ITS DEPLOYMENT EVALUATION

Executive Briefing

Data Collection and ITS

Highlights

- Advancements in image processing and video analytics capabilities have resulted in multimodal data collection including for vulnerable road users.
- Real-time traffic data collection assists TMC operators with critical decision-making.
- Data collected from roadside ITS sensors and detectors are used in many safety and mobility applications (both real-time and offline).

Introduction

Intelligent Transportation Systems (ITS) continue to evolve at an unprecedented rate with advancements in information and communications-based technologies (ICT) such as hardware, software, and connectivity technologies. ITS offers promising solutions via numerous applications and use cases to help achieve the U.S. Department of Transportation's (U.S. DOT) strategic goals, including improving system safety and mobility, providing sustainable transportation options, and enhancing overall system performance. [1] Sensors and detection technologies form the foundation of ITS applications. Advancements in sensor/detection technologies have enabled the generation and collection of large amounts of multimodal transportation data which serve as the building block of modern, data-driven ITS applications. Data from these sensors and detectors are used in both real-time operations applications, such as traffic management, parking management, adaptive signal control, adaptive ramp metering, automated fare collection systems, pedestrian conflict warning applications, etc. as well as passive or offline planning applications, such as traffic signal performance measurement.

This executive briefing will first discuss some of the advancements in roadway infrastructure sensors and detection technologies, the types of data collected, common ITS applications, and use cases. Table 1 shows traditional and emerging infrastructure-mounted sensors/detectors and associated ITS applications that are dependent on the data collected from these sensors. Subsequently, benefits, costs, and best practices associated with ITS sensors/detectors will be discussed followed by a success story.

This brief is based on past evaluation data contained in the ITS Databases at: www.itskrs.its.dot.gov. The databases are maintained by the U.S. DOT's ITS JPO Evaluation Program to support informed decision making regarding ITS investments. The brief presents benefits, costs and best practices from past evaluations of ITS projects.

U.S. Department of Transportation
Intelligent Transportation Systems
Joint Program Office

Last Modified: May 2025

Table 1: ITS Roadside Detection Technologies and Common Applications/Use Cases [2][3][4][5][6]

ITS Sensor / Detector	Types of Data Collected*	Example ITS Applications / Use Cases
Inductive loops, pneumatic road tubes	• Vehicle presence, count, and occupancy • Bicycle counts (dedicated bike lanes/spaces only)	• Travel time predictions • Intelligent lane control • Queue warning systems • Adaptive signal control • Ramp metering
Radars, microwave radars	• Vehicle count, flow, speed, direction of motion	• Traffic signal management • Signalized intersection counts • Traffic condition identification • Animal detection and warning systems
Magnetic sensors, magnetometers	• Lane occupancy • Vehicle presence and status (stopped and moving)	• Traffic surveillance on freeways, intersections, and parking lots • Truck parking management systems
Piezoelectric	• Vehicle classification, weight, and speed • Bicycle detection (dedicated bike lanes/spaces only)	• Weigh in motion applications • Bicycle counts • Pavement quality monitoring
Laser, infrared	• Vehicle speed, position, length, occupancy • Traffic flow • Pedestrian/bicycle counts	• Over height warning systems • Transit and pedestrian collision warning
Ultrasonic	• Vehicle tracking, presence, and occupancy	• Crash prevention • Intersection collision warning • Parking management
Bluetooth/Wi-Fi	• Travel time • Speed	• Real-time traffic condition • Speed limit violations
Weather sensors	• Surface temperature • Wind speed • Water film height	• Weather condition prediction • Road weather information system (RWIS) • Pollution management
Video/thermal cameras	• Object** detection, tracking, classification • Traffic flow and speed • License plate recognition • Incident detection	• Adaptive signal control • Wrong-way detection system • Crash/incident detection • Road user type classification • Red-light violation detection system • Active traffic management strategies
Radio-frequency identification (RFID)	• Vehicle tracking (tolls) • Fare collection (transit)	• Automatic tolling • Automated and contactless fare collection systems

* Additional processing may be required to convert raw input data from sensors/detectors into these data types
**Capable of detecting multimodal traffic counts including pedestrians and bicyclists

Advancements in ITS sensors, as shown in Table 1, have supported enhanced detection capabilities. These capabilities in combination with other technologies, such as Global Positioning System (GPS), LiDAR (Light Detection and Ranging), roadside units (RSUs), cloud/edge computing (AI/ML), etc., have allowed a plethora of ITS applications to emerge.

Benefits

Multimodal Data Collection

Traditionally, ITS sensors and detection systems have focused largely on the collection of motorized vehicle data. However, with advancements in sensing capabilities and AI/Machine Learning (ML), traffic data collection efforts have expanded to include other road user types, such as pedestrians and bicyclists. This has resulted in the development of several safety applications, such as camera-based pedestrian detection and alert systems (2021-B01611) and pedestrians in crossing warning systems (2022-B01675). A study conducted in Europe estimated that the mandatory deployment of vulnerable road user detection and warning systems using a variety of sensors on transit vehicles, including cameras and radars, can have a benefit/cost (B/C) ratio of 10.2 over a period of two years (2021-B01614).

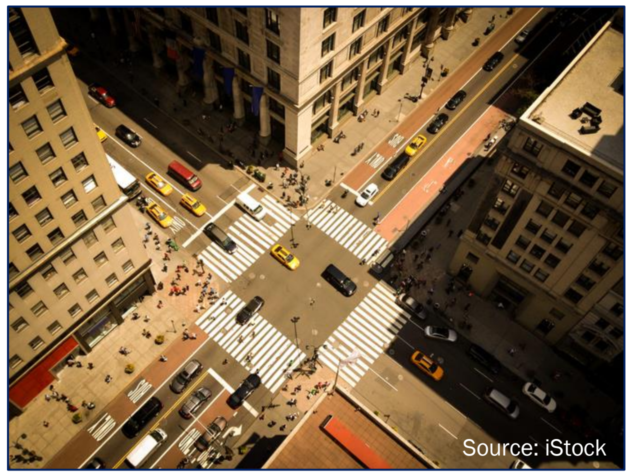

Figure 1: Bird's eye view of Manhattan representing multimodal transport system users.

Data for Real-Time Decision-Making

Real-time data collected from ITS sensors enable traffic management centers (TMCs) and operators to engage in active traffic management, locate and respond efficiently to incidents, and inform the traveling public of hazardous conditions. For example, a wrong-way detection system pilot project in Phoenix, Arizona utilized thermal cameras to detect and alert wrong-way drivers much faster than traditional 911 calls (time savings of 1 minute and 38 seconds on average). 90 thermal cameras were deployed throughout the 15-mile stretch of the I-17 corridor to detect and track wrong-way drivers. Data collected over a two-year period revealed that out of 109 wrong-way identified vehicle incursions, 88 percent of drivers self-corrected on an exit ramp (2022-B01618). Another AI-based roadway safety and work zone detection system uncovered 20 percent more crashes than previously reported and reduced law enforcement's crash response times by 9-10 minutes on average in Nevada. The AI platform utilized real-time data from a variety of ITS roadside infrastructure sensors, in-vehicle navigation devices, and a smartphone navigation app. Additionally, real-time data enabled predictive analytics to help identify areas that were at high risk for collisions, dangerous driving conditions, and traffic congestion (2022-B01642).

Offline Predictive and Analytical Engines

Enormous amounts of traffic data, such as speed, congestion, traffic volume, and incidents are being generated by roadway sensors. These data are collected via field devices, such as controllers and cabinets, and are sent to TMCs for cleaning, processing, and storage. While some of these data are used for real-time decision-making as well as offline analytics, a large quantity often remains on servers without being used. Recent advancements in data analytics and AI/ML have shown promising results in putting these historical or archived raw data to new use. For example, a statewide inclement weather forecasting model in Montana utilized historic data collected from RWIS sensors in combination with drone-based ice detection technology to improve forecasting accuracy. The data were collected and stored in a cloud database enabling web-based automatic data analysis for all the RWIS sites. The prediction models utilizing historic data improved the accuracy of average hourly ice forecasts from 62 to 82 percent, ensuring that de-icing activities took place during winter season more effectively and thereby reducing the possibility of vehicle crashes (2022-B01688). In another example, an AI-based traffic management pilot program in Las Vegas, Nevada utilized data from existing cameras, roadside sensors, and other traffic-related data to develop predictive analytics to recognize traffic patterns, which enabled traffic management professionals to implement timely countermeasures. Data collected during a one-year pilot program indicated that AI and deep learning strategies resulted in an around 17 percent reduction in primary crashes along Interstate 15 and also reduced emergency response time by up to 12 minutes (2020-B01507). Another study indicated the benefits of AI-based machine-vision algorithms and advanced analytics to identify collision near-misses, classify road user types, and detect speeding/lane violations in Bellevue, Washington. The study utilized video footage from a network of high-definition traffic cameras installed by the city (2022-B01617).

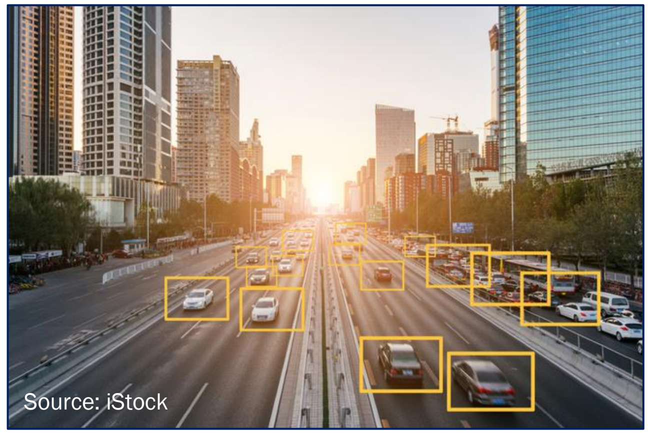

Figure 2: An application of AI/ML in transportation context: traffic surveillance and data collection.

Operations and Management Applications

Many safety and mobility applications have been deployed that rely on data collected from ITS sensors. For example, in Minnesota, a Dynamic Message Sign (DMS) displaying weather alerts based on the data collected from RWIS sensors, cameras, and friction sensors was associated with a statistically significant reduction in average speeds by 3.5 mph and 85th percentile speeds by 2.9 mph in the eastbound direction of the US 12 corridor. Temporary traffic sensors were installed upstream and downstream of the DMS location to gather data to assess the effectiveness of DMS-based weather alerts (2022-B01680). Additionally, several states have deployed statewide Truck Parking Information and Management Systems (TPIMS) across multiple rest areas to provide real-time parking availability information to the truck drivers. Parking detection systems include

Figure 3: Weather alerts and operational conditions being communicated to drivers via DMS.

video-based occupancy detection as well as in-pavement sensors like magnetometers and radar-based detections. For example, TPIMS deployment results from a study in Colorado indicated a B/C ratio of 7:1 (2018-B01256). In Minnesota, 67 percent of truck drivers indicated that the availability of real-time truck parking information resulted in their improved ability to find a parking spot (2019-B01340).

Costs

Table 2 shows various ITS detection systems, their associated capital costs, operations and maintenance (O&M) costs, types of sensors/detectors utilized, and their corresponding hyperlinked examples. The costs represented in Table 2 are for the detection systems comprised of various ITS sensors and detectors and are highly dependent on the location, types and number of sensors/detectors employed.

Table 2: ITS Detection System Costs

Detection System	Sensors and Detectors	Capital Costs	Yearly O&M Costs	Notes
Pedestrian and bicycle detection system	Passive infrared, inductive loops	$5,820 (2021-SC00502)	$10,000	Per site
Pedestrian and bike counters	Infrared, inductive loops, piezoelectric, pneumatic tubes, and camera	$21,600 (Pedestrian and bike counters)	$3,400	Sidewalk and bike lane counters, per site
Ramp signal video detection system	Thermal cameras	$10,500 (2021-SC00487)	$7,000	Thermal camera costs $2,800 per unit
Machine vision-based blind spot warning system	Camera	$5,000 – $6,000 (2020-SC00469)	-	Installation cost per equipped vehicle (buses)
Camera vision-based collision avoidance system	Camera	$8,900 (2020-SC00465)	$240	System hardware cost per bus
Work zone intrusion alert system	Radar, LEDs	$6,600 - $31,000 (2021-SC00488)	$1,200	Per work zone area
Road weather information system (RWIS)	RWIS sensors	$50,000 - $60,000 (2021-SC00491)	$2,600 – $4,600	Per new weather sensor location
Vehicle detection system	Microwave detectors	$45,845 (2021-SC00489)	$1,908	Per device per year
Wrong-way detection system	Radar, camera	$18,000 - $45,000 (2021-SC00501)	-	Per site
Truck parking information system	Magnetometers, microwave radars, video cameras	$2,000 - $30,000 (2020-SC00462)	$200 – $1,200	Per truck parking space (private and public rest areas)

Table 3 below shows example individual sensor/detector costs from a study published by the North Carolina DOT in 2021 (2020-SC00469).

Table 3: Individual ITS Sensor Costs (per unit)

Sensor Type	Sensor Cost
Active Infrared	$200-$7,000
Passive Infrared	$2,000-$4,550
Laser	$8,000
Micro-wave Radar	$5,000
Inductive Loop	$2,500-$4,300
Magneto-meter	$490-$540
Piezo-electric	$4,400
Pneumatic Tube	$2,200-$2,800
Thermal Camera	$4,800
Depth Camera	$9,900-$12,330

Best Practices

The choice of technology in solving a particular problem is of common interest. As with any technology, there are strengths and limitations in using different ITS sensors and detectors. Some ITS sensors may work effectively for one type of application but may not be the best choice for others. Furthermore, some ITS sensors have more intrusive installations (e.g., in-pavement sensors) than others but may yield more accurate traffic data collection results. Conversely, other sensors can be mounted on the roadside infrastructure but may not yield as accurate results. Often, several sensors/detectors may be used in combination to generate and/or collect the needed inputs for data-driven ITS Applications. Example best practices from recent deployments are summarized below:

- According to a study in North Carolina (2021-L01074), pneumatic tubes for **bicycle detection and counting applications** have yielded high system accuracy and low equipment installation costs. The study also recommended the use of passive infrared detectors for counting both pedestrians and bicycles. Another study in Louisiana utilized a **video-based automated pedestrian and cyclist counting system.** It suggests maintaining accuracy of cameras by accounting for varying circumstances (e.g., different light intensities, video time periods, motion patterns, etc.) and adding pedestrian and cyclist tracking to the algorithm for counting (2021-L01070). Another study in South Carolina suggests using thermal cameras to **detect pedestrians** in dark non-lit areas, as they can outperform CCTV night vision under conditions with low to no light (2021-L01076).
- A study in Illinois revealed that travel-time prediction models were more accurate using occupancy data from **loop detectors** when compared to other traffic variables collected and that particular

attention should be paid to malfunctioning loop detectors. This study suggested fusing traffic data from multiple sources to improve the accuracy of traffic prediction models (2022-L01136). Another study in Utah suggested that using data filtering techniques such as Kalman Filtering on loop detectors that report traffic flow and occupancy data improves the accuracy of queue length and wait time predictions that employ these data (2022-L01134).

- A study conducted in New York City suggested employing **quartz** weigh-in-motion sensors rather than traditional **piezoelectric** sensors for more reliable and accurate data collection (2022-L01125).
- Reducing **data latency** is of extreme importance for many real-time applications. A study in Iowa on a computer vision-based **wrong-way detection system** suggests determining the number of traffic cameras needed by analyzing data processing delays to balance system performance and costs. It also suggests considering cloud computing options for better data storage and faster analysis, thus reducing latency issues (2022-L01110).
- A freeway ramp metering application in California suggests keeping the **loop detection health close to 100 percent and data quality at 90 percent** or above at critical locations for successful operation of congestion-responsive freeway ramp metering strategies (2022-L01107).

Success Story

Researchers at the Connected Cities for Smart Mobility towards Accessible and Reliable Transportation (C2SMART) University Transportation Center developed a continuous, real-time pedestrian and bicyclist detection framework that leverages existing ITS infrastructure and computer vision [7]. Researchers used public CCTV traffic camera feeds and deep-learning-based video processing to analyze sidewalk and roadway densities. This framework allowed researchers to capture critical data on pedestrian, bicyclist, and vehicle densities without any additional infrastructure investment. Many innovative detection technologies require investment in new devices or infrastructure such as LiDAR or thermal sensors. In this project, video feeds (traffic data) from existing CCTV cameras in New York City (NYC) were used to detect multimodal road users with an emphasis on pedestrians and bicyclists. This approach offered a cost-effective, low-risk solution for data collection and analysis for decision makers. The low-resolution nature of existing CCTV camera feeds and conversion of vehicles, pedestrians, and bicyclists into untraceable objects helped preserve the road users' privacy. Because the project relied on pre-existing deployed ITS infrastructure, the estimated 3-year system deployment cost for a proposed pedestrian detection system with 68 cameras ranged from $500 to $1700 per year, depending on whether the data are being stored on local servers or on the cloud.

Leveraging existing ITS infrastructure such as CCTV cameras (video feeds) and using computer vision algorithms to process the subsequent data enables real-time object detection for different use cases, is cost effective, and is easily adaptable to other cities or states.

Figure 4: Multimodal data collection using CCTV video feeds and computer vision.

References

[1] U.S. DOT, "U.S. DOT Strategic Plan FY 2022-2026 ," 07-Apr-2022. [Online]. Available: https://www.transportation.gov/mission/us-dot-strategic-plan-fy-2022-2026. [Accessed: 11-Nov-2022].

[2] B. Hanson, "ITS Professional Capacity Building Program - ITS EPrimer - Module 9: Supporting ITS Technologies," 2014. [Online]. Available: https://www.pcb.its.dot.gov/eprimer/module9.aspx.

[3] Institute of Transportation Engineers, "Signal Detection for Bicycles ." [Online]. Available: https://www.ite.org/technical-resources/topics/complete-streets/bicycle-signals/signal-detection-for-bicycles/. [Accessed: 30-Nov-2022].

[4] National Association of City Transportation Officials (NACTO), "Signal Detection and Actuation, Urban Bikeway Design Guide." [Online]. Available: https://nacto.org/publication/urban-bikeway-design-guide/bicycle-signals/signal-detection-and-actuation/. [Accessed: 30-Nov-2022].

[5] Colorado DOT, "Non-Motorized Monitoring Program Evaluation and Implementation Plan," 2016. [Online]. Available: https://www.codot.gov/programs/bikeped/documents/nmm_toolkit.pdf.

[6] J. Guerrero-Ibáñez, S. Zeadally, and J. Contreras-Castillo, "Sensor Technologies for Intelligent Transportation Systems," *Sensors*, vol. 18, no. 4, p. 1212, 2018. https://doi.org/10.3390/s18041212.

[7] U.S. DOT, "Leveraging Existing Infrastructure and Computer Vision for Pedestrian Detection," *ITS Deployment Evaluation*. [Online]. Available: https://www.itskrs.its.dot.gov/sites/default/files/2022-03/case-study/Pedestrian%20Detection%20Case%20Study_FINAL_508_PDF.pdf.