the highest impact, and incrementally build capability.
- **Computing Power:** AI techniques are enabled by massive amounts of data. Many legacy systems/architectures are incapable of dealing with the large quantities of complex data, which can lead to latency, timeout, and storage issues, resulting in safety-critical decisions being voided. A possible solution is to leverage open source tools and cloud computing for data storage, advanced analytics, and computing.

- **Bias:** AI applications are only as good or as bad as the training data. If there is bias in the data, the AI applications can also be biased leading to unethical and unfair consequences.
- **Privacy:** AI is fundamentally designed to use massive amounts of data impacting the privacy of individuals through data manipulation, speech or face recognition, and tracking. Policies and guidelines on what type of user data may be tracked, when and for what purpose will need to be clearly defined.
- **Ethics:** AI applications can be used for profiling to discriminate against individuals/populations based on unfair criteria.
- **Liability:** When a vehicle, device, equipment, or system that is enabled by an AI application is involved, it is unclear who is liable if there is a fatality or significant loss in productivity, or if network security is hacked.

Potential Value to USDOT

Rural areas have more than twice the fatality rate than urban areas; unfortunately, funding is limited. The transportation challenges and characteristics make rural freeway corridors suitable for seeking AI solutions. The USDOT has significant opportunities to help agencies operate and manage their rural freeways:

- **Proactive engagement in policy development:** Deployment of AI solutions for rural freeway corridors that traverse multiple states and jurisdictions require consistency in AI-related policies. The USDOT can play a leadership role in informing and influencing new policies, working with other federal agencies, public sector agencies and the private sector. The USDOT may want to be engaged in providing inputs to the development or refinement of potential policies for ethics, liability, privacy, security, data governance and data sharing related to AI. As agencies begin to use AI-powered UAS devices and robots, the USDOT may also need to consider shaping policies on the safe, secure, and ethical use of robots and drones without compromising the privacy of individuals.
- **Facilitate interoperability of AI-related applications:** Vehicles navigating rural corridors that run through multiple counties and states may be exposed to a range of AI applications. Facilitating interoperability between devices will enable drivers and vehicles to avail of these AI applications safely, reliably, and seamlessly. This will improve the efficiency, safety, and mobility of the rural freeway corridor as well as adjacent transportation systems. The USDOT can play a leadership role in increasing interoperability by working with public sector agencies, vehicle and equipment manufacturers, AI-vendors, and standards developing organizations to develop harmonized standards specifically for AI-related applications across multiple regions.
- **Accelerate adoption of AI:** Agencies are cautious when investing in untested technologies. Some agencies have policies that prevent them from investing in technologies that are in the conceptual or prototype stages. The USDOT can accelerate adoption by funding AI research, proof of concept tests, demonstrations, and deployments that would not otherwise be accomplished by agencies or the private sector without federal support, and by sharing benefits, challenges, and lessons learned from these efforts with the agencies. In addition, the USDOT can conduct training and knowledge sharing activities for developing and implementing AI solutions.

The USDOT can also provide peer exchange opportunities to cohorts of AI researchers, vendors, and current and prospective deployers to facilitate the adoption of AI.

Chapter 8. Underserved Communities

This chapter discusses how AI might potentially be used for addressing challenges relevant to the Underserved Communities scenario. This chapter provides a background of Underserved Communities, an overview of the operational challenges relevant to the scenario, potential applications enabled by AI to address the challenges, a graphical illustration of the concept, actors or entities interacting with the AI-enabled systems, relevant research, tests and case studies, potential benefits, potential barriers to adoption of AI for the scenario, and potential value to USDOT of investing in AI-powered solutions for the scenario.

Background

Travelers do not all have equal access to transportation options that work for them. A lack of options for travelers from underserved communities is a persistent challenge that inhibits their access to jobs, education, healthcare, and other activities. “Underserved” users include under- or unbanked travelers, those with physiological or cognitive/developmental disabilities, those living in rural or low-density communities, older Americans, persons with Limited-English Proficiency (LEP), and more. These travelers may find transporation to be inaccessible altogether, or only accessible under ideal circumstances—for example, a traveler who uses a wheelchair may be unable to get to work on time if the elevator at their nearest subway stop breaks down, while a traveler with LEP may be unable to read information on alternative shuttles posted by the transit authority.

These transportation challenges are faced by a large number of Americans. According to the CDC, 26 percent of adults in the United States live with some type of disability, of which the most common are those that affect mobility. Moreover, these challenges often overlap: People with disabilities are more likely to live in poverty than those without disabilities. This only underscores the need for access to quality transportation services—which allow for greater access to jobs and social services. Barriers to accessing public transit are highly relevant to underserved populations, as they often use transit at higher rates than other populations. For example, travelers with LEP are more likely to use transit than other travelers, while 24 percent of those in poverty have no access to personal vehicles and 20 percent of Americans above the age of 65 do not drive. These factors combine and interact to form unique challenges for individual travelers in accessing and navigating transportation.

With the advent of AI techniques and advanced analytical methods, it is becoming more possible to develop technology-based solutions for existing challenges that may scale up to offer customizeable services and products to a large base of users. This can allow for targeted solutions that meet underserved travelers’ needs.

Relevant Operational Challenges

Agencies are bound to provide equitable service to all users, and there are many initiatives, spearheaded by Federal, State, and local agencies, as well as by private nonprofits and advocacy groups, that work to improve transportation outcomes for users who currently face barriers to access. However, some agencies are finding it difficult to manage the large amounts of data that would be required to optimize and personalize services to travelers with different needs and ability. There exist opportunities for AI techniques and applications to augment existing programs and to be implemented in new, innovative solutions that address existing identified needs.

In this scenario, transportation problems center around providing accessible, equitable, reliable, and affordable transportation services for users who face barriers in accessing conventional transit. Major challenges are listed below.

- **Access to services**
    - Travelers may be **unable to use transportation** services for accessibility or equity reasons.
    - Travelers may not have **access to multiple transportation options**, and be more vulnerable to service disruptions or inconveniences.
    - Travelers may **not be able to book**, use, or pay for certain services depending on their ability to own or use a fare card, bank card, or smart phone.
- **Access to information**
    - Users may not have adequate **access to information** regarding scheduling, booking, and taking their trip, or the information may not be accessible to all travelers.
    - Travelers require **information communication** methods such as signage and announcements to be accessible and understandable.
    - Transit **facilities**, as well as transit vehicles, are not always accessible and convenient for all users. Information about accessibility, such as maps showing accessible entrances, are not usually publicly available.
- **Health and Safety**
    - **Information alerts** may need to be provided to both travelers and to designated caregivers or guardians (e.g., travel alerts or in case of emergency).
    - Travelers with visual, intellectual, or mobility disabilities may have difficulty **crossing intersections** safely.
- **Assistance**
    - Travelers may need **personal, responsive assistance** with various aspects of their trips, including before, during, and after the trip itself. Available assistance may not be helpful or understandable to travelers with visual, auditory, cognitive, or developmental disabilities.
    - Travelers may require assistance in **navigating indoor spaces** such as subway stations or train platforms.

    - Transit options may malfunction or during operation, or otherwise have their accessibility impacted, requiring **on-the-fly identification of issues** and re-routing of passengers.

- **Service Provision**
    - Routes servicing in rural or low-density areas may have low rider-per-hour measures that make them **expensive** for providers.
    - Agencies may be unable to effectively evaluate riders' preferred travel patterns to accurately **estimate demand.**

Potential AI Applications

Application #1: AI-Enabled Routing and Wayfinding Tools for Pedestrians

Objective: Make pathfinding applications more intuitive, flexible, and responsive

Summary: AI may be used to improve routing applications Infrastructure sensors provide data that can be analyzed to allow a program to intelligently and dynamically modify routing algorithms. Deep learning can also be used to build off of past performance, identifying successful routes and modes and coming to anticipate traffic conditions to calculate optimal routes for each user. Using AI in this case allows for extremely fine-grained user profiles that would not be possible with conventional algorithms. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn adapt, and decisions & actions (see Figure 2).

Application #2: Navigation Applications with AR and Localized Points of Interest

Objective: Assist travelers with navigation by using augmented reality (AR) to visually and intuitively display helpful information

Summary: AI can assist travelers with navigation by using AR to visually and intuitively display helpful information. For example, a navigational app could use GPS (for outdoor trips) and connections to station-run Bluetooth beacons (for indoor segments) to provide effective localized information. The app can then provide a live AR overlay that shows colored route lines through the station or along sidewalks to ease navigation and provide more effective orientation for travelers, as well as providing virtual labels or live translation of signage to allow users to identify points of interest such as elevators, escalators, fare machines, and egress points. Using a decision algorithm, the app can take into account any user accessibility needs to identify which specific doorways or transit vehicles the traveler should board, and plotting the most efficient, direct, and accessible path possible. Displaying navigation elements via AR and tailoring them to individual users' needs allows customizable, personalized support for users. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #3: AI Interpretation of User Input

Objective: Allow for inputs and outputs that might otherwise be too complex for conventional programs.

Summary: AI can be used to interpret a wide range of communication types and methods beyond conventional menus and written inputs. For example, using Natural Language Processing in combination with the scheduled trip itinerary, a program would be able to display context-sensitive information to inform users, caregivers, or transportation providers of specific instructions or information. The navigation app would be able to use a traveler's location and the current step of the trip chain to contextualize instructions or questions, such as "What bus do I need to get on," or "Are you looking for a fare machine?" This would enable users, such as those with cognitive disabilities, to be able to more effectively understand wayfinding instructions and to communicate clearly with caregivers or transit staff. By processing and responding to user-asked questions with AI-enabled decision-making, the app would also be able to provide responsive, flexible support for users who might feel overwhelmed or uncomfortable in an unfamiliar environment. AI techniques allow processing of diverse range of inputs beyond conventional menus or limited voice-recognition prompts. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #4: Environmental Mapping and Guidance

Objective: Respond dynamically to travelers' environments and provide detailed, context-sensitive directions.

Summary: Combining a device's camera with image processing of transit infrastructure feeds such as CCTV would allow an AI-driven program to actively build and map a traveler's immediate surroundings through simultaneous localization and mapping (SLAM). This would allow it to respond dynamically to provide detailed travel instructions, such as alerting users with visual disabilities who are traveling through unfamiliar spaces to curbs, obstructions, and uneven ground. For example, a wayfinding application could use imagery analysis to identify a firetruck stopped by the sidewalk and inform the traveler of the upcoming obstruction, rerouting if needed. This functionality could moreover be used to enable safer intersection crossings for travelers, by keeping track of curbs, other pedestrians, and nearby vehicles. AI enables SLAM and allows for the application to identify unexpected events and respond accordingly. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #5: AI-Enabled Payment Assistance

Objective: Enable advanced forms of identity verification

Summary: AI enables fare payment methods and verification that are more sophisticated than current physical fare media like smart cards or tickets. For example, an AI-driven system could be able to perform biometric identifications using facial features or fingerprints to quickly and accurately identify travelers. This would eliminate the need for travelers to have or manipulate physical fare media, which would enable users with physiological or cognitive/developmental disabilities to more comfortably access transit. In particular, this would enable travelers to make use of multimodal or multi-stage trips, as having a single unified method of identity verification and payment would allow them to simply use identification they have at all times—themselves—rather than needing to carry losable or difficult-to-manipulate fare cards or tickets. AI allows for more secure biometric methods to validate identity rather than through use of conventional tickets or smart cards. Secondly, AI allows for learning from travelers' behavior to identify suspicious activity. This application uses AI for two system functions: reason & analyze and learn & adapt (see Figure 2).

Application #6: AI-Powered Safety Monitoring and Alerts

Objective: Ensure robust safety net for travelers in case of emergency

Summary: Using contextual analysis and even biometric monitoring, AI can ensure that vulnerable travelers have a flexible and responsive support system in place. For example, a wayfinding app can track its location and communicate with transit infrastructure to ensure that users are correctly following their expected routes. In the event that a user stops suddenly, falls, or diverges from the wayfinder's route, the app can analyze the unexpected behavior and, as appropriate, provide guidance to the user or send an alert to a designated caregiver or health services. This would allow for greater security and greater independence among users, particularly those with cognitive disabilities. AI techniques can help identify unexpected behaviors and determine appropriate responses, including whether an alert should be sent and what advice to give to the traveler. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #7: VR for Testing

Objective: Reduce development costs and train users

Summary: AI functionalities, such as AR and VR, may be used to improve on current methods to create and refine assistive applications. An app developer may, for example, use VR to effectively field-test a wayfinding app in order to determine how users respond to it, but without needing to devote resources to a full field rollout. Likewise, a user may use VR to see whether a particular app meets their needs and is appropriate or necessary for their situation, enabling them to determine whether greater independence is possible without running the risk of encountering any potentially dangerous or stressful situations. Users may also use AR and VR to virtually run through a trip ahead of time, which would enable them to remember visual landmarks and cues while en route. AI can be used to create immersive, realistic simulations beyond those that are currently used. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Application #8: AI-Powered Assistive Robotics

Objective: Enable robotic applications to develop sophisticated approaches to administering aid

Summary: Machine Learning techniques may be used to make automated assistants more intuitive and responsive to input by users. The use of robotics, for example robotic assistants to guide travelers through dense or complex interior spaces or across busy intersections, is itself expected to increase the accessibility of travel for many users. By also incorporating AI systems, these applications would be able to make use of the significant amounts of data that would be generated in order to refine their responses. Applications could, for example, become more effective at anticipating user needs, identifying obstructions and other pedestrians, or even identifying travelers who appear in need of assistance. AI techniques such as NLP make identification of user needs feasible. This application uses AI for all four system functions: sense & perceive, reason & analyze, learn & adapt, and decisions & actions (see Figure 2).

Concept Illustration

Figure 9 shows implementations of AI to make travel more accessible and equitable for users. For example, AI may be used to make routing and wayfinding tools more powerful (#1). AR techniques may be used to make wayfinding more visually accessible and intuitive to users, for example by adding overlays or arrows to destinations (#2). AI analysis techniques can also allow users to communicate clearly with services and operators even when they have limited English proficiency or use ASL (#3). Image recognition techniques can help inform users of their environment and warn them of curbs or other obstructions (#4). Identity validation methods allow for more flexible payment systems (#5). AI mapping techniques can also track users' expected routes and perform biometric monitoring to issue alerts when users are lost or suffering from medical emergencies (#6). VR and AR can be used to assist in the development and testing of accessibility-related applications (#7). Finally, machine learning techniques can allow for assistivve robotic applications to develop sophisticated responses to user interactions (#8).

Figure 9. Graphical Illustration of Potential AI Applications for Underserved Communities.

Actors and Actor Profiles

Actor #1: Person Who Is Blind

Anna is a manager at an insurance company who is blind and uses a cane as a mobility aid. She lives independently and recently moved to an urban area to be relatively close to her workplace. She had previously carpooled with a coworker, but her new residence is near a bus route that takes her within a few blocks of her office. Anna installs an app on her smartphone that provides turn-by-turn audio directions to help her navigate to and from the bus stop. The AI functionality of the app enables it to coordinate with CCTV cameras on and near her usual route, which lets it identify obstructions and warn her about them in advance. For example, one day a delivery truck was parked by the curb and workers were unloading large pallets into a nearby store. Anna's phone identified the objects as being potentially dangerous to navigate between and told her to turn right earlier than usual. Using its ability to responsively learn and adapt, the program took note of typical delivery windows, so the next time one was scheduled it anticipated the obstruction and instead routed Anna on a path that was overall more efficient than its previous, last-minute, diversion. Anna was impressed by how fluidly her app has responded to unexpected events and appreciates being able to walk to her bus stop with full independence and confidence.

Actor #2: Wheelchair User

Sam is on his way to visit his doctor for a regularly scheduled checkup. Sam has a physiological condition that affects his coordination, and he prefers to use a wheelchair to move around freely. He's been reluctant to use public transportation because he isn't familiar with the layout of the subway stations near him, and his old route-planning app couldn't be modified to direct him to the accessible elevator entrance instead of the main escalators. Recently, though, he's downloaded a new trip planning and payment app, and decides to try it out. He inputs his mobility settings, and it analyzes the optimal route based on its database of previous successful rides for similar user profiles. Without his even needing to ask, it finds a route that avoids rough terrain, steep curbs, and potentially hazardous street crossings. Sam easily follows the path it has come up with, opting to listen to its context-based turn-by-turn instructions as he travels. When he gets to the station, the app communicates with a biometric scanner to use facial recognition and imagery instead of a fare card. Sam is able to easily access the subway platform without needing to get out his fare card and scan it, and his app even identified the train model arriving at the station and directed him to move so he'd be right next to the designated wheelchair section when the doors opened.

Actor #3: Person with Developmental Disability

Carrie is a young woman with a developmental disability. She currently lives with her parents, who help take care of her day-to-day needs while also encouraging her to be as independent as possible. In order to take transit trips on her own, Carrie uses a wayfinding app that has a live AR overlay. The app uses its location and orientation in order to display a colorful route line and to label key items along her journey. For example, Carrie's bus is pointed out so she doesn't have to worry about getting on the wrong one. Even if she does, though, her app can analyze her path and compare it to the city's bus data to determine which route she accidentally got on, and then provide dynamic instructions to her as well as sending a text to her parents so they're aware of what happened. Carrie's father, seeing the alert, called her to help her figure out her way back—only for her to answer that she was already following the modified route and would be only a few minutes late by the time she arrived.

Actor #4: Person with Limited English Proficiency (LEP)

Deng is a residential assistant whose work takes him to many different parts of his city. He only recently immigrated to the United States, and while he has picked up some English, he is not entirely comfortable having conversations in it. In order to navigate the sometimes-confusing subway system, he takes advantage of his wayfinding app's built-in AR guidance, as well as the small mobility assistant robots that have been installed in some of the larger thoroughfares. His app communicates with Bluetooth hotspots throughout the station to determine his position and uses image analysis to display visually intuitive overlays for fare stations, gates, egresses, and the train platforms his trip will lead him to. When he is unsure where to go next, Deng can raise his app to scan a sign and get a live translation, or he can approach an assistive robot. He uses his app to interpret his spoken questions and instructions and transmits them to the robots so they can understand his needs and guide him appropriately. With this help, he is able to confidently navigate no matter his destination.

Actor #5: App Developer

Reggie is an independent app developer who is working on a wayfinding app that can help travelers navigate busy streets and crowds. He wants to create a working prototype before getting funding to significantly expand its functionality and reliability, but until then his budget is tight and he needs to save resources wherever he can. He realizes that being able to test his app periodically will allow him to make smaller, more effective changes, rather than occasional big ones, and decides to use VR to lower the difficulty of procuring a testing environment. Reggie asks his testers to put on the goggles and take a virtual trip using a simulation of the app. This lets him track how they approach the service, understand use cases, and analyze how they respond to its directions, all without needing to find a real-life place to test or running the risk of one of his testers getting injured in a bustling crowd.

Relevant Research, Tests and Case Studies

Transit Applications

As current AI deployments are scattered, it can be difficult to get a sense of projects that have been put into practice. To get a sense of the state of the practice, the International Association of Public Transport (UITP) performed a survey of current AI applications in transit. As recounted by one interviewee, it found that most current AI applications were related to improving customer experience. For example, Transport for London (TfL) has implemented an AI-driven chatbot that can respond to questions and provide information to travelers. Other fields in which AI were being used included in optimizing demand prediction and vehicle dispatching.

Route-Planning

AI techniques such as Machine Learning can be used to create and refine user profiles and improve the overall user experience. One interviewee described the project Tiramisu, which was funded by NIDLLR and then spun off into a separate company. Tiramisu uses Machine Learning to generate and filter information displayed to travelers. The interviewee noted that it has proven to be particularly useful for travelers with visual or cognitive disabilities, as it reduces the amount of information that they need to sort through. The filters respond to different locations and times of day to customize its display. The program was deployed in 2011 and shifted to primarily use AI in 2018; it has thousands of users, though it is limited to Pittsburgh.

An interviewee noted that a particularly promising potential use of AI was in optimizing dynamic routing programs. For example, a system could apply deep learning while plotting the path of a pickup or delivery vehicle, or of on-demand transportation services like dial-a-ride or paratransit, and use data from previous trips to determine the route that would be the most direct and efficient. By building a nuanced profile of journeys executed in a wide variety of times and road conditions, the algorithm could account for many more variables than is currently possible.

Robotics

Multiple AI techniques can be used for accessibility robots in transportation hubs. For example, Machine Learning from human responses can be used to arrive at optimal behaviors, or more traditional AI techniques can be used to handle interactions such as transferring customers to different robots or kiosks. This is expected to make the use of assistive robotics more intuitive and approachable from a user standpoint, encouraging as wide a usage as possible. An interviewee noted that, while there are projects to implement this behavior, they are still largely in the proof-of-concept phase.

Text Processing

One interviewee noted that the use of AI in accessibility applications does not have to necessarily be limited to vehicles and train stations. It is also important that the information released by transit agencies, which can often be very information-dense, is easily accessible to all users. Many data-heavy documents such as bus schedules and operating budgets can be difficult for conventional screen-readers to parse. However, natural language processing can be used to present this information in formats that are much easier for users with visual disabilities to access and understand. Users would, for example, be able to ask queries in conversational language and receive context-sensitive answers. The interviewee noted that this concept was a projected capability rather than being currently implemented.

Potential Benefits

Using AI to address mobility for underserved communities has numerous potential benefits, including:

- Increased access to and utilization of transit
- Greater independence for users, including the ability to travel spontaneously
- Greater perceived reliability of transportation systemHigher access to employment and potential for higher earnings due to independent mobility
- Better access to ADL (activities of daily living), including community resources such as groceries, schools, and libraries
- Increased ridership/fare revenue of transit

- Increased cost distribution among providers of transportation services
- Increased use of multiple modes of transportation per trip
- Reduced crowding in transit stations
- Decreased travel time and improved reliability of travel and travel time estimates
- Increase in flexibility of travel services
- Increased number of trips taken by individuals
- Decreased cost of providing transportation for agencies
- Increased reliability of trip planners and wayfinders
- Improved public perception of transit agencies

Potential Barriers to Adoption of AI for Underserved Communities

There are several barriers and challenges that will have to be overcome in the course of pursuing AI implementations. These include:

- **Need for high-quality video:** Proper application of image recognition would require access to high-quality video feeds of targets
- **Training data:** Most machine learning techniques would find it difficult to respond to rare events or scenarios that were not present in training data
- **Data storage:** Many AI applications will generate large amounts of data, which agencies may find difficult to securely store and manage
- **Parsing spoken inputs:** Natural language processing applications may be inaccurate or insufficiently trained to interpret and respond to partial or accented phrases
- **Calibration:** Optimized wayfinding apps would have to be manually calibrated to ensure proper weighting of variables.
- **Data availability:** Many types of data that would be helpful are difficult to source or do not exist, and would have to be collected manually.
- **Training expenses:** Education and training would be costly but necessary for agencies to understand how AI differs from other tech applications.
- **Prioritization:** Agencies may be reluctant to even begin looking at AI, as they may consider other priorities to be more important.
- **Procurement:** Agencies need established procurement frameworks to begin the process of implementing and using AI applications.
- **Risk-aversion:** Agencies are typically very conservative with risk and may be unwilling to implement new or untested technologies.

- **Human error:** Operational error, such as delayed pickups or missed reservations, can cause optimized routes to lose their advantages, and must be dynamically corrected for.
- **Data readability:** Data provided by agencies is often tailored to human use, and must be de-abstracted in order to be machine-readable.
- **Problem-solving:** Developers should be sure to engage with stakeholders to appropriately identify problems and ensure that the solution meets users' needs.

Potential Value to USDOT

USDOT has significant opportunities in the field of AI, particularly as it relates to accessibility. Some of these include:

- **Opportunity for leadership:** USDOT can serve as a leading force through its investment, and effectively "set the agenda" of topics and applications to be addressed.
- **Qualitative benefits:** Funding research, pilots, and demonstrations can help to build a comprehensive body of work that makes AI more attainable and less risky for agencies to implement.
- **Peer-to-peer coordination:** Through guidance and knowledge-sharing activities, USDOT can help agencies across the country coordinate their efforts together, for example by centralizing a resource of benefits, best practices, and lessons learned.
- **Establishing confidence in AI:** Agencies are unlikely to make much investment in new technologies without a robust network of resources and support.
- **Get local agency buy-in:** Local and regional agencies must be on-board with AI for it to be effectively implemented. By prompting action in data collection and data sharing, USDOT can significantly impact even private-sector activities by widening the scope of potential deployments.

Chapter 9. Conclusions

Artificial Intelligence is revolutionizing every walk of life, allowing machines to learn from experience, adapt, and perform tasks that have historically required human cognition. The US government elevated AI as one of its key priority science and technology areas. In response, the ITS JPO established research in AI as a priority area to accelerate adoption of AI by state and local agencies for addressing transportation problems. As the USDOT embarks on advancing AI in transportation, it is essential to focus on high-value scenarios that can be used to motivate and inform stakeholders, accelerate the impact of AI deployment, and form a template for potential field tests and deployments that demonstrate the transformational power of AI. Otherwise, a scatter-shot approach may misinform stakeholders and unnecessarily demotivate deployment—simply because AI cannot be applied as a panacea with uniform results.

This report provided a description of five practical real-world scenarios where AI can be applied to address specific transportation problems. Relevant AI applications were identified based on a review of literature and interviews of public and private sector researchers and deployers of AI-powered applications.

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Appendix A. Volunteer Expert Stakeholder Questionnaire

This appendix shows the questionnaire used to interview the expert stakeholders.

Questionnaire

The United States Department of Transportation (USDOT) ITS Joint Program Office (JPO) has established research in Artificial Intelligence (AI) as a priority area to accelerate adoption of AI by state and local agencies for addressing transportation problems. The ITS JPO would like to identify practical real-world scenarios where AI offers the potential to address transportation needs. Towards this end, this interview is being conducted to discuss your experience using AI to address transportation problems, including the AI applications employed, types of data used, benefits experienced, challenges faced, and any lessons learned.

Your input is highly valuable and will help shape and inform future USDOT investments in AI.

INTERVIEW QUESTIONS

1. **Problem**: What was the specific transportation problem that was addressed or considered with AI?
2. **AI**: How was AI applied?
    a. **Applications**: Are you applying multiple AI applications to address this problem (e.g., AI-enabled adaptive signal control, dynamically priced lanes with AI-enabled demand prediction, AI-enabled ramp metering)?
    b. **Collaborators**: Are you collaborating with other agencies or universities?
    c. **Data**: What are the data requirements? What kind of data do you need? Do you need any proprietary data?
3. **Maturity**: What is the maturity (e.g., prototype, deployment) of the AI application?
    a. **Location**: Has this been implemented/deployed? If so, where?
    b. **Scale**: How large is the deployment (e.g., how many intersections)?
4. **Benefits/MOEs**: How did it improve the current state?
    a. **MOEs**: Have you measured the benefits? If yes, what improvements did you see? Did AI application help address the problem?
5. **Cost**: What is the rough order-of-magnitude cost estimates?

6. **Challenges**: What challenges or issues did you face? What challenges or issues do you foresee if the application were to be applied at scale?
7. **Lessons Learned**: What are some of the lessons learned? Will you broaden the geographic scope of the AI application?
8. **New Research/Concepts**: Are you funding or conducting research on the use of AI to address other transportation problems? If yes, what are those? Can you elaborate on ways we could be using AI to solve ITS problems? (NOTE: This will help USDOT shape future investments.)
9. **References**: Can you share with us documentation (e.g., published reports, papers, briefings) you may have on your research or implementation of AI for ITS problems?

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