Predictive Analytics for Traffic Management Systems

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Traffic management systems (TMSs) help transportation agencies manage roadway capacity as well as traffic demand to deliver safe, reliable, and efficient travel. As agencies look to actively manage their transportation systems, they turn to various analytic techniques—often embedded in decision support methods and tools—that help them better monitor those transportation systems, assess system performance, formulate responses, and implement the responses. This report focuses on predictive analytics, which refers to a class of analytics that develop and apply mathematical models to predict what may happen in the near or long term. The potential for predictive capabilities in traffic management is proven in the context of image and video analyses (e.g., incident detection), and significant research is under way for broader predictive analytics applications. This report explains how predictive analytics may improve the management and operations of TMSs and specific TMS functions, actions, and services. The report also lists issues when agencies are considering different potential paths to integrate prediction into the real-time operation of TMSs.</td></tr>
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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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LIST OF ABBREVIATIONS

AI	artificial intelligence
API	application programming interface
ATMS	advanced traffic management system
CCTV	closed-circuit television
CHART	Coordinated Highways Action Response Team
CRASH	Crash Reduction Analyzing Statistical History
DMS	dynamic message sign
DOT	department of transportation
DST	decision support tool
ETL	extract, transform, and load
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GPU	graphics processing unit
IaaS	infrastructure as a service
IMRCP	Integrated Modeling for Road Condition Prediction
IT	information technology
ITS	intelligent transportation systems
KC Scout	Kansas City Scout Traffic Management Center
MDOT	Maryland Department of Transportation
SaaS	software as a service
TDOT	Tennessee Department of Transportation
THP	Tennessee Highway Patrol
TIM	traffic incident management
TITAN	Tennessee Integrated Traffic Analysis Network
TMC	traffic management center
TMS	traffic management system
TPU	tensor processing unit
TrEPS	traffic estimation and prediction system
TSMO	transportation system management and operations
UI	user interface
USDOT	U.S. Department of Transportation
VDOT	Virginia Department of Transportation
VSL	variable speed limit
WSDOT	Washington State Department of Transportation

CHAPTER 1. INTRODUCTION

PURPOSE AND FOCUS

Predictive analytics is the process of using data and models to predict what may happen in the future. More specifically, it entails both the development of a model that uses historical data and the application of the model by the use of current data to forecast potential events or outcomes. The purpose of this report is to support agencies that are considering the integration of predictive analytics tools and methods into the active management and operation of traffic management systems (TMSs). Specifically, the report focuses on issues to consider, possible requirements to integrate, and potential opportunities to use predictive analytics in the context of real-time management and operation of TMSs. The report highlights current practices for considering, incorporating, and using predictive analytics in the planning of improvements to or the management and operation of TMSs. The report's objectives are to:

- Define predictive analytics.
- Explain how predictive analytics may improve the management and operation of TMSs.
- Explain how the use of prediction may improve the functionality, actions, and services of TMSs.
- Identify options for implementing predictive analytics in the real-time management and operation of TMSs.
- Identify issues to consider with regard to different potential paths that would integrate prediction into the real-time operation of TMSs.

This report provides an overview of ways agencies might consider with regard to predictive analytics in the management and operation of TMSs and traffic management centers (TMCs) to aid in a range of decisionmaking. Prediction in the context of TMSs will be delivered through decision support tools (DSTs), which use knowledge, data, and methods through offline or online interactions. Offline interactions may be computer or noncomputer based.

Knowledge-driven DSTs provide specialized problem-solving expertise based on the processing of stored facts, rules, procedures, and similar forms of knowledge. The tools attempt to emulate human reasoning but with more consistent results. Expert systems are the best known type. They use databases of knowledge generated by previous expert users and a system's business rules to emulate the decisionmaking capabilities of an expert user of the system. Based on that knowledge, such tools suggest actions to traffic operators. Knowledge-driven tools are different from table-based tools (e.g., decision tables) in the way knowledge gets extracted, processed, and presented. The knowledge-driven DST attempts to emulate human reasoning, while the table-based tool responds to all events in a predefined manner. The following are the primary characteristics of knowledge-driven DSTs:(1)

- Provide recommendations based on human knowledge.
- Apply a heuristic (i.e., practical or rule-of-thumb) technique for problem-solving.

Data-driven DSTs use data to aid in the decisionmaking process. They use data from databases that can be queried and that facilitate the processing and analysis of data to develop insights that support decisionmaking. Statistical analysis software is one of the most common types of DST. The effectiveness of a data-driven DST depends on the quality of the data gathered and the effectiveness of the decisionmaker's analysis and interpretation. Ongoing advances in the ways data can be accessed, analyzed, and visualized enable agency staff who do not have technology backgrounds to work with analytical tools, analyze data, and make more informed decisions. The following are primary characteristics of data-driven DSTs:[(1)]

- Summarize data into usable information.
- Use large amounts of data and have a well-organized way to query and visualize the results of the analysis conducted.
- Offer flexible reporting and analytical capabilities.

Model-driven DSTs use mathematical models and simulation tools that express the theoretical relationships between data elements or key variables of interest for the analysis being conducted. Such tools can be used online or offline to simulate the behavior of a transportation system or parts of a system by using different values for certain parameters. Model-driven DSTs use different types of analysis tools (e.g., statistical software and traffic analysis software) to assess the available data, evaluate the data, and report on conditions. Traffic analysis tools that use data captured by a TMS could be used offline or online to assess how a transportation network would perform based on various potential actions. Model-driven DSTs can be used in real time as parts of a TMS to predict the possible outcomes of actions an agency's TMS is considering implementing, thereby enabling the agency to assess impacts on key metrics like travel time, environment, and person and vehicle throughput. The following are primary characteristics of model-driven DSTs:[(1)]

- Provide what-if analysis based on historical and assumed (e.g., scenario-based) data.
- Apply algorithms, simulation, and optimization tools to provide decision support.
- Use data and parameters provided by decisionmakers to help in the analysis of a situation but without the need for intense amounts of data input.

Examples of those approaches and interactions are classified in table 1, modified from Federal Highway Administration (FHWA) report *Decision Support Methods and Tools for Traffic Management Systems*.[(1)]

Table 1. DSTs mapped to decision support classifications.[1]

Approach	Incident Response Plans	Decision Trees	Performance Measurement Tools	Real-Time Traffic Analysis Tools	Lookup Tables
Knowledge driven	Yes	Yes	No	Yes	Yes
Data driven	No	Yes	Yes	Yes	Yes
Model driven	No	No	Yes	Yes	No

Examples of noncomputer-based, offline DSTs, illustrated in table 1, are incident response plans and paper-based decision trees that can be printed and collated into reference information. Offline tools generally support decisions associated with short-term and long-term activities. Performance measurement dashboards that summarize or report data are examples of computer-based offline DSTs.

In contrast, online DSTs are real-time and computer based. Examples of computer-based online DSTs include a range of traffic analysis tools. With agencies' greater and greater access to data and computational capabilities, current knowledge-driven and noncomputer-based DSTs such as incident response plans may indeed evolve to become informed by data- and model-driven information such as origin–destination analyses and transplanted to computer-based systems. As DSTs shift toward data- and model-driven computer-based tools, the importance of computer-based DSTs grows, along with their potential to both improve traffic operations personnel real-time decisionmaking and enhance TMSs' operational capabilities.

Computer-based DSTs have the potential to process vast amounts of data, replicate an agency's operational processes, and support the decisionmaking of TMSs or operators at TMCs. DSTs can aid operations personnel with monitoring and assessing conditions (e.g., environment, facility, and network), detecting and verifying incidents, and identifying and evaluating appropriate response strategies for planned and unplanned events. DSTs also can help agencies achieve more consistent decisionmaking between staff involved in managing traffic, TMC operations staff, and TMSs.

In the context of DSTs, embedding predictive analytics represents taking a model-driven approach through computer-based interactions. As is the case for the broad set of computer-based DSTs, predictive analytics has the potential to improve the real-time decisionmaking of traffic operations personnel and enhance the operational capabilities of TMSs.

Ever-increasing access to traffic data—in both volume and variety (e.g., connected vehicle, unmanned aircraft systems, and lidar)—and the expanding operational strategies available to agencies are increasing the complexity of making operations-related decisions in realtime. Thus, an agency introducing any new DST at a TMC or in the broader transportation operations organization must consider whether the tool eases or adds to complexity and decisionmakers' workload.

As agencies plan for the next generation of their TMSs, planning typically includes consideration of possible enhancements to improve the performance and decisionmaking capabilities of the agencies' TMSs. The potential use and incorporation of DSTs into TMSs are appropriate to consider in the planning, design, and development of improvements to a TMS or in the preparation for a new TMS. TMS capability enhancements may include access, integration, and the use of new sources of data by adding or expanding data subsystems. New TMS capabilities may include the addition of new DSTs and physical components or subsystems. As agencies plan for the next generation of their TMSs, including the incorporation of predictive analytics, they must place at the center the need to improve the capabilities and performance of their TMSs so as to improve roadway operations, support agency efficiency, and meet broader organizational goals.

This report benefits a range of practitioners involved in the planning, design, implementation, management, and operation of TMSs, including:

- State departments of transportation (DOTs), local agencies, metropolitan planning organizations, regional authorities, toll authorities, and other organizations that manage or support TMSs.

- Key public agency professionals, including TMS managers, performance management groups within DOTs, information technology (IT) departments, and data governance groups.

- Contractors, consultants, and researchers.

CONTEXT FOR PREDICTIVE ANALYTICS

Predictive analytics are complex analyses of data through the use of mathematical models. Predictive analytics often encompasses advanced statistical techniques in the analysis of historical data to find usable patterns and trends. The found patterns and trends support the development of mathematical models that demonstrate sufficient statistical fit to generate predictions based on current data. Results from the application of predictive models using real-time data predict outcomes that help decisionmakers or even a TMS component take an action. Noteworthy in the evolution of predictive analytics are three factors:

- The availability and accessibility of tools that support analyses and visualizations.
- The availability of computational power to support real-time analyses.
- The availability of data in volume, granularity, and quality that support analytics and in particular, the development of predictive models.

A TMS is a system that comprises a complex, integrated blend of hardware, software, processes, and people performing a range of functions and actions. TMSs are complex operational systems that deploy and use technology—such as field equipment, advanced communications, IT, and software tools. TMSs collect and synthesize traffic data, integrate external systems, and facilitate the command and control of intelligent transportation system (ITS) field devices.(2) Further, TMSs are staffed with operators who actively manage and perform a range of functions and actions that facilitate improvements in the efficiency, safety, and predictability of travel in a surface transportation system.(2)

Predictive Analytics in the Context of TMS

Effective traffic management requires both active traffic management, which provides dynamic and adaptive adjustments to changing current and future conditions, and management of the TMS, including data, software, hardware, processes, and staff.[(3)] Active traffic management involves a cyclical process and framework to manage the performance of the transportation network. The cyclical process and framework consist of:

- Monitoring system performance.
- Assessing and predicting system performance.
- Proposing dynamic actions.
- Selecting and implementing the selected actions.

The levels of responsiveness in the active management framework context are:

- Static—Responses to variations in conditions that are preset and updated based on the calendar.
- Reactive—Responses that occur in regard to observed problems with the static plans requiring real-time monitoring.
- Responsive—Responses to variations in conditions that occur in realtime after they are detected.
- Proactive—Responses that get adjusted in anticipation of future conditions.

Predictive analytics has the potential to help traffic operators and managers by bringing efficiencies to the active management cycle and advance responsiveness from static and reactive to responsive and proactive. The application of predictive analytics could assist in the real-time formulation of proactive changes to the management and operation of different strategies or control plans. In the past, most agencies implemented static operational strategies that reflect temporal variations (e.g., time of day, day of the week, or seasonal trend).

Advancements in data quality and coverage along with advances in data management and processing practices have enabled agencies to move toward reactive, responsive, and proactive levels of operational strategy implementation.[(3)] For example, predictive analytics could estimate the length or duration of a traffic queue along a roadway associated with a crash, a work-zone-related lane closure, or adverse weather. Or the predictive model might be developed specifically for roadway crashes. That narrower, crash-specific prediction may support traffic incident management (TIM), traveler information, or queue-warning operational strategies and their related functions such as disseminating traveler information or providing coordination between agencies. Specific to a function will be such actions as sending data to another system, calling an incident response unit to set up advance warnings, or displaying public advisories on dynamic message signs (DMSs) regarding predicted queue length. The specific code or algorithm that predicts queue length or duration may reside as a stand-alone software with only a user interface (UI) that requires human operator inputs. Or the algorithm may be housed within the TMS software subsystem and include application programming interfaces (APIs) that interact with a data subsystem to directly ingest incident and roadway-specific data needed for prediction or a traveler information component such as a DMS.

A few agencies have developed, have implemented, and are using prediction tools to support TMC operations. When the tools are in use, they are generally stand-alone systems. TMC operators may be required to manually input information to generate the prediction, interpret the information, and take actions involving the use of different operational strategies, control plans, or sharing of information with other systems or service providers.

Of note, a handful of vendors cite the use of predictive analytics in their product offerings. Many have since removed such terms as predictive analytics from their product features, finding the predictive capability unable to match the skills of an experienced operator. In the products reviewed, the methods used for predictive analytics are proprietary—meaning that no information is available on the data or methods used for developing the prediction model, on the fidelity of the predictions, or on the factors that may affect prediction fidelity. Such products are essentially black-box offerings, with no information on the analytical methods or data they use. A software product implemented in Pittsburgh, PA; Atlanta, GA; and Portland, ME, is an example. The product supported the coordinated operation and optimization of traffic signals by predicting traffic volumes in realtime to improve safety and traffic flow. The product used data collected from video detectors incorporated into an algorithm that adjusted signal-timing plans at intersections to foster coordination operation. Because the product is proprietary, information is not available on kinds of data are collected, what prediction is occurring, or how the prediction is being incorporated into the adjustments being made to the signal-timing plans at each intersection or being made to improve travel between traffic signals.

Predictive Analytics Beyond the TMS

The education, energy, healthcare, and retail industries are using predictive analytics for offline applications to improve different programs, services, and applications. For example, to mitigate higher than expected readmissions for specific clinical conditions and avoid Centers for Medicare & Medicaid Services penalties for high readmission rates, an enterprise applications provider conducted big-data analyses, developed and deployed predictive models, and created a UI to incorporate the model into clinical workflow. The provider based models on historical patient data and socioeconomic data to bring to the hospital staff's attention those patients with high readmission risk. The staff's use of the model reduced occurrences of patient readmission by 6,000, avoided $4 million in Medicare penalties, saved $72 million in medical costs, and improved resource use by focusing on high-risk patients.[(4)]

Predictive analytics already benefits a variety of different types of online and offline transportation decisions. For example, transit agencies use algorithms to predict and share real-time bus and train departures and arrivals. While that function has traditionally used simple linear interpolation algorithms based on average time-of-day speeds, it now uses a blend of historical and real-time speeds along with precise bus location data to predict arrival times with high accuracy. With the prevalence of bus location data and the incorporation of predictive analytics into the real-time management and operation of a transit management system, the prediction of transit arrivals, departures, and travel times becomes possible.

The services are typically incorporated into a proprietary software program or service that transit agencies procure or subscribe to for a fee. Similarly, predictive analytics has enabled freight and fleet operators to use virtual diagnostics and historical vehicle maintenance data to predict the likelihood of vehicle wear and tailored preventive maintenance decisions, resulting in longer in-service times. Pavement management systems also use predictive models to prioritize and implement preventive maintenance strategies or treatments to extend the lifecycles of roadways. Common among the models are both the use of historical data to develop and test models and the application of those models with real-time information to formulate a prediction that supports an operations action.

Evolving TMSs and Predictive Analytics

The use of predictive analytics in TMSs is expected to incrementally evolve in complexity and in the ways the information might get used (e.g., offline traffic analysis and support) in TMSs. In the course of time, time-predictive analytics has the potential to support the active management and use of operational strategies, functions, actions, and services. Given the potential benefits of incorporating predictive analytics into the online, real-time operation of TMSs, value accrues in raising awareness of these potential future benefits with staff responsible for traffic management, TMSs, and transportation system management and operations (TSMO) programs. Important to understanding the potential benefits of implementing and using predictive analytics in the real-time management and operation of a TMS are the challenges and costs of developing, integrating, maintaining, and supporting the use of such tools. Integrating and using the tools in realtime require changes to the physical (e.g., subsystems and components) and logical (e.g., operational strategies such as ramp metering, functions such as detection of incidents, and actions such as confirming incidents) structure of a TMS.

While predictive techniques continue to be developed, tested, and refined for TMSs, they have not yet become incorporated into the online or real-time management or operation of TMS services, functions, and actions. The current lack of TMS-integrated predictive analytics applications will remedy as agencies invest in updates to or replace components of their TMSs.

Agencies have begun to include requirements for capabilities and structure in support of incorporating online prediction into the next generation of their TMSs. For example, as part of a broader transportation-monitoring program known as the Regional Multimodal Mobility Program in northern Virginia, the Virginia Department of Transportation (VDOT) is procuring a TMS with the ability to monitor traffic and other conditions so that the department can identify, verify, and predict changing conditions that may affect traffic in northern Virginia and the Fredericksburg metropolitan area. The intended advanced prediction capabilities will forecast travel conditions some minutes into the future and enable their TMC operators to proactively respond with a view to prevent or mitigate predicted issues. Information on a specific prediction and how it would function is not yet available.[(5)]

The changes to the physical and logical elements of a TMS also will affect the subsystems, components, and day-to-day services (e.g., maintenance, repairs, monitoring, evaluation, and reporting) supported by a TMS and the supporting program (e.g., policies, procedures, and staff support). Implementing predictive analytics into a TMS (online or offline) may involve a review of the policies, procedures, and decisionmaking of the program supporting the TMS, specific processes conducted during the lifecycle of the system, or specific actions.

Further, different human cognitive skills may be required to interpret the outputs of predictive analytics, particularly with regard to the strength of the model. For example, the model may be far stronger at predicting outcomes from certain incident types or geographic areas (e.g., data-rich corridors) compared with others. Without information about and understanding of the strength of a prediction (e.g., the likelihood of the prediction's certainty and precision), the decisionmaking may treat all predictions equally. And by doing so, an operator may take actions that perhaps would have benefited from further reflection. Human factors implications for TMS managers and operators also have to be considered to ensure that information gets delivered in a timely, informative, and actionable way—without overloading the operator. Lastly, the introduction of predictive analytics may markedly change TMS workflow, workload, and operator-versus-semiautomated decisionmaking.

ORGANIZATION OF REPORT

This report is organized into seven chapters that guide the reader through definitions and context, technical requirements, implementation considerations, use cases, and future directions as follows:

- Chapter 1. Introduction. This chapter provides an overview of the purpose of the report, the audiences that would benefit from reading this report and introductory information on TMS and predictive analytics.

- Chapter 2. How Prediction Can Improve Traffic Management System Operations. This chapter explains how predictive analytics could improve TMS actions and services as well as the deployment of operational strategies.

- Chapter 3. Options for Implementing Predictive Analytics. This chapter presents options to consider regarding how predictive analytics might get integrated into the management and operation of TMSs.

- Chapter 4. Predictive Analytics Considerations. This chapter presents the high-level requirements and issues to consider in an assessment of options for implementing predictive analytics within a TMS, taking into consideration current TMS capability, resources, funding, and data.

- Chapter 5. Readiness Checklist. This chapter provides information on the range of issues to consider in support of assessing, selecting, obtaining, integrating, and using predictive analytics in the management and operation of TMSs.

- Chapter 6. Case Studies: Using Predictive Analytics to Manage Traffic. This chapter describes how agencies have developed predictive analytics tools, the tools' capabilities, the enhancements the tools provide, and the challenges associated with integrating the tools into the agencies' TMSs.

- Chapter 7. Trends, Issues to Consider, and Future Direction. This chapter previews trends and forthcoming advances that may support agencies' ability to assess and use predictive analytics services. The chapter also summarizes knowledge gaps for the integration of predictive analytics within TMSs.

CHAPTER 2. HOW PREDICTION CAN IMPROVE TMS OPERATIONS

This chapter transitions from the introduction provided in chapter 1 to predictive analytics in the context of TMSs' current decisionmaking processes, tools, operational strategies, functions, actions, and services. The chapter first defines predictive analytics in the context of DSTs and operational strategies. Next, the chapter summarizes TMS structure—clarifying a TMS' physical and logical elements—with specific focus on elements within data and software subsystems predictive analytics that may be incorporated. Data requirement details and further discussion are in chapters 4 and 5. Chapter 2 ends with an example of the Florida Department of Transportation's (FDOT's) integration of data into the department's TMS data subsystem, the relationship of a software subsystem, and the potential of predictive analytics in a TMS.

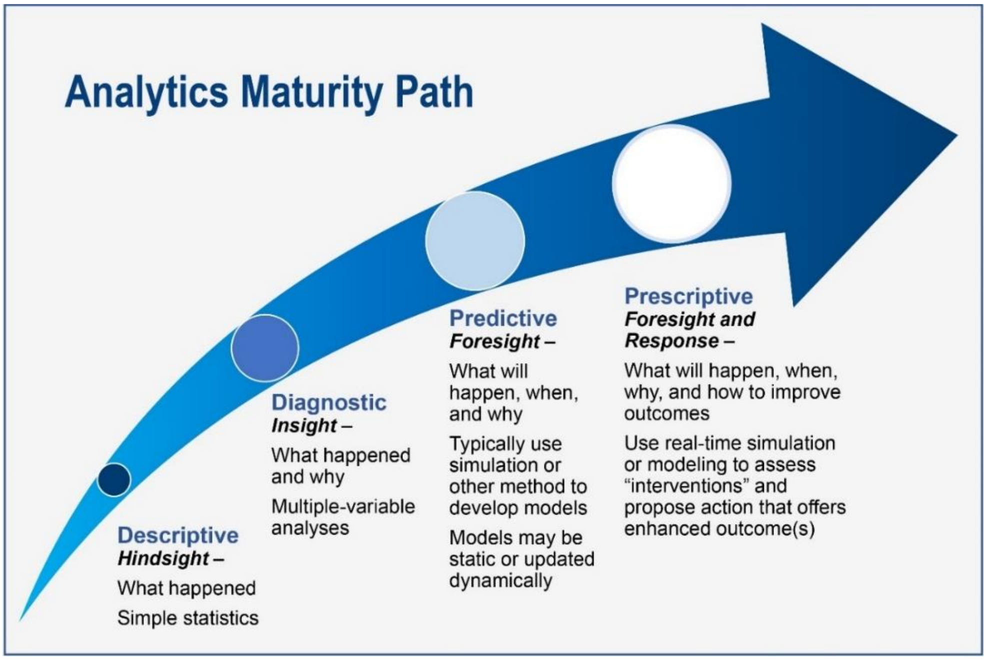
Central to the pursuit of all data analytics are, first, an understanding of the need—whether for a specific operational strategy, function, or action. Second is an understanding of how an existing function, action, or service currently supports that need and what data are already engaged. Third is an understanding of what new or modified function, action, or service might better support the need. After all that, agencies can begin to explore whether available data can be analyzed and how analytics might get embedded within the TMS to support the need and improve operations.

PREDICTIVE ANALYTICS: DEFINITION AND CONTEXT

Often, such terms as predictive analytics, machine learning, and artificial intelligence (AI) are used interchangeably, and even though they are related, they differ from one another. This section first defines and provides examples of predictive analytics in the context of the range of data analytics without delving too deeply into detailed methodologies or classes of techniques. The following section discusses predictive analytics and the relationships between commonly used terms such as machine learning and AI.

Predictive Analytics in the Context of Data Analytics

Broadly, data analytics is the science of examining datasets to identify patterns, provide answers to inquiries, and draw inferences. Data analytics makes use of specialized software, automated processes, and algorithms. The realm of data analytics can be organized into four ordered categories with advancing-capability maturity: descriptive, diagnostic, predictive, and prescriptive analytics (figure 1). Generally, that ordering reflects the need for proficiency in one before advancing to the next. Each category is highlighted in the figure, with examples related to traffic operations.



Source: FHWA.

Figure 1. Illustration. Analytics maturity path illustrates four classes of analytics.

Descriptive analytics, the type of analytics most frequently used in TMSs, involves the analysis of data collected by TMS components to describe real-time, current-state conditions, historical conditions (i.e., daily, weekly, monthly, quarterly, or yearly), and trends (i.e., temporal and spatial changes). Common descriptive analytical measures include counts (e.g., traffic volume, active incidents, customer complaints, and active snowplows), averages (e.g., segment speed and travel time), and deviations from average or percentages (e.g., delay, travel time reliability, and percentage of devices online).

Descriptive analytics provides insights into the historical and current states of a transportation system. Descriptive analytics can support real-time decisionmaking when viewed by operators with expertise to interpret the data. For example, if the real-time traffic flow or average speed on a road segment declines, an operator may decide to access a closed-circuit television (CCTV) feed in the proximity of the road segment. Conversely, historical descriptive analytics provide insights into policies, processes, staffing, and management decisions. For example, operators may use percentage online data to prioritize sensor maintenance or may choose to modify safety service patrol routes based on the spatial and temporal frequencies of incidents. Such analytics are common with TMS data subsystems as well as with online and offline DSTs. Descriptive analytics supports various operational strategies, functions, and actions.

Diagnostic analytics is the process of using data to determine the causes of trends and correlations between variables. Diagnostic analytics helps organizations better understand the internal and external factors that affect outcomes. From a transportation perspective, diagnostic analytics may explore integrated data to clarify whether a descriptive statistic suggests an anomaly rather than a natural variability in the data. The integration of data may inform how weather patterns or events, planned special events, holidays, shifts to telework, or workforce training or turnover affects operations.

Diagnostic analytics is frequently a component of a TMS data subsystem and informs policies, processes, staffing, and management decisions but also can be embedded in TMS subsystems to reduce TMS operator workload and the time required to monitor and assess transportation performance. For example, an advanced TMS could include subsystems with logic that makes prominent on a TMC monitor wall the CCTV feeds closest to road segments where diagnostic analytics identified an anomaly based on multiple criteria—such as when traffic volume and speed from a sensor deviate by a temporal threshold and event data from a free navigational application show reports of debris on the roadway. Note in that example that anomaly detection applies diagnostic analytics; however, the translation of that detected anomaly to the logical action to display a camera is not diagnostic analytics but, rather, a process rule. Similarly, TMS software that proposes a set of candidate DMSs and even message sets based on the operator's entry of incident location and other data are not using diagnostic, predictive, or prescriptive analytics. Rather, the software is applying logic rules based on proximity and directional logic.

Predictive analytics, the focus of this report, makes a significant leap beyond descriptive and diagnostic analytics by developing and applying mathematical models to make statements about the future state of a system. "Mathematical modeling" refers to the development process of creating a mathematical representation of a real-world scenario to make a prediction or provide insight. "Simulation" typically refers to application of the mathematical model. Predictive analytics can answer questions in realtime or for operations management, such as:

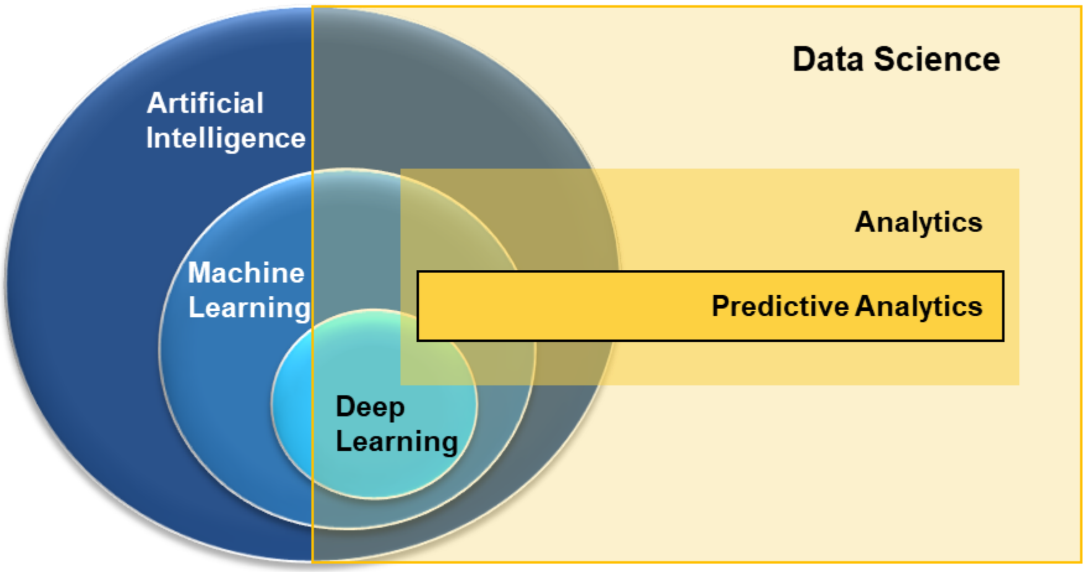
- How long will the roadway be blocked for this crash?
- Does this image show a vehicle traveling in the wrong direction?
- How many or which devices may fail in the next 3 mo?

Figure 1 shows that prescriptive analytics proposes what will happen, when, and even why. In contrast, diagnostic analytics identifies what happened and why. In developing and applying mathematical models to predict outcomes, operators may use traditional statistical methods such as regression or more advanced methods in the realm of machine learning and broader AI. The fidelity of the prediction depends on many factors, but at its core is a function of data quality (e.g., accuracy, completeness, reliability, relevance, and timeliness) and model quality (e.g., robust, precise, descriptively realistic, accurate, generalized, and useful). Traffic Management System Structure outlines the ways predictive analytics could support TMS management and operations.

Prescriptive analytics goes one step further than predictive analytics by prescribing a real-time operational change, prescribing a change in processes, or even enacting the change through automation—with a human in the loop to interrupt the automation. Prescriptive systems may entail the simulation of multiple alternatives, refined to reach a proposed action. Autonomous vehicles use neural network models (a class of flexible nonlinear regression and discriminant models, data reduction models, and nonlinear dynamical systems) to make calculations in realtime that help a vehicle make a decision similar to one a human driver would make. In a TMS, prescription analytics could be applied to improve dynamic tolling that optimizes mainline and managed lanes.

Predictive Analytics in the Context of Commonly Used Terms

This subsection places predictive analytics in the context of commonly used terms—often as buzzwords—to clarify that predictive analytics may be performed by using traditional and newer data; that it may use AI, machine learning, or deep learning; or that it may not. Figure 2 illustrates the terms, and definitions and key takeaways follow.



Source: FHWA.

Figure 2. Illustration. Commonly used terms and relationships in setting the predictive analytics context.

AI, a term coined by John McCarthy in 1955, which he defined as "the science and engineering of making intelligent machines."[(6)] Today, "AI" generally refers to the branch of computer science involved with building smart machines capable of performing tasks that typically require human intelligence. AI includes a range of techniques such as machine learning and deep learning.

Even though AI technologies have existed for several decades, the technologies' increasing volumes, varieties, velocities, and veracities of data have enabled AI techniques and applications to transform industries. And while predictive analytics has existed for more than a century, its resurgence focuses on taking advantage of the new data and AI.

Machine learning, a subset of AI, focuses on building methods that "learn" based on experience or data. Machine learning can use mathematical models such as regression, classification, clustering, and natural language processing. Machine-learning algorithms may include supervised learning, wherein a model learns to predict human-given labels; unsupervised learning, which does not require labels; and reinforcement learning, wherein the model does not require labels and autonomously strives to optimize. Again, data with greater volumes, varieties, velocities, and veracities are key to robust machine-learning models. Moreover, machine learning supports a range of analytics, including prediction.

Deep learning is a subset of machine-learning algorithms that use a brainlike logical structure of algorithms called artificial neural networks, which capture nonlinear patterns in data. Neural network models of the past had failed due to lack of data with sufficient volume, variety, velocity, and veracity, as well as due to lack of computing power. With the growth in the volume, variety, velocity, and veracity of data and the growth in cloud computing power, deep-learning techniques have been successful in the areas of vision (image classification), text, audio, and video.

With regard to data growth, data are growing larger, being delivered faster, and becoming more complex (unstructured), which can make the data difficult—or impossible—to process in a timely manner by using traditional computational methods (e.g., a personal laptop). Examples of such data in transportation with respect to volume, velocity, and variety are archived, connected-car data, which can be a few terabytes per month; real-time data vehicle probe data with dynamic segmentation; and unprocessed lidar or video data such as CCTV or unmanned aircraft systems. Those data also can offer complexity through the lens of veracity. For example, event reports from a free navigational application have greatly varying accuracy based on number of vehicles on the roadway that are using the application, because the number of vehicles changes by time of day. Predictive analytics—when used with these newer, high-volume, variety, velocity, and veracity data—requires changes in the ways data are managed and changes in the tools that support modeling. Traditional predictive analytics (e.g., simple regression models) may be used for developing predictive models and applying the models to support functions and actions within a TMS.

Predictive analytics, as noted in Predictive Analytics in the Context of Data Analytics, is one class of analytics. Predictive analytics is typically used in the field of data science, which begins with an understanding of business needs, collection of data, and the use of statistics, scientific computing, scientific methods, processes, algorithms, and systems to extract or extrapolate knowledge and insights from noisy, structured, and unstructured data.

Figure 2 shows that data science does not require the use of AI, machine-learning, or deep-learning computational techniques. Likewise, the development and application of predictive models, or predictive analytics, does not necessitate AI, machine-learning, or deep-learning techniques and tools. Before exploring those computational techniques, agencies must establish confidence in and gain mastery of descriptive statistics. Too many examples of the application of those advanced computational techniques yield models that show great so-called fit but are flawed in their logic. For example, a machine-learning technique to differentiate dogs from wolves was found to be highly accurate in its prediction; however, researchers later found that the model was based on the presence or absence of snow in the image. Likewise, machine-learning application to differentiate cancerous versus noncancerous growth relied on the presence of a tape measure in the image.

TMSs use mainly real-time and historical data and descriptive and diagnostic analytics to describe current conditions and to make decisions about operational strategies. Some TMSs provide simple decision support heuristics, but generally, the systems do not include models that learn or self-correct. Some TMSs are now using smart infrastructure such as commercial traffic signal control that may apply prescriptive and optimization that uses AI; however, the optimizations are through black-box capabilities, which offer limited to no visibility with regard to the algorithms or methods applied. While predictive analytics is not currently used in most TMSs, it represents the next level of analytics that could help TMSs support safer, more efficient transportation operations.

A key consideration in the maintenance of predictive analytics models is that they require regular monitoring, refining, and updating based on changes in the data. Predictive analytics models are not one-and-done exercises. Rather, predictive analytics models must be routinely reassessed and retuned as travel behaviors, event frequencies, and response strategies shift. Predictive models based on big data must be continuously monitored given that small changes in data can produce significant changes in predictive analytics model fidelity, which stands in contrast to traditional models such as linear regression based on a far smaller volume of data that do not change much even with minor shifts in data quality.

TRAFFIC MANAGEMENT SYSTEM STRUCTURE

This section summarizes the key terms, frameworks, and concepts outlined in a report, *Review of Traffic Management Systems—Current Practice*, by Kuciemba et al., which are relevant to understanding how and locating where predictive analytics may fit within the broader structures of a TMS, including technologies, tools, operational frameworks, and procedures.(3)

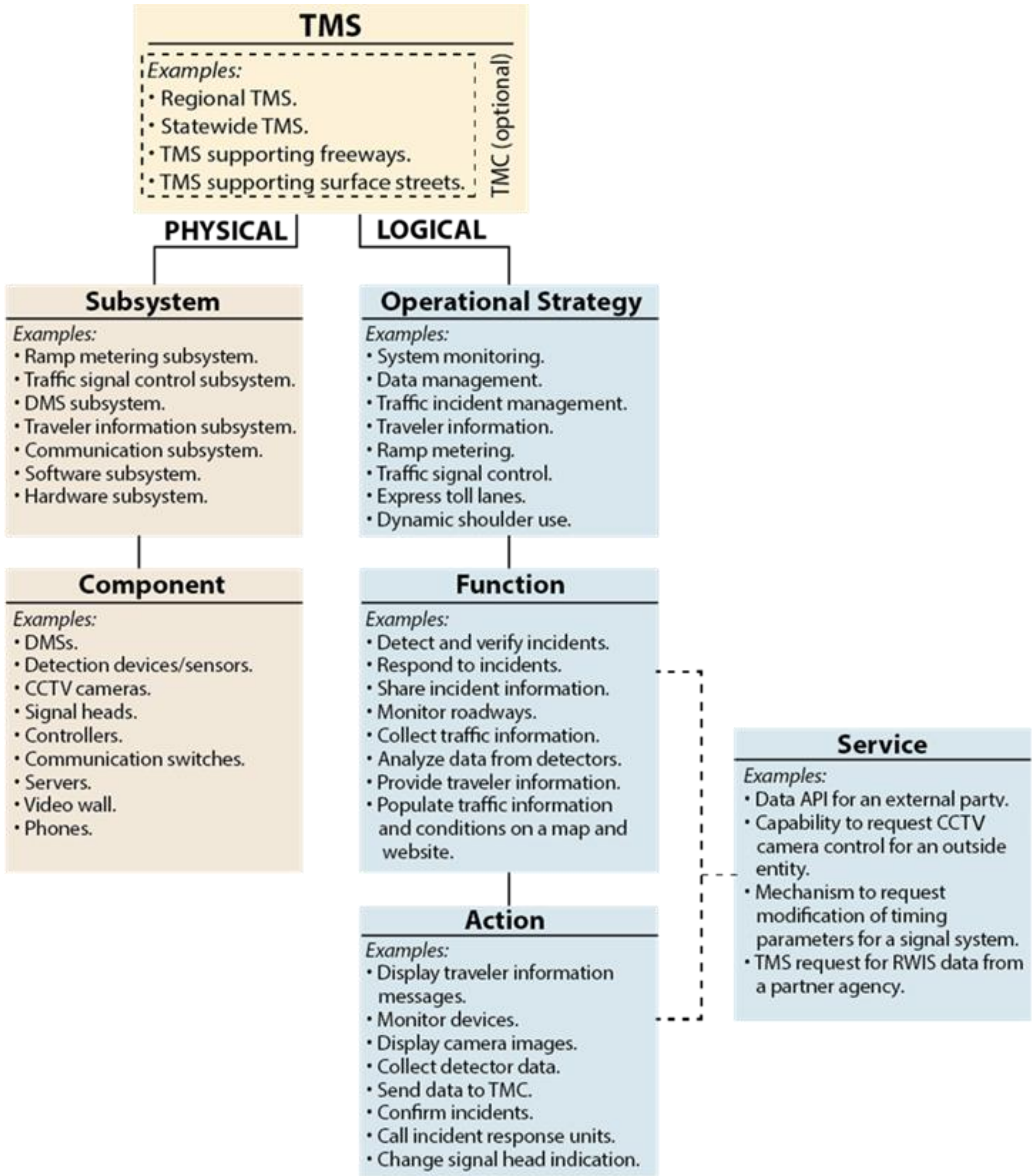
More complex TMSs comprise multiple subsystems. Figure 3 diagrams a flowchart of a TMS with examples. The lines in figure 3 depict the structure's relationship for both the physical elements and the logical elements of a TMS; the lines do not depict a flow of data or information. As noted in the preceding section, Context for Predictive Analytics, TMS structure is composed of physical elements and logical elements. The physical elements are the subsystem and components. The logical elements are the operational strategies, functions, actions, and services.

The TMC is an important component of operating a TMS because it is typically the location where the TMS's physical elements connect to one another, connect to communications and computing power, and typically house TMS operators. In figure 3, the TMC is illustrated at the right within the upper gray box, signifying that it spans both physical and logical elements. The following subsections delve into the physical and logical elements of a TMS.

Physical Elements of a Traffic Management System: Subsystems and Components

The physical elements in the TMS structure are shown on the left side of figure 3. The physical elements carry out a specific operational strategy (e.g., ramp metering subsystems) and can be organized as subsystems and components.

The subsystems constitute a group of self-contained and interactive components that support one or more operational strategies. Examples of common subsystems that compose a TMS are ramp metering, traffic signal control, DMSs, and communications. Subsystems have become increasingly complex as technology and components have evolved. Other subsystems (e.g., data management subsystems and CCTV subsystems) are designed to support and interact with multiple subsystems and operational strategies (e.g., TIM and traveler information).



Source: FHWA.
RWIS = Road Weather Information System.

Figure 3. Diagram. Traffic management system with examples.[(3)]

Components include devices or hardware elements that serve purposes as parts of a larger subsystem or TMS. As these technologies and components have evolved, so too have the operation, management, and maintenance of the systems.

Components from the subsystems can range from changeable message signs, detection components, CCTV cameras, signal heads, controllers, and communication switches to other computer technologies. The components may work either in isolation from one another or together with components serving other subsystems to perform functions that achieve the overall objectives of the system.

The selection of ITS components and technologies is guided by the concepts of operations, use cases, and operational strategies the TMS may implement; the subsystems and how the components are linked (e.g., via APIs) to the subsystems; and how all of them work together to meet overall TMS and agency goals, objectives, and performance measures. Agencies can better understand the capabilities of their subsystems and components by performing a systematic analysis of how each operates or how each is intended to perform.

Logical Elements of a Traffic Management System: Operations Strategies, Functions, Actions, and Services

Operational strategies are sets of functions and combinations of actions that achieve transportation agency objectives for safety, mobility, and reliability. Examples of operational strategies, such as active traffic management and road weather management, enhance the safety, reliability, and performance of an existing roadway by more quickly restoring losses in roadway capacity and controlling demand for the roadway.

The implementation of operational strategies necessitates specific actions, functions, and services. An action is a basic, singular task completed by a system component or a person. A function is a series of actions or a combination of actions that support an operational strategy. A service is a set of functions and/or actions that support system operations.

The logical elements of a TMS (as shown in figure 3) include the following defining characteristics:

- Active management: Composed of static, reactive, responsive, and proactive response strategies.

- Operational goals, performance measures, and reporting: Articulated clearly, well defined, and core to a successful TMS, as well as assessing a TMS's performance. Agencies must define system performance to achieve goals and collect data to monitor the performance of those goals.

- Operating environment: Describes the types of facilities the TMS is monitoring and managing. The facilities may include freeways, surface streets, and travel on multiple facilities or corridors. Monitoring and managing environments may be different from each other. For example, a TMS will monitor facilities whose queuing or incidents frequently affect the facilities the TMS manages.

- Operational strategies that the system implements: Includes the functions, actions, and services that support the operational strategies. The right side of figure 3 lists examples.

- Operational deployment model: Describes the type of operational implementation model for a TMS, including centralized, distributed, virtual, hybrid, and temporary.

- Geographic coverage of the TMS: Describes the area that a TMS serves.

Physical Subsystem and Predictive Analytics

As outlined in the report *Decision Support Methods and Tools for Traffic Management Systems*, "there are generally certain procedures that must be followed for an operator or analyst to integrate and use a DST. The DST (and/or its software) may need to be integrated with a software subsystem, data subsystem, computing hardware, and DST-generated data users (*sic*) or decisions."(1) Software, hardware, and data subsystems are key to supporting the required operational strategies, functions, actions, and other activities of TMSs. Those three subsystems work in concert to support essentially every operational strategy of a TMS. This section first summarizes the subsystems within the TMS structure by drawing from Kuciemba et al. and identifies how predictive analytics model development and application relate to the TMS subsystems.(3)

Depending on the predictive analytics use case or how it will support an operational strategy, function, or action, the predictive analytics will affect other subsystems such as ramp metering, traffic signal control, and traveler information, which are explored in a later section of this chapter titled How Predictive Analytics Could Support Traffic Management System Management and Operations.

Data Subsystem

The data subsystem provides data processing and storage for the TMS and supports access to the data by other subsystems and external users. Data subsystems support specific functions and actions such as transmitting, processing, analyzing, interpreting, reporting, and archiving data. The data subsystem uses APIs to interface with other subsystems or components such as infrastructure-based devices (e.g., inductive loop, laser, radar, video detectors, and wireless-technology systems) and, increasingly, roadside infrastructure-free sources to access data for use in TMSs. Data subsystem functionalities may include timely retrieval of data from sources—from real-time to manual; maintenance of a data catalog; data transformations for storage and retrieval for use; securing data; managing users and access; encrypting data communications; maintaining data availability; and delivering diagnostic and status information.

The data subsystem typically includes components that extract, transform, and load (ETL) data as well as a data dissemination component. Central to the data subsystem is the data warehouse component that maintains subcomponents such as a data catalog, analytics, reports, and data store. The data store may include structured and unstructured data.

As technology has advanced (e.g., fiber optics, wireless, Internet of Things, mobile data, and cloud-computing-based management solutions), opportunities abound for transportation operators to use data sources (e.g., vehicle probe, connected-car, or free navigational app-based data) that complement or potentially supplant roadside devices. The advances offer the potential to provide information to supplement the information TMSs use in considering locations where data may not be collected currently. With more data, previously unmet decision support needs may become tenable through the introduction of needs-driven analysis tools and techniques that use newer data sources. With more and more data integrated into the TMS data subsystem, proactive use of new operational strategies also may be possible.

TMS data storage and processing have traditionally used dedicated, on-premises equipment. In recent years, a TMS's data subsystem may consist of different sources of data that get stored, processed, and analyzed in different locations. Data may be stored locally on a server at the TMC, via a server at another Government facility, or remotely via a cloud-computing-based database leased from a private vendor. Thus, access to the data may be via the Internet. The shift to using a combination of servers and databases leased on a cloud means data subsystems are becoming increasingly virtualized and more accessible from any place with an Internet connection.

One example of a data subsystem that includes the use of a leased database on a cloud is the Kentucky Transportation Cabinet.(7) The data subsystem for the cabinet's TMS transitioned to a cloud-computing database beginning in 2021. Previously, data were stored on an on-premises server supported by the IT department.

Another example is VDOT's TMS data subsystem, which integrates the archiving and sharing of data into five of its TMCs.(3) VDOT has created a data subsystem portal called SmarterRoads, which shares a range of different types of data sets, including incidents, work zones, road conditions, and road signs.(8) Users can access the portal via the Internet.

The analysis of data for exploring trends—and the use of those trends to develop prediction models—may require the collation of data from the multiple data storage locations. Once the predictive model has been developed, an agency may embed it within an analytics subsystem of a data warehouse. The predictive model also may place different requirements on components of the data subsystem; for example, it may require access to data sources more quickly and place different requirements on the ETL component APIs.

Software Subsystem

The software subsystem includes programs that support a TMS's functions and services. Examples of software subsystems are the rules engine, database software, and analytics-related subsystems (e.g., algorithms and simulation). Software products may be unique to a DST or relevant to the broader TMS. Broader TMS software may include ETL tools, operating systems, database software, security software, and UI software. DST-specific software may include rules engines, algorithms, simulation, and other analytics software that may be maintained either on-premises or by using leased cloud-computing services.

Once predictive models have been calibrated and transformed into algorithms or simulations, they may be incorporated as a DST software subsystem. The software will likely have to interact with the TMS UI and database software or may require its own UI. Again, depending on the model's real-time data and speed needs and algorithm platforms, a TMS may have to explore different software as well as software that may be hosted on in-house servers or a cloud.

Computing Hardware Subsystem

A DST and its accompanying software program may be parts of a field device, a traffic controller, or a broader TMS or TMC. The computing hardware may be owned and managed by a vendor, may be owned by an agency but managed by a vendor, or owned and managed by TMS operators. Within the transportation agency, the hardware is shared to reduce overall costs.

The performance requirements of the computing hardware relate directly to the functionality of the TMS, the processing power needed, and the amount of data involved. Real-time DSTs may introduce a greater need for data and processing power.

The earlier, Kentucky Transportation Cabinet example and the migration of the cabinet's data subsystem to a cloud vendor accompanied a migration of software and computing hardware to a cloud. The cost and capabilities of in-house data subsystem software and hardware could not keep pace with cloud-computing offerings—especially because the agency began accessing larger volumes and varieties of data, all of them having geographic information components.

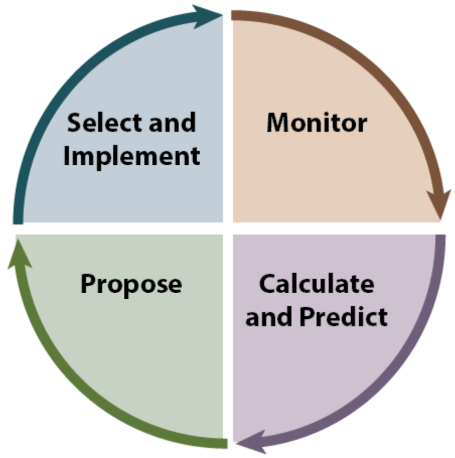
Planning for Potential Changes to a Traffic Management System

Predictive analytics algorithms, simulations, and DSTs may require minimal, moderate, or substantial changes to a TMS's physical and logical components at the subsystem, component, cabinet, or device level. A TMS typically has certain established processes and steps associated with the planning, developing, and implementing of the overall TMS as well as TMS subsystems and components that support new or better operational strategies, functions, actions, and services. Processes may involve the development of a concept of operations, cost estimates, system requirements, and other planning efforts for larger-scale changes. The scope and magnitude of change dictate the level of planning for the inclusion of predictive analytics in support of TMS operational strategies, functions, or actions. Chapter 4 presents more considerations.

HOW PREDICTIVE ANALYTICS COULD SUPPORT TRAFFIC MANAGEMENT SYSTEM MANAGEMENT AND OPERATIONS

Decisionmaking bridges a TMS's physical and logical elements and is a critical component of active management. Operational decisionmaking is more closely associated with the logical elements of a TMS structure but also relies on the subsystems and components in the physical system to collect and analyze the data that support decisionmaking. Further, decisionmaking includes the human operator in management of the physical and logical elements of a TMS system, which requires strong knowledge of the transportation system, clear understanding of an organization's operational procedures and their real-time application, and the processing and assimilation of a wide range of data and information.[2]

Figure 4's multicolor circle represents the decisionmaking framework associated with traffic management.



Source: FHWA.

Figure 4. Diagram. Traffic management decisionmaking cycle.[(2)]

The framework consists of four decision stages and functions presented within the center circular cycle:[(2)]

- Monitor: Collect and process data from various field devices, third-party data sources, and collaborators to evaluate current conditions in the transportation network. The monitor function may include subfunctions such as transportation network data, travel patterns, device status, weather and roadway conditions, and events.
- Calculate and predict: Apply advanced data processing and analytics that combine real-time data with historical data to predict the future state of the transportation network. This phase also involves detecting and predicting the risk of events that could adversely affect traffic performance and warrant an operational response. Subfunctions herein may include weather forecasts, events, traffic conditions, and prediction functions.
- Propose: Generate one or more response plans, actions, functions, and operational strategies to mitigate the effects of traffic events based on the calculate-and-predict function. Subfunctions are maintenance activities, operational response, and traveler information.
- Select and implement: Select and execute the response plan deemed most likely to effectively improve performance.

The levels of analytics introduced in Predictive Analytics: Definition and Context, which are descriptive, diagnostic, predictive, and prescriptive, loosely map to the four decision stages of the traffic management decisionmaking framework, as illustrated in figure 4. Descriptive analytics reflects the monitoring stage of the decisionmaking cycle. Diagnostic and predictive analytics reflects the calculate-and-predict stage. Predictive and prescriptive analytics can support the propose-and-select stage of decisionmaking.

Prediction is a capability that supports operational strategies, control plans, functions, actions, or services. Often, the prediction is embedded within a DST to support the propose, select, and implement elements of decisionmaking. The DST can be noncomputer based or computer based, as well as online or offline.[2] DSTs that use predictive analytics have to be computer based but can be used online or offline as follows:

- Offline decision tools benefit from predictive analytics: Predictive analytics models are usually developed and used for creating offline DSTs that introduce operators to choices that extend beyond the operators' current practices, knowledge, experience, and intuition. If the model or analytics is based on incomplete data or if the operating paradigm shifts, the tool's prediction may not be part of an operator's knowledge of the system. The predictive model may need recalibration with some frequency, and such model updates typically are parts of tool updates. The models have to align with and be implementable in adherence to an agency's policy and management guidelines as well as operators' expert judgment.

- Predictive models also can improve decision trees—which human operators use for completing structured processes through a series of simple questions and limited answers—to reach decisions consistent with their organizations' accepted policies and procedures. Operators could use predictive analytics to adjust the questions and thresholds within a decision tree and thereby improve outcomes and simplify operator workload.

- Online decision tools benefit from predictive analytics: Predictive and prescriptive analytics has the potential to simplify and even automate decisionmaking related to traffic management by applying integrated data to traffic conditions, weather, and transit system performance. For example, traffic camera software that uses AI and deep learning might detect incidents and alert TMC operators.

Predictive analytics could support some of the most common operational strategies in a TMS—through every phase of the traffic incident timeline (detect, verify, respond, and return to normal traffic flow) and in coordination with TSMO strategies such as part-time shoulder use, ramp metering, variable speed limits (VSLs), traveler information, and road weather management. The following subsections give examples of the strategies' use.

TIM

TIM is a central operational strategy in most TMSs, because the efficient management of incidents is closely related to the management of travel. The ability to predict the likelihood, frequency, severity, location, duration, and network impact of a roadway crash is a focus area of prediction-analytics-related research. Such efforts are typically based on States' crash data and sometimes integrated into vehicle probe speed data, traffic volume data, weather data, and roadway geometry data.

Prediction as noted in How Predictive Analytics Could Support Traffic Management System Management and Operations would support such subfunctions as maintenance activities and operational response within the propose, select, and implement functions of the decisionmaking framework. However, an important consideration is that real-time predictive analytics for TIM is generally at the research or proof-of-concept stage and not at the stage for routine use.

Nonetheless, outlining the key considerations for building capability maturity for integrating predictive analytics into TIM is a critical step toward the routine use of predictive analytics in TMSs.

The TIM process consists of five phases: incident detection, verification, response, clearance, and recovery.[9] Descriptive and diagnostic analytics can accelerate detection and verification functions and actions. Predictive analytics embedded within online DSTs may support clearance and recovery functions and actions. Predictive analytics that proposes high-risk road segments based on demand, road weather, and other factors also may support offline decisions associated with safety service patrol positioning.

Device vendors have harnessed the power of predictive analytics to offer camera systems with video analytics that can detect and verify slowdowns, roadway crashes, and wrong-way vehicle movements. Data from those components can channel to multiple subsystems (e.g., data subsystem and software subsystem). The data can be shared with the UI subsystem to offer visual alerts through a graphical UI that enhances the alert function for operators. The data reduce workloads and improve the timeliness of the monitor, and, potentially, calculate and propose components of the decisionmaking process.

In the context of predictive analytics and the ability to estimate in realtime networkwide impact, severity, and duration, few models have yet to provide predictions that match expert judgment. Likewise, the application of predictive analytics to estimate the frequency and locations of crashes based on demand and weather conditions also is in the research and testing phase.

Research efforts such as by Zhan et al. show that an M5P tree algorithm achieves better prediction results than traditional regression and decision tree models.[9] Specifically, the researchers demonstrated that lane blockage is the main cause of congestion during freeway incidents and that for incidents involving lane blockages, prediction of lane clearance time instead of incident clearance time is more beneficial. The model showed that several variables affected lane clearance time, including number of lanes blocked, time of day, types and number of vehicles involved, response by Florida’s Severe Incident Response Vehicle Team, and TMC response and verification times.

Part-Time Shoulder Use

Part-time shoulder use is a congestion relief operational strategy—mainly for freeways—that converts shoulders to travel lanes during certain hours of the day. Some major arterial roadways also permit part-time shoulder use, often for buses only. Opening a shoulder may include a policy that dispatches a vehicle to confirm the lane is clear of any debris or stopped vehicles. Agencies that permit part-time shoulder use typically do so as a static strategy based on fixed time-of-day and day-of-week schedules for peak periods defined through descriptive analytics. For example, Colorado DOT based the days on which to open shoulders on historical data and trends in preceding years.[10]

The deployment of dynamic part-time shoulder use as an operational strategy is expanding, with facilities on I–35W in Minneapolis, I–66 in Virginia, I–70 in Colorado, and I–670 in Ohio.[11] The strategy opens shoulders when certain congestion thresholds are reached. Recently, Ohio

DOT implemented the strategy in the SmartLane project, featuring a 9-mi stretch on I–670 between downtown Columbus and John Glenn Columbus International Airport. The project involved converting the eastbound shoulder into a lane for drivers during peak hours. In some cases, lane and shoulder control also may include operator judgment.

Predictive analytics delivered through camera systems with video analytics may expedite the enactment of dynamic part-time shoulder use, supplanting protocols that require a vehicle to verify the lane is clear. Predictive analytics that uses deep-learning models based on real-time cameras, traditional detector-based volume data, and crowdsourced data from vehicle probes or connected-car providers could transform the practice from static or dynamic. As models improve, they may predict earlier and with greater confidence when a part-time shoulder use strategy should be enacted and for what duration to prevent congestion and queuing. The predictive model or algorithm could reside within the software subsystem and would require APIs to access data from the data subsystem. The predictive model may transmit information through a UI software subsystem to an operator's UI as an alert or through a map-based system. The operator may then use the alert to access the CCTV cameras related to the corridor to ensure the lane is free of blockages or other actions or functions so as to support the decision to initiate or end the part-time shoulder use operational strategy.

Ramp Metering

Ramp metering is an operational strategy that measures, analyzes, and monitors the volume of traffic on freeway entrance ramps and adjacent main lanes and subsequently controls the flow of traffic on ramps onto the freeway in an attempt to keep traffic flowing smoothly.(3) Ramp metering can be pretimed or traffic responsive with local or systemwide operations.(12)

Ramp metering could benefit from algorithmic advances in real-time, dynamic operations, but the predictive potential would require improved lane-specific volume and speed data. Still, even though traffic-responsive algorithms have applied machine-learning techniques in simulated test platforms, the levels of programming complexity, certain challenging training procedures, and demanding data requirements have precluded such algorithms' real-world application.(13) While no real-world application of advanced predictive techniques in ramp metering exists, improved heuristic-based metering processes based on descriptive analytics do exist. As an example, the Washington State Department of Transportation (WSDOT) uses real-time descriptive analytics for adaptive ramp metering, implementing a fuzzy logic ramp metering algorithm on 126 ramps in the Greater Seattle area in 1999. The algorithm was compared with a local and a bottleneck-based algorithm at two different study sites. The research team found that the fuzzy logic algorithm metered traffic more restrictively than the two others when preventing a mainline bottleneck, secondary queue formation, or an excessive queue. The research team also reported improvements in systemwide travel time and throughput using the fuzzy logic algorithm.(14) The WSDOT fuzzy logic ramp metering algorithms as well as others embedded in commercial products reflect real-time applications using descriptive analytics for adaptive ramp metering in the routine practice stage.

Variable Speed Limit

The VSL operational strategy collects traffic, weather, construction, and maintenance information and provides traveler information in the form of recommended safe speeds.[3] In urban areas, speed information is typically part of a larger traffic management strategy, while in rural areas, speed information is typically part of a weather management strategy. VSL promotes safe and efficient travel on urban freeways by gradually decreasing advisory or regulatory speeds during adverse conditions such as poor visibility, wet or icy pavement conditions, and traffic queuing. Currently, VSL is driven mainly by heuristics or manual decisionmaking related to weather, incidents, and congestion; however, VSL has the potential for enhancements with more granular, real-time data as well as historical data analytics to support event-responsive speed variations.

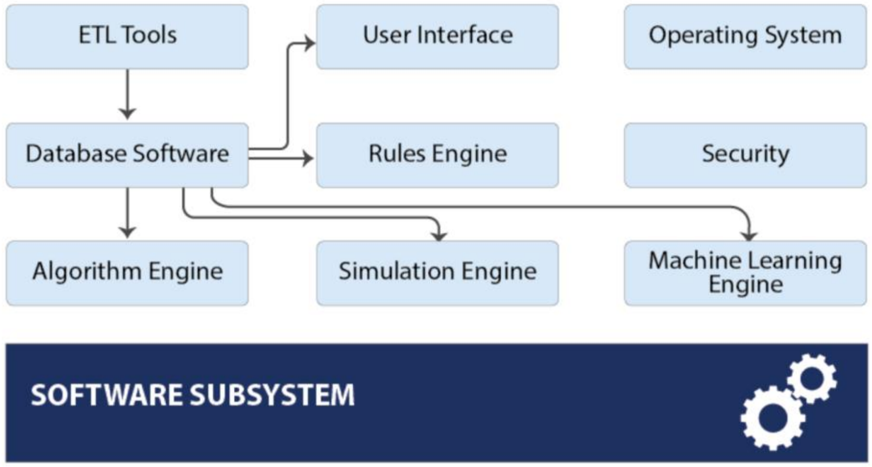
While the VSL strategy is currently and primarily rule based, promising preliminary research has demonstrated that predictive analytics may improve safety.[15,16] For example, one study applied a simulation model in Auckland, New Zealand, against a well-known VSL algorithm.[17] The simulation results showed that the proposed algorithm outperformed the existing one, improved the motorway system's efficiency performance, increased critical bottleneck capacity by 6.42 percent, and reduced total travel time by 12.39 percent compared with a no-control scenario.

Those research efforts suggest models based on efficiency optimization goals and that VSL strategies need extensive development through the customization of models for local conditions (e.g., roadway geometry). And, like ramp metering, VSL requires a large volume of data from vehicles to improve prediction accuracy.

A VSL-focused predictive model would require an API to the data subsystem, would likely reside in a software subsystem (e.g., algorithm engine or machine-learning engine), and would provide an API for a UI to view prediction. If the predictive model included a simulation engine, it may predict, for example, likely resultant traffic flow and overall delay associated with a range of potential temporal and spatial adjustments to the speed limit at the half hour or hourly forecast timeframes. The operator may then review predictions and choose whether to take specific actions such as accessing an existing VSL UI to implement a change. As confidence in the predictive model increases, the UI may get supplanted with an automated software subsystem that interfaces directly with the DMS and VSL subsystems.

EXAMPLE: FLORIDA DEPARTMENT OF TRANSPORTATION TRAFFIC MANAGEMENT SYSTEM

This section summarizes FDOT integration of data sources into the TMS software subsystem to enable future predictive analytics. In a TMS, the software subsystem includes programs that support the functions and services of the entire TMS and specific software programs installed for other subsystems that support decisionmaking.[2] Figure 5 illustrates a hypothetical software subsystem for a TMS. The boxes cited as algorithm engine, simulation engine, and machine learning, with arrows coming from the software, may likely include arrows between the three engines.



Source: FHWA.

Figure 5. Diagram. Hypothetical software subsystem and installed software in a TMS.[(2)]

The TMS software subsystem uses APIs to integrate data used by multiple software programs installed on this subsystem or to share data with other subsystems.[(2)] An API is a description of the routines, protocols, and tools for interfacing and exchanging data with a software application or program. Two types of APIs are typically developed and integrated into the software system as follows:

- Data providers, which provide data for the TMS: The provider usually dictates its interfaces and the processes, protocols, and requirements (e.g., formats) for receiving and using data from its system. The provider furnishes the associated API documentation (e.g., data dictionary, release notes, configuration guide, and user guide) to follow to access the data.

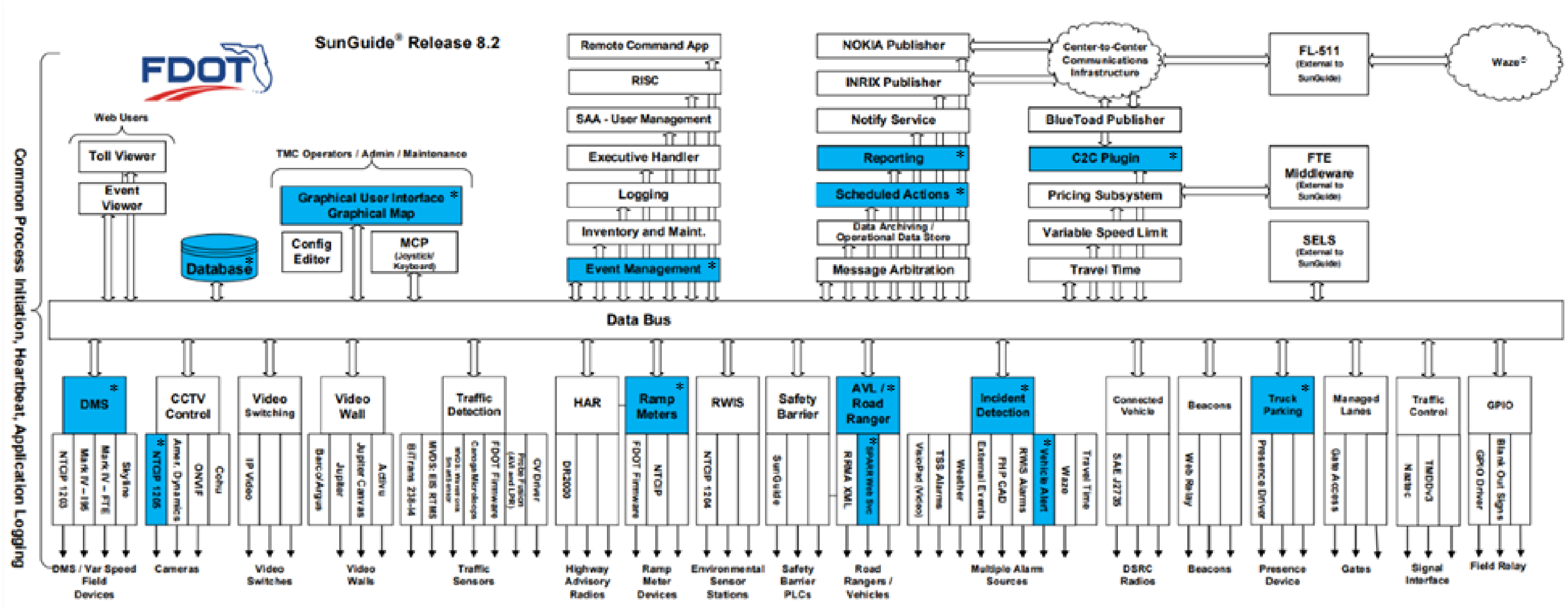
- Data subscribers, which receive data from the TMS: The TMS dictates the data interfaces, and subscribers develop their interfaces to meet the requirements specified for the appropriate processes, protocols, and formats. The TMS should provide the subscriber with an associated schema or data definition.

FDOT's SunGuide® software system enables regional Florida TMCs to integrate numerous hardware, software, and network applications as well as exchange data with other TMCs.[(18)] SunGuide's standardization of common TMC functions makes the various FDOT district facilities more interoperable. Operators can use the software to perform incident management tasks, obtain data from vehicle detection systems, display videos from roadside cameras, and use the Florida 511 advanced traveler information system to alert motorists via messages on DMSs, highway advisory radio, web-based content, and other communications channels.

FDOT established processes that integrate a subset of data obtained from a free collaboration with a navigational application into the data subsystems of its TMS. In this case, SunGuide's integration of the data represents a data provider API. The SunGuide advanced traffic management system (ATMS) software, used by 14 agencies in 16 TMCs in Florida, ingests the processed navigational app event data provided via an API and enables operators to create ATMS events without manual data entry.[18]

The navigational app event data are first stored centrally in realtime—outside ATMS. The data also are filtered in realtime to exclude all event types except “accident” and “hazard on road” and translated using FDOT’s geographic information system shapefile (linear referencing system) to determine the State road and county of each event. Then the software subsystem distributes to each FDOT district the subsets of incident and hazard on road data relevant to each FDOT district. Each district can apply additional filters before an incident from this data source appears on the TMC operator map as a flashing icon. After incident verification, the operator can push the report as an ATMS event with typical traveler information and scene deployment response as required.

Figure 6 illustrates the SunGuide ATMS architecture, which shows the multiple operational strategies, subsystems, and components that interface by using the data bus. FDOT ingestion of the free navigational application data comes through the Florida 511 system (upper right). The incident detection operational strategy uses data from that source along with eight different data systems (below data bus, right of center). Others in this group include, for example, the agency’s wrong-way-driving-detection subsystems, Road Weather Information System alarms, and Florida Highway Patrol computer-aided dispatch.



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*= Modified
Admin = administration; Amer. = American; AVI and LPR = automatic vehicle identification and license plate recognition; AVL = automatic vehicle location; Config = configuration; C2C = customer to customer; CV Driver = connected-vehicle driver; DSRC = dedicated short-range communication; FHP CAD = Florida Highway Patrol computer-aided dispatch; FTE = fault-tolerant Ethernet; Ga to Access = global assembly to access; GPIO = general-purpose input/output; HAR = highway advisory radio; IP = Internet Protocol; Maint. = maintenance; MCP = manual control panel; MVDS: EIS RTMS = microwave vehicle detection station: electronic integrated system remote traffic microwave sensor; N az to c = Naztec driver–traffic signal communication; NTCIP = National Transportation Communications for Intelligent Transportation Systems Protocol; PLCs = programmable logic controllers; RISC = rapid incident scene clearance; RRNA XML = Road Range service synchronizes information Extensible Markup Language; SAA = system administration application; SELS = Statewide Express Lane Software; SPARR = Smartphone Application for Road Rangers; TMDDv3 = Traffic Management Data Dictionary version 3; TSS = traffic signal system; Var = variable.

Figure 6. Diagram. SunGuide ATMS architecture.[18]

The FDOT Wrong-Way Driving system for limited access roadways uses a camera system with predictive analytics on the edge, which means the algorithms within the local camera system predict a vehicle's countertraffic movement. The prediction triggers heuristics that flash a wrong-way sign that the errant road user may view. The prediction also triggers many other actions as illustrated in figure 7.[19] The FDOT architecture and its data and software subsystems could support future predictive analytics applications such as truck-parking overflow or queue duration predictions and implement prediction models to improve the active management of their transportation system.

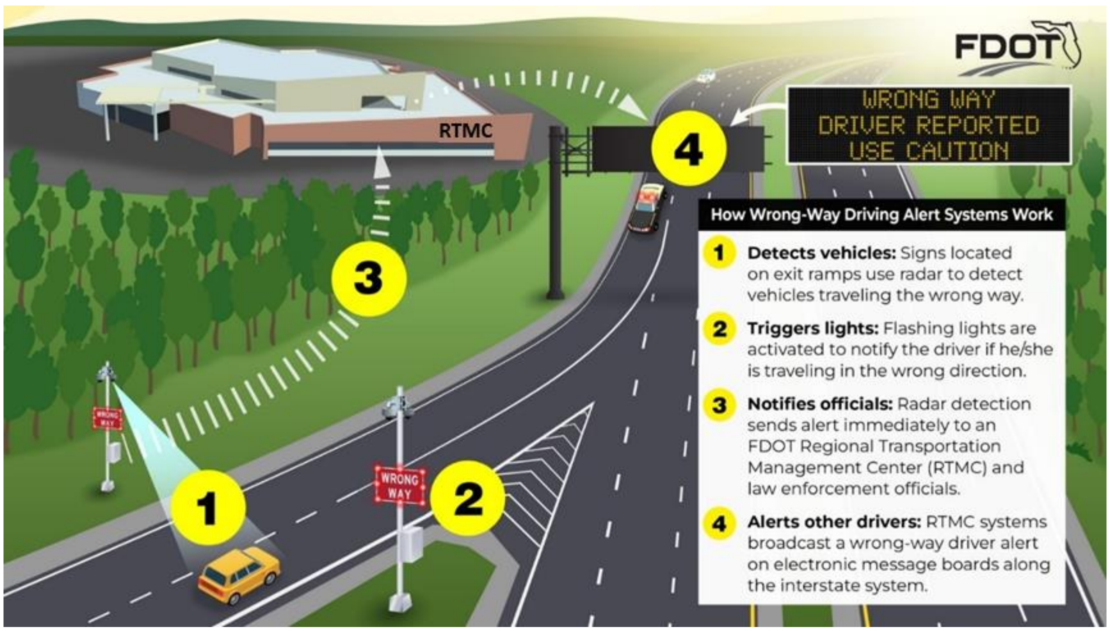


Figure 7. Illustration. FDOT Wrong-Way Driving alert system.[19]

FDOT collaborated with the University of Florida to develop video-processing and machine-learning methods to automatically detect and classify trucks traveling on Florida highways. High-resolution FDOT videos at two freeway locations served as the training and evaluation data developed deep-learning algorithms for detecting the location of a truck in a video frame and developed a hybrid truck classification approach that integrates deep-learning models and geometric truck features for classifying trucks into one of the nine FHWA classes 5–13. Researchers developed additional models to recognize and classify truck attributes. Prediction accuracy for truck classification was higher than 90 percent.[20] The agency also has explored other prediction capabilities, but none are yet integrated into the TMS.

IMPLICATIONS FOR IMPLEMENTING PREDICTIVE ANALYTICS

The implications of integrating predictive analytics—along with the data and technologies needed to support them—are that the TMS elements and the data subsystem will have to be modernized to incorporate the integration of data and analytical models in support of predictive analytics. That modernization becomes more important as technology continues to advance at a rapid pace, which creates opportunities for agencies to further modernize field equipment;

leverage crowdsourced, mobile, and connected data; and modernize data management practices to integrate and analyze these large-volume and high-velocity data.

Currently, TMS decisionmaking is supported primarily by descriptive and diagnostic analytics. While the operator and manager will continue engagement in the interpretation of analytics to improve decisionmaking, involving predictive and prescriptive analytics will mark a significant change in current operating procedures and active traffic and demand management processes. Agencies should recognize that predictive analytics will reside in the physical side of a TMS, within components, and as a part of subsystems, as well as in the logical side of a TMS to support operational strategies and functions. To be effective, predictive analytics has to become accepted by and integrated within TMS operators' and managers' decisionmaking.

CHAPTER 3. OPTIONS FOR IMPLEMENTING PREDICTIVE ANALYTICS

In chapter 2, predictive analytics was defined within the broader context of analytics and then introduced from the perspective of support of TMS operational strategies, functions, actions, and services.

Operationalizing the predictive model may involve making a stand-alone DST or embedding the predictive model or algorithm into physical subsystems and logical functions, actions, or services within the TMS. This chapter focuses on where predictive model development and use may reside in TMSs either at the subsystem, at the component, or as a stand-alone capability. The chapter then explains how analytics may be implemented from the perspective of local or vendor-managed servers, operating systems, and software.

The information presented in this chapter discusses predictive analytics from a technical deployment perspective. Organizations must recognize that before any deployment decisionmaking, they must first define the need and then adhere to standard processes when considering the introduction or adjustment of any technology, tool, or capability within either the physical or logical components of a TMS. Report *Decision Support Methods and Tools for Traffic Management Systems* delves in significant depth into considerations associated with the selection and use of DSTs[1]—also introduced in chapter 5 of this report.

WHERE WILL THE PREDICTIVE ANALYTICS RESIDE?

Predictive Analytics Development and Use Within Traffic Management System Data and Software Subsystems

Analytics has traditionally been implemented within a data and software subsystem of a TMS or within the data system managed by the broader operations enterprise. That implementation reflects the inherent need to store a large amount of historical data and rapidly process them to develop, optimize, and run predictive models. In this approach, data are collected by field components such as detectors and sensors or by using third-party external services through an API and transfer to the data subsystem by using wired or wireless networks. The various data are stored for a predetermined amount of time in on-premises or cloud storage—often called a data warehouse. The warehouse stores structured and unstructured data and may include a data dissemination component. Analysts access the data to train and test multiple predictive models until one of the models meets an acceptable level of precision. The successful predictive model is then deployed to a software subsystem (e.g., an algorithm or simulation engine), where it is monitored for accuracy and eventually replaced by a new, more suited model that has been trained on more recent data. That approach to predictive analytics is referred to as core-level, centralized implementation.

- Core-level implementation may be performed by a consultant or university collaborator working with a State or local traffic management agency. While this approach to predictive analytics has been the norm for years, it is not without drawbacks. One drawback is that as soon as the fundamentals used for training the predictive model change, the model will not prove useful. Core-level implementation also involves significant costs attributable to the following features:

- Storage of a large amount of historical data to train the predictive models: These data may now include probe vehicles; navigational application-based, connected roadside equipment; an unmanned aircraft system; and connected-car, micromobility, and other newer data.

- High network bandwidth as required between the data collection device and the data center to ensure the efficient transfer of a large amount of data to the data center.

- The need for predictive models' rapid detection of changes.

- Implementation of security measures designed to hide and alter personally identifiable information such as drivers' photos and license plates, which are present in the collected data so that the data can be used in predictive analysis without risks.

- The emergence of data-hungry, deep-learning prediction algorithms.

The migration of on-premises data centers to cloud-computing-based data centers has led to reductions in costs, but the rapid increase in data volume and complexity challenges cloud-computing implementation. Thus, developers and researchers have been exploring faster and less costly ways to implement predictive analytics.

Predictive Analytics Development and Use Within Field Components

Technological advances now enable prediction to be migrated closer to sources of data often referred to as edge components. The advances include:

- Data stream processing, which is the processing of data as data get produced or received.

- Miniaturization of chipsets, power, and network modules that support greater processing for longer durations and that leave a smaller physical footprint.

The edge components may include traffic signals, traffic signal controllers, vehicle detectors, signal detectors, environmental sensors, and CCTV cameras. When the edge components are able to execute data stream processing and more advanced computation, they can be referred to as edge computing.

Edge computing enables the application of prediction models without moving the data to the TMS data subsystem via communication subsystems, which reduces the cost of implementing predictive analytics while also improving speed and security. More specifically, this approach:

- Lowers hardware computing costs by distributing processing across device hardware.

- Lowers storage costs by reducing the amount of data needing storage in the data center.

- Lowers networking costs by reducing the volume of data to be transmitted to the data center.

- Lowers security costs by storing and processing sensitive data at the source across many devices and by sending only nonsensitive data to the data center.

While edge predictive analytics enables the analysis of data without having to move the data to a centralized location, it does not entirely replace the predictive analysis that takes place within the TMS data subsystem. Edge computing capabilities are advancing but not yet capable of handling the vast volumes and variety of data and computing power needed to train predictive models. Current capabilities can, however, run trained predictive models on new data as the new data are being generated. In particular, anomaly detection models such as rollover detection in video feeds can be pushed down and executed directly on edge devices to drive alerts that prompt immediate action. The data causing those alerts also can be transmitted to data centers for use as input for more complex predictive analytics models maintained within the software and/or data subsystems, thereby combining more data inputs than edge devices. At some point, models also may become developed and trained at the edge component level or at the roadside cabinetry or controller level.

Predictive Analytics Using Integrated Edge Computing and Traffic Management System Data Subsystems

Based on the symbiotic relationship between edge predictive analytics and centralized predictive analytics, many vendors already offer solutions that integrate the two. Each of the major cloud-computing providers has released field devices with computing capability (e.g., cameras), and IT equipment vendors also are marketing edge device solutions. Telecommunications providers also see an opportunity to either directly support edge analytics via their own business-to-business or business-to-customer solutions or by opening up their infrastructures to collaborators to accomplish the same. Vendors are now offering various levels of implementation of predictive analytics, meaning that TMS technicians can implement and refine algorithms or models to modify the operation of afield device or component and enable the device to process and share data so as to further refine predictive models embedded within the field component or to support the refinement of models housed within the TMS software subsystem.

In implementing predictive analytics as part of a TMS, agencies have to select the most appropriate location for their predictive analysis (core versus edge). Beyond the core and edge paradigm, predictive analytics for a TMS can be implemented as part of an existing system in many different ways depending on an organization’s resources; skills; existing device capabilities; willingness to adopt a cloud; willingness to outsource data, processes, and decisionmaking to vendors; and desire to avoid vendor lock.

The next subsection summarizes four different approaches to implementing predictive capabilities. Organizations may be able to implement varied predictive needs by using a single approach, but far more likely will be the use of different approaches based on predictive need. For example, the TMS may establish a prediction capability by using a homegrown, prediction software subsystem housed within agency servers that pulls processed device data into the data subsystem or by using device components with prediction software embedded within the device. Conversely, the TMS might access prediction capability through an API data feed from a vendor, such as a vehicle probe data and analytics provider that has developed and integrated prediction modeling and delivers the prediction results in realtime.

COMPUTER SERVICE OPTIONS FOR USE IN PREDICTIVE ANALYTICS

Making the decision on where and how to implement predictive analytics requires awareness of terminology related to computer systems. This section first introduces the concepts in computer systems so that readers may better understand the various strategies for implementing predictive analytics. The section then presents four different ways predictive analytics can be implemented, the hardware and software they are composed of, and how the hardware and software interact with existing TMS logical and physical components.

Computer Systems Architecture: Terminology Context Setting

TMSs include physical components that are field based as well as servers located in a physical transportation agency building—such as a TMC—that house data and software. Some agencies, for a host of reasons, have transferred the responsibility for servers and storage to a vendor. In addition, some agencies have transferred responsibility for networking firewalls and security to a vendor. Such outsourcing of functionality is often referred to as infrastructure as a service (IaaS), and the vendor is referred to as a cloud-computing provider. Agencies may go further to outsource the standing up of operating systems, development tools, and specific software or applications. When the entire technology stack is outsourced, it is often referred to as software as a service (SaaS).

In outsourcing an agency's computing infrastructure, platform, or software to cloud vendors, the agency should rearchitect its systems to make the most of the cloud environment. Five approaches relevant to more efficient and more resilient capabilities for computer systems are cloud-native, platform-independent, and microservices architecture. Each is defined as follows:

- Cloud-native architecture refers to applications that are designed to capitalize on the inherent characteristics of a cloud-computing software delivery model. The applications are typically hosted and run in a cloud. Four key principles of cloud-native applications are microservices, containerization, continuous delivery, and development-operations methodology for development.

- Platform-independent architecture refers to software that can be used on a variety of hardware, operating systems, and software architectures. Being platform independent means an application requires less planning and less translation across an enterprise. For example, platform independence will enable an organization with many types of computers to write a specialized application once and have it used by virtually everyone rather than having to write, distribute, and maintain many versions of the same program.

- Microservices architecture is an application development approach wherein a large application is built as a suite of components or services. Each service is independently deployable, organized around business capabilities (e.g., TMS logical operational strategy or function), owned by a small team, loosely coupled with other components, and highly maintainable and testable. Microservices architecture enables the rapid, frequent, and reliable delivery of large, complex applications. It also enables an organization to evolve its technology stack.

- Containerized computing refers to self-contained, lightweight virtualization technology. Containers are similar to virtual machines, except they virtualize only the guest operating system and applications instead of an entire computer. Containers are quicker and easier to set up than a virtual machine. Containers are good choices for moving away from traditional, on-premises infrastructure; making an existing monolithic application cloud native; and developing applications that run for hours at a time. Containers support greater vendor neutrality and support any programming language but are kept running, thus leading to potentially higher costs.

- Serverless computing refers to a practice whereby workloads run on a server that hosts the functionality behind the scenes, but the server is not managed by the developer. Serverless functions are usually small, lightweight programmatic functions with a single purpose. That single purpose can be anything from getting details out of a database to displaying a notification. Most cloud providers offer serverless functions, which they may refer to as functions as a service. Providers bill only for the time the client's serverless functions spend running.

Agencies may consider deploying a small application or one that can easily split into many smaller microservices as a serverless application. A larger, more complex application may be better suited as a containerized application. Sets of tightly coupled services that cannot easily be broken down into small microservices are strong candidates for containers. With the preceding context outlined, the following four sections outline the four approaches to how predictive analytics can be implemented from the perspective of cloud or local services.

Develop Prediction Within the Traffic Management System Data and Software Subsystems

This approach uses servers or virtual servers to house software that supports predictive model development using machine-learning software and its algorithms. In this scenario, the device components do not have the needed computing power to implement machine learning and focus on relaying device data to a central location on-premises (data subsystem warehouse) where it is stored and analyzed to perform prediction that is then delivered to the operator through TMS UI software. The predicted data also may feed to a rules engine—a software program via an API to support business rules. The TMS serves as the main command and control interface to manage and monitor the acquisition and storage of device data, data preparation processing, predictive analysis development, monitoring, and prediction events communication. The TMS has three main components: computing servers, device components, and UI software. Each component is described as follows:

- TMS in-house or vendor-based (cloud) servers—A set of computing servers equipped with machine-learning acceleration hardware such as a graphics processing unit (GPU), a specialized processor originally designed to accelerate graphics rendering, or a tensor processing unit (TPU), a specialized matrix processor developed for neural network workloads and machine learning. Servers host data and software subsystems to support the following functions:

- Collect and store device and third-party data.
- Prepare the collected data for machine-learning development.
- Develop and test machine-learning models.
- Perform prediction on upcoming or historical data by using created machine-learning models.
- Communicate predicted events to the UI software, back to the data subsystem, or to a rules engine for further automated actions.
- Monitor collected data quality.
- Monitor the machine-learning model's prediction performance.
- Receive commands from TMS.

To perform those functions, the TMS data and software computing servers run the following software components:

- Main API—Sends data ingestion, data preparation, model development, model deployment, predictions, and relaying prediction performance to the prediction management subsystem on the TMS.
- Event API—Sends the predicted events generated by the machine-learning framework to the TMS rules engine (event management subsystem).
- Data API—Receives data sent by the device.
- Machine-learning framework—Creates, tests, and runs machine-learning models in TMS data and software subsystems and generates predictions by applying them to new data from edge devices.
- Model repository—Stores machine-learning models generated by the machine-learning framework.
- Data repository—Stores both raw data collected from edge devices and data prepared for machine-learning model development.

- Edge device components—A set of device components (e.g., cameras, pneumatic tube counters, radar/laser, signal detectors, and environmental sensors) connected with little to no computing power scattered across the physical transportation network, which perform the following functions:

  - Capture raw data from devices.
  - Preprocess data if needed or if capable.
  - Cache captured data to avoid loss of data.
  - Communicate raw data or preprocess data to TMS computing servers.
  - Receive commands from the TMS rules engine and other physical subsystems.

To perform those functions, the computing servers run the following software components:

  - Main API—Operates data capture, optional data preprocessing and edge device calibration and adjustment and data communication services from the device management subsystem on the TMS.
  - Data API—Sends data to the TMS data and software subsystem computing servers.

- Machine-learning subsystem(s)—A set of rules or even a machine-learning subsystem may have to be added to the existing TMS to enable the integration of computing servers and edge devices that perform the following tasks:

  - Set up and monitor data collection between edge devices.
  - Set up and monitor data flow between edge devices and computing servers.
  - Set up, deploy, and monitor device data preprocessing pipelines.
  - Develop, deploy, and manage data preparation pipelines.
  - Update devices' firmware.
  - Adjust devices' data output settings.
  - Calibrate devices.
  - Monitor devices' data quality.
  - Monitor machine-learning model performance.
  - Discard and replace unsatisfactory machine-learning models.
  - Create, test, and deploy machine-learning models.
  - Receive and process predicted events from TMS data and software subsystem computing servers.
  - Communicate with other TMS subsystems.
  - Run prediction management graphical interface.
  - Manage accounts and access to edge devices and TMS data and software subsystem computing servers.

  To perform those functions, the TMS machine-learning subsystems may have to run the following software services:

  - Main UI software—Main UI services provide a graphical UI so that TMS operators can operate the prediction subsystems.
  - Access management services—Access management services provide identity access management for users and services of the TMS prediction subsystems.
  - Event management services—Event management services provide a distribution and monitoring interface for all predicted events submitted to various TMS subsystems.

- Prediction management services—Prediction management services provide a machine-learning development and deployment interface to the computing servers that house the data and software subsystems.
- Data management services—Data management services provide a data management and data preparation interface for the computing servers that house the data and software subsystems.
- Device management services—Device management services provide a data management and device calibration interface for devices.

Develop Prediction Within the Traffic Management System Data and Software Subsystems and Device Components

This approach to the implementation of machine learning to develop and refine predictive models is similar to the on-premises or cloud IaaS approach. The approach also is meant for deployment directly onto servers or virtual servers. The key difference is that instead of using devices with little computing power, this approach uses devices capable of applying predictive models directly to the local device data being collected. The device focuses on relaying not just raw data but also device prediction data (events) to the TMS data subsystem. The device also may be able to store and analyze events to perform even more complex predictions that are then sent to the TMS data subsystem via an API and, potentially, to neighboring roadside infrastructure.

The Florida wrong-way-detection and -notification system described in Example: Florida Department of Transportation Traffic Management System is an example of this configuration. A sign located on an exit ramp is instrumented with a device to detect wrong-way movements. The detection algorithm communicates and triggers flashing lights that notify the wrong-way traveler. The device, a component of the traffic detection subsystem, also transmits an alert to the regional TMC through its data bus and to the DMS subsystem, which will activate field DMSs. The event also is pushed to the TMC operator graphical UI, where the operator can take specific actions to address the hazard—such as law enforcement mobilization or safety service patrol deployment.

This option may include a predictive model within the field device as well as a predictive model within the TMS data and/or software subsystems.

- TMS in-house or vendor-based (cloud) servers—The computing servers, either those housed by the agency or those of a third-party vendor, are equipped with machine-learning acceleration hardware such as GPUs or TPUs, which perform the following functions:
  - Collect and store device data.
  - Collect and store devices’ predicted events data.
  - Prepare collected data for machine-learning development.
  - Develop and test machine-learning models both in the TMS subsystem and within field devices.

- Perform prediction based on real-time and historical data by using machine-learning models created within the TMS data and software subsystems.
- Perform prediction on edge devices as the devices collect data.
- Communicate predicted events between field devices and the TMS data subsystem and, potentially, directly within an operational-strategy-associated subsystem such as DMS or traffic signal control.
- Monitor collected data quality.
- Monitor machine-learning model prediction performance both for the device and the data and software subsystems.
- Transmit alerts and data to the operator UI and receive commands from the operator UI.
- Deploy (push) new predictive models for field devices—typically as a software upgrade push.

To perform those functions, the TMS data/software subsystem computing servers run the following software components:

- Main API—Sends raw data and edge-predicted events data ingestion, raw and edge predicted events data preparation, and edge sensor and TMS data and software subsystem machine-learning-model development; deploys predictive models both in the TMS data/software subsystems and on edge devices; performs predictions; and relays prediction performance to the prediction management subsystem on the TMS.
- Event API—Enables TMS data and software subsystems to receive predicted events generated by edge devices and for the predicted events generated by TMS data and software subsystem and edge devices to be sent to the TMS event management subsystem.
- Data API—Receives raw data sent by the edge devices.
- Machine-learning framework—Creates, tests, and runs edge device and TMS data/software subsystem machine-learning-models from collected data or edge device predicted events and generates both TMS data and software subsystem and edge device predictions by applying them to new data or edge device predicted events.
- Model repository—Stores machine-learning models generated on the TMS data and software subsystems or edge devices by the machine-learning framework.
- Data repository (not shown)—Stores raw data and edge-device-predicted-events data collected from edge devices as well as data prepared for machine-learning-model development.

- Edge device components with computational capabilities—A set of devices scattered across the physical transportation network and connected to the TMS data and software subsystem and the TMS, with enough computing power to enable each device to preprocess data and perform predictions in situ. Devices provide the following functions:

- Capture raw data from devices.
- Preprocess collected raw data if needed or if capable.
- Cache captured data to avoid loss of data.
- Perform machine-learning-related data preparation on collected raw data.
- Perform predictive analysis on collected raw data.
- Receive commands from TMS.
- Receive and deploy a new prediction model from TMS data and software subsystem.
- Communicate raw or preprocess data to TMS data and software subsystem computing servers.
- Communicate predicted events to TMS data and software subsystem.

To perform those functions, edge computing devices run the following software components:

- Main API—Operates data capture, optional data preprocessing, predictive model deployment, device calibration and adjustment, and data communication services from the TMS device management subsystem.
- Event API—Enables each edge device to communicate to the TMS data and software subsystem and the TMS event management subsystem the predicted events they generate.
- Data API—Sends raw data to TMS data and software subsystem computing servers.

- Machine-learning subsystem(s)—A set of subsystems added to an existing TMS within the software subsystem, facilitating the integration of computing servers and edge devices, which perform the following tasks:
    - Set up and monitor data collection across edge devices.
    - Set up and monitor data flow between edge devices and TMS data and software subsystem computing servers.
    - Set up, deploy, and monitor edge devices' data preprocessing pipelines.
    - Develop, deploy, and manage data preparation pipelines.
    - Update edge devices' firmware.
    - Adjust edge devices' data output settings.
    - Calibrate edge devices.
    - Monitor edge devices' data quality.
    - Set up and monitor data flow between edge devices and TMS data and software subsystem computing servers.
    - Monitor machine-learning-model performance on TMS data and software subsystems and edge devices.

- Discard and replace unsatisfactory machine-learning models on TMS data and software subsystems and edge devices.
- Create, test, and deploy machine-learning models by using containers on TMS data and software subsystems and edge devices.
- Receive and process predicted events from TMS data and software subsystems and edge devices.
- Communicate with other TMS subsystems.
- Run prediction management graphical interface.
- Manage accounts and access to edge devices and TMS data/software subsystem computing servers.

To perform those functions, the TMS machine-learning subsystems run the following software services:

- Main UI services—Main UI services provide a graphical UI so that TMS operators can operate the prediction subsystems.
- Access management services—Access management services provide identity access management for users and services of TMS prediction subsystems.
- Event management services—Event management services provide a distribution and monitoring interface for all predicted events submitted to the TMS.
- Prediction management services—Prediction management services provide a machine-learning development and deployment interface to TMS data and software subsystems and edge devices with computing capabilities.
- Data management services—Data management services provide a data management and data preparation interface to TMS data and software subsystem servers.
- Device management services—Device management services provide data management, predictive model management, and device calibration service for edge devices with computational capabilities.

Develop and Run Predictions by Using Containerized Computer Services

This implementation is similar to the on-premises or IaaS implementation with devices capable of computing because it enables the implementation of predictive analytics at both the TMS data and software subsystems and field components. Rather than running systems by using on-premises servers or on-premises or hosted virtual servers, this implementation follows principles of modern data systems, often referred to as cloud-native implementation.

Using this approach, data and process management found that the first two types of implementations can be deployed, scaled, and refreshed by using containers within a cloud but also within device components where containers can be deployed directly on device hardware and operating systems, similar to app updates pushed on a phone or laptop. In this type of implementation, a TMS manages and monitors all containers composing the system to optimize system performance, detect errors and failures, and recover quickly and seamlessly. TMS data and software subsystems will still serve as the main command and control interface to manage and monitor data acquisition and storage, data preparation processing, predictive analysis development, monitoring, and prediction events communication at both the TMS data and software subsystem and edge device levels. Many examples of cloud offerings for containerized implementation of predictive analytics can be found among leading cloud providers.

This implementation is composed of three main components, two of which are the TMS data and software subsystems, and which are implemented as a group of containers distributed atop a lightweight container management operating system. The features of the three main components are summarized as follows:

- TMS in-house or vendor-based (cloud) servers—A set of containers running on-premises or in a cloud-based container management and orchestration environment. Each container is able to access storage, data processing, and machine-learning acceleration services (virtualized GPU or TPU) made available by the container management environment each container will use to perform the following functions:
    - Collect and store edge device data.
    - Collect and store edge devices' predicted events data.
    - Prepare collected data for machine-learning development.
    - Develop and test machine-learning models for both TMS data and software subsystems and edge devices.
    - Package machine-learning models as stand-alone containers for TMS data and software subsystems and edge devices.
    - Deploy new containers on both TMS data and software subsystems and edge environments.
    - Manage and monitor deployed containers.
    - Perform prediction on upcoming or historical data by using created machine-learning models in the TMS data and software subsystems.
    - Perform prediction in the loop on edge devices as the devices collect data.
    - Communicate predicted events between edge devices, TMS data and software subsystems, and other TMS subsystems as well as UIs.
    - Monitor collected data quality.
    - Monitor machine-learning model prediction performance at both the TMS data and software subsystems and edge device levels.
    - Receive commands from the TMS.

  To perform those functions, core computing servers run the following software components:

    - Main API—Allows for raw data and edge-predicted-events data ingestion and preparation, edge and TMS data and software subsystem machine-learning model development, container development both in the TMS data and software subsystem and on edge devices; performs predictions; and relays prediction performance to the prediction management subsystem on the TMS.

  - Event API—Enables the TMS data and software subsystem to receive predicted events generated by edge devices and for the predicted events generated by TMS data and software subsystem and edge devices to be sent to the TMS event management subsystem.
  - Data API—Receives raw data sent by edge devices.
  - Machine-learning framework—Creates, tests, and runs edge and TMS data and software subsystem machine-learning models from collected data or edge-predicted events and generates both TMS data and software subsystem and edge device predictions by applying them to new data or edge-predicted events.
  - Model repository—Stores the machine-learning models generated on the TMS data/software subsystem or edge by the machine-learning framework.
  - Data repository—Stores raw data and edge-predicted-events data collected from edge devices as well as data prepared for machine-learning-model development.
  - Container orchestration framework—Automates much of the operational effort required to run containerized workloads and includes a wide range of things needed to manage a container's lifecycle, such as provisioning, deployment, scaling (up and down), networking, and load balancing.

- Device components with computational capabilities—A set of containers running on a device container management and orchestration environment running across a distributed network of devices scattered along the physical transportation network. Each container is able to access storage, data processing, machine-learning acceleration services (virtualized GPUs or TPUs), and virtual device interfaces made available by the edge container management environment each container will use to perform the following functions:

  - Capture raw data from devices.
  - Preprocess collected raw data if needed or if capable.
  - Cache captured data to avoid loss of data.
  - Perform machine-learning-related data preparation on collected raw data.
  - Perform predictive analysis on collected raw data.
  - Receive commands from the TMS.
  - Receive and deploy new container model from the TMS data and software subsystem.
  - Manage and monitor deployed containers.
  - Communicate raw or preprocess data to TMS data and software subsystem computing servers.
  - Communicate predicted events to TMS data and software subsystem and the TMS.

To perform those functions, the edge containerized environment runs the following software components:

- Main API—Operates data capture, optional data preprocessing, predictive model deployment, device calibration, and adjustment and data communication services from the device management subsystem on the TMS.
- Event API—Enables each edge device to communicate to the TMS data and software subsystem and TMS event management subsystem the predicted events they generate.
- Data API—Sends raw data to TMS data and software subsystem computing servers.
- Device container orchestration framework—Automates much of the operational effort required to run containerized workloads across a network edge device, including a wide range of things needed to manage a container's lifecycle, such as provisioning, deployment, scaling (up and down), networking, and load balancing.

- Machine-learning subsystem(s)—A set of subsystems added to an existing TMS, facilitating the integration of the TMS data and software subsystem and edge container environments, which perform the following tasks:
    - Set up and monitor data collection across edge containers.
    - Set up and monitor data flow between edge and TMS data and software subsystem containers.
    - Set up, deploy, and monitor edge container data preprocessing pipelines.
    - Develop, deploy, and manage containerized data preparation pipelines.
    - Manage and orchestrate both edge and TMS data and software subsystem containers.
    - Update edge devices' firmware and operating systems.
    - Adjust edge container data output settings.
    - Calibrate edge devices.
    - Monitor edge devices' data quality.
    - Set up and monitor data flow between edge and TMS data and software subsystem containers.
    - Monitor machine-learning model performance on TMS data and software subsystem and edge containers.
    - Discard and replace unsatisfactory TMS data and software subsystem or edge containers.
    - Create, test, and deploy machine-learning models by using containers on TMS data and software subsystem and edge devices.
    - Receive and process predicted events from TMS data and software subsystem and edge devices.
    - Communicate with other TMS subsystems.

- Run prediction management graphical interface.
- Manage accounts and access to edge devices and TMS data and software subsystem computing servers.

To perform those functions, the machine-learning subsystems run the following software services:

- Main UI services—Provide a graphical UI so that TMS operators can operate prediction subsystems.
- Access management services—Provides identity access management for users and services of TMS prediction subsystems.
- Event management services—Provides a distribution and monitoring interface for all predicted events submitted to a TMS.
- Prediction management services—Provides a machine-learning development and deployment interface to the TMS data and software subsystem and edge computing devices.
- Data management services—Provides a data management and data preparation interface for TMS data and software subsystem servers.
- Device management services—Provides data management, predictive model management, and device calibration service for edge intelligent devices.
- Container management services—Provides a semiautomated means to orchestrate the containerized predictive data pipeline in a TMS data and software subsystem and edge environment to enable the TMS to manage a containerized predictive data pipeline's lifecycle, including provisioning, deployment, scaling (up and down), load balancing, and retirement.

Outsourcing Predictive Analytics Implementation

This approach to developing and implementing machine learning or other forms of predictive models is similar to the cloud-native approach. It is running on a containerized environment for both the TMS data and software subsystems as well as for the edge device. Rather than having to manage containers directly to orchestrate the different data pipelines to collect data, train models, deploy them and monitor them; this implementation is done on top of a cloud vendor infrastructure and machine-learning-software service. This solution circumvents most of the difficult and cumbersome orchestration tasks and provides a straightforward way to implement predictive analytics data pipelines from devices to the TMS data and software subsystems and/or UI. This implementation allows the use of already-trained and ready-to-use proprietary machine learning that is made available by the vendor.

The TMS data subsystem serves as the main command and control interface that manages and monitors the acquisition and storage of sensor data, data preparation processing, predictive analysis development, monitoring, and prediction events communication through the vendor service as follows:

- Vendor infrastructure—A machine-learning computing environment offered as part of a cloud-computing service that abstracts the hardware and low-level software needed to implement predictive analytics. Vendor infrastructure offers a suite of services to create, test, deploy, and manage predictive data pipelines. The vendor infrastructure environment performs the following functions:

    - Collect and store raw data from edge devices.
    - Prepare the collected data for machine-learning development.
    - Develop and test machine-learning models by using collected data.
    - Perform predictions on upcoming or historical data by using created machine-learning models.
    - Communicate predicted events to TMS.
    - Monitor collected-data quality.
    - Monitor machine-learning-model's prediction performance.
    - Receive commands from TMS.
    - Deploy and manage new predictive models on TMS data and software subsystem and at the edge.
    - Communicate predicted events to TMS.

  To perform those functions, TMS data and software subsystem computing servers run the following software components:

    - Vendor API—Allows for the management of multiple data pipelines performing such tasks as data ingestion, data preparation, model development, prediction, and predicted-event communication to the TMS.
    - Event API—Enables the predicted events generated by the data pipelines implemented on the vendor service to be sent to the TMS event management subsystem.

- Machine-learning subsystems—A set of subsystems added to the existing TMS enabling its integration with vendor services for performing the following tasks:

    - Set up and monitor data collection between edge devices.
    - Set up, deploy, and manage data preparation pipeline.
    - Deploy predictive data pipeline at the edge.
    - Monitor edge data pipeline prediction quality.
    - Monitor machine-learning-model performance.
    - Discard and replace unsatisfactory machine-learning models.
    - Create, test, and deploy machine-learning models.
    - Communicate traffic management predictions to TMS subsystems.
    - Run prediction management graphical interface.
    - Manage accounts and access to the vendor service.

To perform those functions, TMS machine-learning subsystems run the following software services:

- Main UI services—Provide a graphical UI so that TMS operators can operate prediction data pipelines deployed on the vendor service.
- Access management services—Provide identity access management for the vendor service for users and services of the TMS prediction subsystems.
- Event management services—Provide a distribution and monitoring interface for all predicted events submitted to the TMS by the vendor service.
- Vendor management services—Enable TMS users and services to send requests and actions and receive data, models, and data pipeline status information through the vendor service API.

When outsourced, a vendor product may be provided as a stand-alone system with its own web-based interface. Or the vendor may push the prediction to the TMS data subsystem, which then promulgates the information—based on logic rules—to the relevant operational-strategy-associated subsystems and to the operator UI to inform specific actions and support specific functions.

CHAPTER 4. PREDICTIVE ANALYTICS CONSIDERATIONS

Several key considerations are involved in the planning for the adoption and use of predictive analytics in a TMS. This chapter covers high-level considerations for implementing predictive analytics, such as current TMS capability, resources, funding, and data. The more significant range of issues to consider in the pursuit of predictive analytics is organized across the following three categories:

- Data and data management—Predictive analytics typically requires data and unique computing capabilities. Agencies adhering to data management policies and practices may find their data and computational tools insufficient for the use of predictive analytics in traffic management decisionmaking. For example, most agencies do not store their CCTV camera video beyond a limited duration, if at all. Thus, the opportunity to develop machine-learning models may be limited. Predictive analytics that rely on smaller event datasets that make use of regression models may still be viable. An example of such an application is given in chapter 6: the Maryland Department of Transportation (MDOT) incident duration and queue length prediction too.

- Human resources and institutional considerations—Predictive analytics in a TMS may represent a shift from reactive decisionmaking to more future-oriented, proactive decisionmaking for TMC operators and managers. Using real-time information from the TMS, TMC operators and managers currently make decisions based on descriptive and diagnostic analytics, experience, and intuition. The introduction of predictive analytics into traffic management may influence how traffic management staff use and trust data. Other considerations include managers' and operators' workflows, tasks, technology interfaces, and organization policies and practices.

- Implementation and maintenance considerations—Predictive analytics from the modeling perspective is not static. Rather, predictive analytics models should be routinely reassessed, retuned, or even rebuilt as travel behaviors and patterns; event types, locations, and frequencies; data sources and quality; and even weather events change.

The information presented in this chapter discusses predictive analytics from a data, resource, and policy perspective. Organizations must recognize that before any TMS deployment decisionmaking, including predictive analytics, they must begin with defining the need and then adhere to standard processes. That beginning includes the introduction or adjustment of any technology, tool, or capability within either the physical or logical components of a TMS. Report *Decision Support Methods and Tools for Traffic Management Systems* delves in significant depth into considerations associated with the selection and use of DSTs.[1] The considerations are also introduced in chapter 5 of this report.

DATA AND DATA MANAGEMENT CONSIDERATIONS

For predictive analytics to become operable in a TMS, transportation agencies have to adopt data management practices and policies that support cost-effective options for processing, integrating, and analyzing large volumes and a variety of data. Currently, TMSs typically operate using databases or subsystems with relatively small, structured, human-manageable datasets stored on internal servers. And few people within the organization prepare or analyze the data. Within the TMS, data are collected to meet a specific need. Developing predictive models is an exploratory exercise; it may not be immediately clear which data and what duration of an archive may prove valuable or may not. Thus, data not traditionally managed for a TMS or managed at a level of granularity needed for TMS DSTs may be different from the data needed for a predictive model.

Databases or subsystems used by TMSs typically take an ETL process, a rigid data model (database schema), and a schema-on-write, or schema-first, approach to bringing data into the system. During the process, data get transformed, filtered, and removed so that the data will fit into a structured table. As such, data that get stored are processed versions of the original data. In addition, data access rules (governance) are applied that aim to preserve the processed data and to avoid potential corruption or deletion of the data not only for the TMS but for the broader transportation enterprise. Most agencies' data management focuses on maintaining transformed and processed data.

An alternative method involves archiving of data in an unaltered, unprocessed, raw format called the schema-on-read or schema-last approach. The method enables raw data to come into the system and takes a shared and distributed approach that enables many users to create unlimited numbers of processed data sets, analyses, and data products from raw data. The method represents a fundamental concept of modern data management that needs to be understood.[(21)] Users then develop processes to clean data specific to their uses. The transformation process, if flawed, can be revised and reapplied to the raw data for consistency.

Data for Predictive Analytics

Data considerations for predictive analytics necessitate answers to the questions "What kinds of data?" and "How much data?" within the context of moving from a traditional data management approach to a modern, big-data-management approach as follows:

- Volume is the main aspect of a big dataset, and big data are generally considered to be more than a terabyte; however, the size characterization of big data is continuously changing.
- Variety refers to structured and unstructured data present in big-data workflows as well as the ability to combine and use those various data types to gain insights that were difficult or even impossible to attain before analytics powered by big data. Structured data are easy for machines to handle—especially when it comes to searching, sorting, and storing data in relational databases. Unstructured data are the opposite: they include video files, audio files, free-form text, and other data that do not conform to traditional data structures and are therefore difficult for machines to categorize. Examples of unstructured data that may be of potential value in predictive analytics are lidar data, unmanned aircraft system video data, citizen reports delivered via social media services, and data from response vehicles with camera systems.
- Velocity is defined as the speed at which data get generated, which may vary by data source. For example, crowdsourced data are typically high-velocity data sources, with

information transmitted every 1 or 2 min—and, potentially, even more rapidly—compared with traditional transportation data sources. Data latency also is a change—with information accessed with less than a 5-min delay rather than typical delays such as with certain wireless-technology reader data that require a vehicle to pass two stationary points before data get collected. The volume of these data also can vary because the data can surge in response to newsworthy events. For instance, an agency using social media and crowdsourced data to gather information from users on road closures due to flooding might receive a 10- or even a 100-fold increase from reports compared with a "normal" day.

- Veracity refers to how accurate or truthful a dataset may be. In the context of big data, veracity is not just about the quality of the data themselves but also about the trustworthiness of the data source, the data type, and data processing. The veracity associated with certain big data can vary dramatically based on shifts in the user base market share upon which the data get collected. For example, the number of the first detection of incidents in Iowa DOT by using data from a free navigational application nearly quadrupled during a 4-yr period, indicating greater market share and data value.(22) Conversely, during March 2020, with travel restrictions in place, the number of reports in Massachusetts declined instantly by more than 50 percent from the free navigational application data. Likewise, the veracity of vehicle probe data may decline significantly during night hours on roadways with low traffic volumes.

- Value denotes how big datasets contribute to improving the performance of an agency and a TMS. Value involves determining a benefit and estimating the significance of that benefit across the enterprise. Big data and its management are not trivial in terms of cost; thus, when pursuing a big-data application—whether for descriptive, diagnostic, descriptive, or prescriptive analytics—an agency has to estimate value. That value will be a function of data quality as well as of potential uses across the enterprise. For example, vehicle probe speed data may be of tremendous value from an operations perspective, but it can generate value for planning model calibration and validation, for work zone management, and even for project prioritization.

One additional critical element to consider—particularly with predictive analytics—is attention to the training data needed to develop predictive models and to the testing data needed to validate predictive models. Whether for machine-learning-focused, high-volume, and variety-data-supported predictive analytics or for traditional predictive analytics, a model cannot offer robustness without data of sufficient variety and representativeness. For example, the predictive models the finance industry developed to detect potentially fraudulent transactions are based on hundreds of millions—or billions—of dollars of transactions and with numerous data fields. Moreover, the models are often self-adjusting based on new data. For some transportation applications, data may just not be sufficiently voluminous or may not be well labeled to support predictive modeling.

The question of training data and the volumes of data needed is a function of the specific need for prediction and its intended use. Such data considerations will influence TMS data, communications, and hardware subsystems requirements such as the database system(s) chosen to organize data, the need for software and servers that support high-velocity stream processing, and the methods of cleaning and visualizing data. Conversely, if model development is approached using external entities (e.g., a consultant or university collaborator), the focus will be on transfer or access to the larger volume of data and security associated with certain data types.

Modern Data Management

Data management for predictive analytics requires evolution from traditional data management at agencies Pecheux, Pecheux, and Ledbetter described how data from emerging technologies have the potential for new insights and solutions and require modern data management methods:

> The volume and speed at which these data are generated, processed, stored, and sought for analysis is unprecedented and will fundamentally alter the transportation sector. With increased connectivity among vehicles, sensors, systems, shared-use transportation, and mobile devices, unexpected and unprecedented amounts of data are being added to the transportation domain, and these data are too large, too varied in nature, and will change too quickly to be handled by traditional database management systems. As such, modern, big data methods to collect, transmit/transport, store, aggregate, analyze, apply, and share these data at a reasonable cost need to be accepted and adopted by transportation agencies if they are to be utilized to facilitate better decision-making.(22)

Data subsystems are designed to be flexible when it comes to changes in hardware and software, to allow for structured data and unstructured data, and to distribute data management and storage in a cloud. Data subsystems also feature decoupled software and hardware, which allows for flexible updates and upgrades—in contrast to traditional data management systems, which are characterized as having more rigid and inflexible designs that include predefined hardware and software requirements, database schemata, and other system requirements that are not easily modifiable.

Figure 8 shows the differences between a current TMS data subsystem—in the box labeled "Traditional data system"—and a modern data subsystem—in a black box. Most TMS data subsystems have processes to organize, clean, and store structured data in a relational database, and they use these data to publish reports, deliver analytics dashboards, and push data to other subsystems or a UI.

The modern data system approach involves loading raw data into a data lake or flexible storage platform. Within the data lake, data at any scale—whether unstructured, semistructured, or structured (traditional relational database)—are maintained. The flexible storage platform offers the flexibility to develop decentralized analytical pipelines that are created based on individual requirements. The data lake, with regard to a TMS, may be a transformation of data subsystems, but more realistically, it may reside outside the TMS—perhaps with the transportation agency enterprise data system. The TMS data subsystem would then access various data from the data lake to support predictive model development. Conversely, analysts may use the enterprise data lake and its tool to support model development, exporting necessary data from the TMS data subsystem to the data lake. The analytical pipelines are similar to traditional ETL and leverage relational database systems. In addition to data lakes and modern data system architecture—and central to understanding big data in transportation—are certain concepts as follows:(21)

- Cloud-computing services are online virtual infrastructure, software, and other IT services that are hosted on large external server clusters rather than on-premises. Cloud-computing services are often ubiquitous with big data and offer scalability, flexibility, reliability, availability, and cost-effectiveness. Cloud-computing storage services are typically the first cloud-computing services that organizations adopt because such services can greatly reduce the costs associated with storing, managing, archiving, sharing, and securing large amounts of data compared with on-premises storage. As noted in Chapter 3, cloud-computing services require changes to computer systems architecture to realize the benefits of the platform.

- Distributed computing is a method of efficiently performing a single computing task by dividing it across multiple servers. It is widely used in big data, since individual servers are too small to handle big-data-processing tasks on their own. Distributed computing is implemented through distributed computing frameworks that run on clusters of servers. Distributed computing frameworks enable computing tasks to scale easily, since they need only the addition of new servers to their clusters to improve their performance rather than having to upgrade or replace them.

- Distributed storage is the technique of storing large amounts of data on a distributed network or cluster of drives and servers. Typically, cloud-computing service providers manage this process by use of a method that is transparent to users.

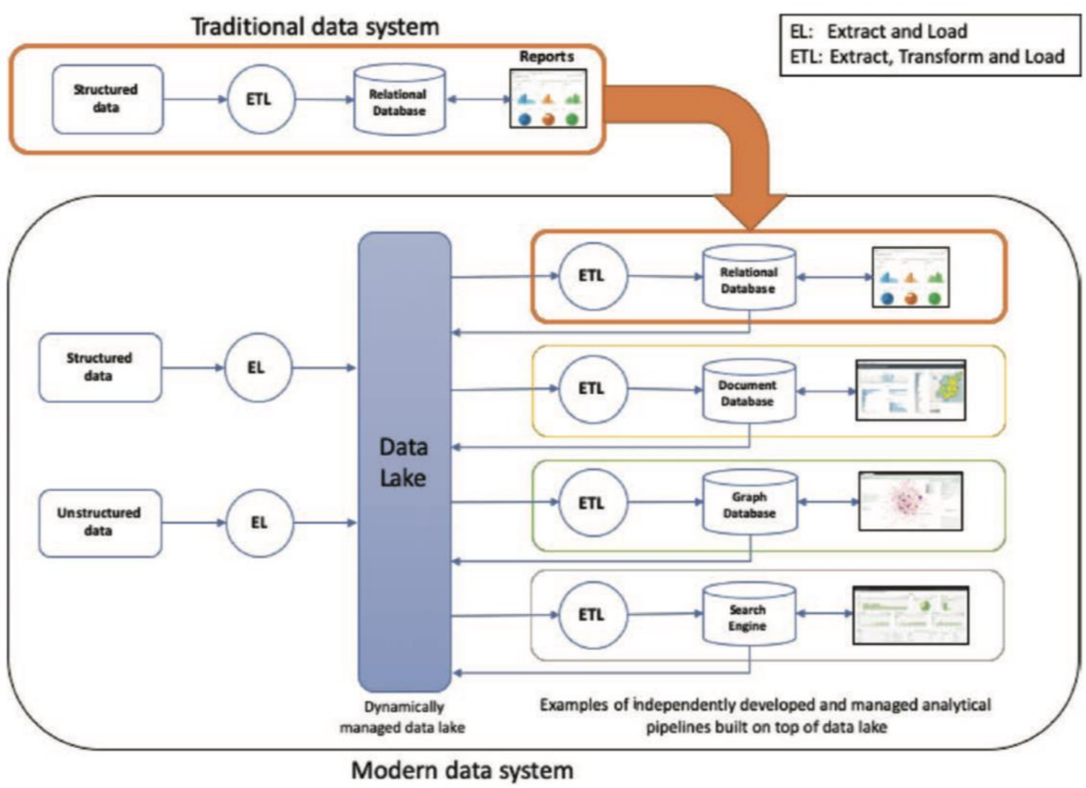


Figure 8. Diagram. From traditional data systems to modern data system architecture.[22]

HUMAN RESOURCES AND INSTITUTIONAL CONSIDERATIONS

Data and predictive analytics will be part of a larger workflow system at agencies that consist of human operators, managers, leaders, collaborators, and other stakeholders who currently use technologies and tools to meet traffic management goals and objectives. In addition, agency personnel operate within an organizational structure composed of roles, responsibilities, policies, procedures, work culture, and in many cases, a TMC environment.

The TMC itself is a complex environment, with many channels of dynamic information continuously flowing in and out through automated and human-interface activities. Some TMCs operate with staff around the clock, while some are staffed during weekday peak periods. Some TMCs are colocated with other response functions such as for public safety (e.g., 911 or law enforcement) and emergency response. TMC operators may access multiple platforms and tools depending on their TMSs, often spread across two, three, or even more monitors.

Advanced, emerging, and continuously evolving technologies and tools—such as big data, modern data management practices, and predictive analytics—will be used by human operators for planning, resource allocation, and operational strategies, including specific actions to take within seconds, minutes, or longer time horizons such as weekly or quarterly. Interaction between the predictive analytics information interface and human knowledge, reasoning, and decisionmaking will determine the quality of the outputs or outcomes of each task. For example, operators have to multitask and work effectively on both onsite and remote teams, within their own agency, and with other organizations while being able to respond quickly and effectively to network performance.[(23)] Because humans are the mediators of the information at a TMC, their work and the design of their environments affect the implementation and use of predictive analytics.

Predictive and prescriptive analytics may introduce new types of data and processes that affect decisionmaking at TMCs—potentially beyond the changes in decisionmaking that are already being ushered by the introduction of descriptive and diagnostic analytics that integrate many real-time data. For example, agencies that typically assess their safety service patrol routes on an annual or less frequent basis might use predictive analytics to adjust routing quarterly. Conversely, some TMC operators who had to manually bring CCTV feeds to the main screen now do not have to do so, because the nearest CCTV feeds to the geolocation of an incident are brought up passively. At the operator and manager levels, predictive analytics will not replace commonsense decisionmaking; rather, it will be a new set of data points to interpret in decisionmaking.

The critical role of predictive analytics in effective decisionmaking makes operator, manager, and institutional trust necessary, and the future-oriented outputs of predictive analytics warrant careful consideration with human decisionmaking. Predictive analytics does not generate an exact result or absolute truth, but, rather, a predicted value with an associated confidence score and statistics with confidence bands and levels of uncertainty.[(21)] For example, early research indicates a significant level of false-alarm rates associated with predictive analytics, which has implications for user trust and the successful uptake of predictive analytics at an agency or TMC.[(24)] Given that predictive analytics makes a statement about the future—with varying degrees of certainty—the introduction of predictive analytics should adhere to agile development processes with frequent feedback from end users. Predictive analytics developers have to consider human and organizational factors within the broader, complex TMS context that includes personal knowledge; team experience; other data, including descriptive analytics; and organizational policies, procedures, and culture.

Situating predictive analytics and the interpretation of the outputs from decisionmaking among the myriad contextual factors is critical to building user trust and increasing the accuracy of predictive analytics for the long term. For example, when operators make an incorrect decision, such as responding to a false alarm, they lose trust in automation.[(25)] Further, operators may be prone to unintentional human error as a result of human and organizational factors such as task overload or decreased vigilance.[(26)] As such, careful consideration and analysis of the human factors at TMCs—such as operator cognitive processes, the usability of predictive analytics output and results, workflow, environment design, teamwork, and communication—should be applied because they may influence the uptake and effective use of predictive analytics.[(23)]

Lastly, recognizable tradeoffs occur between building internal capacity at a TMC for predictive analytics versus using external expertise, including vendors and other third parties. Because predictive analytics requires a requisite level of technical knowledge to develop and implement—in addition to the requirements for big data—TMCs might use vendors, universities, consultants, other experts, and customized or off-the-shelf solutions to support their internal knowledge bases. Agencies also might consider that internal knowledge and capacity are necessary to serve critical decisionmaking functions.

IMPLEMENTATION AND MAINTENANCE CONSIDERATIONS

Predictive analytics can take various implementation approaches for TMSs, as discussed in chapter 3 and as follows:

- On-premises or cloud with traditional devices.
- On-premises or cloud with edge devices having computational capabilities.
- Cloud native (containerized) with smart devices.
- Cloud-native SaaS with smart devices.

Table 2 provides a generalized comparison of the approaches across such features as cost, ownership, and resiliency. Each approach has advantages and disadvantages along a continuum of implementation features for predictive analytics. Each feature is discussed in table 2.

Table 2. Comparison of predictive analytics implementation approaches.

Implementation Features for Predictive Analytics	On-Premises or Cloud With Traditional Devices	On-Premises or Cloud With Computing-Capable Devices	Cloud Native With Computing-Capable Devices	Cloud Vendor SaaS With Computing-Capable Devices
Cost	L	H	M	M[1]
Real-time functionality (e.g., ability to conduct analytics)	L	M	H	H
Expertise in managing a system that supports real-time prediction	L	L	L	M
Resiliency (e.g., cyber, natural disaster, and staff expertise)	H/L	H/L	M/H	M/H
Flexibility (e.g., peak demand, growth in data, and new models)	L	L	H	H
Institutional fit with traditional TMS culture	H	M	L	L
Ownership and analytics transparency	H	M	L	L
Delivery speed and uptime (e.g., data access by vendors and users)	L	L	H	H

[1]Depending on the scale, it can be low, but the cost can increase exponentially as data and models grow.
H = high; L = low; M = medium.

Brief discussions of each implementation feature are presented below:

- Cost—The costs associated with using on-premises architecture with traditional devices are managed within an agency and relatively fixed; however, the computational needs for predictive-model development are limited to tools that may not support big-data analytics. Thus, on-premises traditional devices have relatively stable and lower costs compared with the three other approaches. The introduction of smart devices, may generate potentially far greater volumes of data and complementing data transfer costs from the edge to the central system. Additionally, higher costs are associated with the smart devices themselves, which may include infrastructure costs as well as monthly service costs. The use of cloud-native architecture or SaaS gains efficiencies in storage and computational costs by provisioning servers only as needed.

- Real-time functionality—The fixed nature of on-premises server computation power or the use of cloud-computing services without architecting to take advantage of cloud-computing capabilities limits real-time functionality for predictive analytics. Many agencies simply do not have the computational power and speed needed for big-data analytics that supports real-time decisionmaking. By using smart devices, even with on-premises architecture, agencies can use the vendor-developed and -tested predictive analytics embedded in the device to support greater functionality.

- Expertise in managing a system that supports real-time prediction—Transportation agencies' IT departments are evolving to support greater real-time data pipelines and descriptive and diagnostic analytics. In some cases, the management of such systems is now the responsibility of the ITS or operations group rather than the State or governor-level IT organization. In other cases, the pendulum is swinging in the opposite direction. Data governance processes as well as expertise with tools and services that passively monitor the fidelity of predictive models still need further focus and development within a transportation enterprise. Staffing shortfalls strain the ability to quickly grow and maintain that expertise.

Moreover, at times, analytics may require the processing of personally identifiable information, and thus, agencies may have to self-exclude from accessing data that support model development and fidelity assessments. That is where a SaaS architecture for predictive analytics systems management may have strength. Many vendors already access a host of high-fidelity data to support the streaming descriptive and diagnostic analytics products their TMSs already consume, and many of the same capabilities position those vendors to manage systems for real-time prediction.

- Resiliency—If transportation IT and employees diligently practice such protocols as diversification of infrastructure (multiple, redundant servers), maintenance of physical security, monitoring of applications and systems hardware, and security procedures, then the on-premises architecture can be highly resilient. However, in many circumstances, staff shortages and turnover within transportation enterprises along with systems that often remain untouched for years, if not decades, result in nonresilient systems. Because providing resilient systems is a core value proposition by cloud service providers, such vendors allocate resources to ensure resilience with multiple levels of redundancy. Moreover, they tend to replace and upgrade computing infrastructure more quickly and have workforces that can continually advance skills to meet future cyberthreats.

- Flexibility—Flexibility represents the great divide between on-premises versus cloud-native architectures. Surges in demand for applications (e.g., 511 website hits during a hurricane), the generation of data (e.g., free navigational app reports during post–Super Bowl traffic), and significant growth in data and processing needs (e.g., using real-time connected-car or fleet dashboard cameras) may quickly exceed the capacity of on-premises servers. Cloud-native or cloud-computing SaaS is able to provide the right set of servers for data storage and varied computational needs and offers both tremendous flexibility and potential cost savings. Agencies have to respect that flexibility, lest wayward or poorly defined computations result in unexpectedly high costs.

- Institutional fit with traditional TMS culture—TMSs have been developed mainly through the traditional systems engineering process. That is, a TMS is often a large, complex system designed to ingest specific data in specific formats and via specific processes and to share these data in standardized interfaces. A TMS is difficult and costly to change; adding new data sources, changing operator interfaces, and evolving workflows embedded in the TMS software take up significant amounts of time and resources. The on-premises architecture is well aligned with the traditional TMS culture in terms of access and the use of tools to support the TMS, modification request processes, procurement processes, and the like. Thus, implementing predictive analytics model development as a core function that interfaces with the TMS aligns with traditional TMS culture. Leveraging cloud-native and cloud-computing SaaS architectures requires containerization and migration of some components of the TMS, nontraditional procurement mechanisms with variable costs, and a skills realignment within the staff that develop, test, refine, implement, and manage systems.

- Ownership and analytics transparency—When agencies use predictive analytics through on-premises architectures, they build and own the predictive models, the input data, and the outputs and interfaces. When accessing devices with computational capabilities, most often the sensors are vendor controlled, and the edge analytics also are vendor-controlled black-box processes. The agency acquiesces to that element of ownership. In moving to a cloud-native platform, organizations can access a range of predictive-modeling tools (i.e., tools that help develop a model). Such tools represent another potential black box and may be changed by the cloud provider. Likewise, interface and visualization tool offerings available through the cloud-native environment may evolve. And, most significantly, if the agency chooses to switch its cloud provide or SaaS vendor, the predictive models may not be portable because of their ownership by the SaaS vendor.

- Delivery speed and uptime—This aspect is the percentage of time that an agency's server, website, and applications are active and able to function during a period—whether a week, a month, or a year. Generally, the uptime and delivery speed for cloud-native and cloud-computing SaaS architectures are greater than those for on-premises options given cloud systems' redundancies and dynamic allocation to support access. Thus, cloud-native descriptive, diagnostic, and predictive analytics tools have better uptimes and delivery speeds compared with on-premises architectures. Cloud vendors can offer uptime of 99.9 percent (down 8.8 h in a year) or even 99.9999 percent (down about 30 s in a year); the higher the required uptime guarantee, the higher the cost. Except for mission-critical systems that are required to function even if cellular or the Internet goes down, most cloud-native and SaaS architectures offer better value.

SUMMARY OF PREDICTIVE ANALYTICS CONSIDERATIONS

While traditionally, transportation agencies have been implementing and integrating new processes in-house with support from their IT infrastructures, predictive analytics presents agencies with challenges as follows:

- Most transportation agencies are operating traditional IT hardware and systems that are not capable of handling the data and computing load required to develop and deploy predictive analytics.

- Predictive analytics development requires a large amount of labeled data, which transportation agencies typically lack.

- Deploying predictive analytics IT infrastructure on-premises may be cost prohibitive.

- Cloud infrastructure adoption at transportation agencies is just starting, and agencies are still learning how to use the cloud.

- Transportation agencies may not have enough data to train efficient predictive data models.

- Vendors have more data and for about a decade have been developing predictive algorithms to be used as a service. They may be able to provide cost efficiencies that agencies may never reach.

Consequently, it is likely that agencies will first and foremost implement predictive analytics by using the SaaS implementation because it is the easiest to integrate and implement. Other implementations (i.e., on-premises or cloud IaaS using traditional devices, on-premises or cloud IaaS using predictive-devices implementation, and cloud-native predictive analytics) require significant effort, time, and expenses. Agencies will have to evolve their IT infrastructures and data to the level required to perform predictive analytics. Conversely, agencies may turn to their university or consultative support to collaborate in the development of in-house models.

Further, it is likely that some transportation agencies with relatively low traffic such as those of Idaho, Montana, Utah, and Vermont may have difficulties in building datasets that are representative of their amounts of traffic and the rarity of events they would like to predict. As an alternative, State transportation agencies might consider collaborations when developing predictive analytics through such programs as a Federal pooled-fund study. By combining data among States, agencies may generate more representative datasets that can better train predictive models.

CHAPTER 5. READINESS CHECKLIST

This chapter guides agencies through a readiness assessment checklist for predictive analytics. Agencies can use this readiness assessment checklist to begin thinking about the current and future capacities necessary to integrate predictive analytics into TMSs and TMCs. The readiness checklist consists of five levels:

- Policy readiness.
- System readiness.
- Data readiness.
- Acquisition readiness.
- Maintenance readiness.

The readiness checklist is intended—after some initial work has been completed—to confirm the need for predictive analytics capability and a corresponding DST. The needs assessment effort should come first and be foremost. FHWA report *Decision Support Methods and Tools for Traffic Management Systems* specifies a five-step process for identifying needs for a DST as follows:(1)

1. Identify stakeholder and DST goals, making sure to include end users as well as those with institutional, operational, or technical responsibility.

2. Elicit and document user and system needs through outreach mechanisms such as workshops and interviews and use the interactions to also educate stakeholders.

3. Reconcile, validate, and prioritize stated needs to resolve conflicts or close gaps and thereby deliver a unified, prioritized vision of DST needs.

4. Verify whether the system is feasible and necessary, delineating what may or may not be addressed.

5. Define project scope, budget, and time constraints.

In the context of the five-step process, the five readiness components presented herein overlap step 4.

POLICY READINESS

Policy readiness refers to the practices, governance structures, and procedures associated with data and analytics. Table 3 summarizes key questions and considerations for policy readiness.

Table 3. Policy readiness checklist and considerations.

Policy Readiness Questions	Policy Readiness Considerations
Does your agency have a policy regarding the cloud and cloud services? If so, what does the policy entail?	The use of the cloud is a requirement for most advanced predictive analytics methods such as machine learning. Might that policy hurdle be overcome through a university or other kind of collaboration?
Does your agency have an open data policy? If so, what does the policy entail? Might it limit what kinds of data that predictive models can use?	Open data refers to publicly available data structured in a way that enables the data to be fully discoverable and usable by end users.
Does your agency have policies regarding the ways analytics are to be used for informing decisions and specific types of actions? If so, what types of decisions and actions are involved?	Agencies may have written policies or procedures describing how real-time data and descriptive analytics currently are used for informing TMS actions. For example, is operator verification required for events?
How are data and analytics actively managed in the TMS?	Agencies may have documentation and procedural practice codified to inform the active management of data and analytics in a TMS and at a TMC.
What policy or cultural barriers might limit governing and managing data and analytics at your agency?	Barriers might include lack of precedence in data policy, lack of precision in written policies that reflect the realities of the TMS, and lack of institutional support.

SYSTEM READINESS

System readiness refers to the components necessary for predictive analytics, such as data systems, sensors, communications, and cloud infrastructure. Table 4 summarizes key questions and considerations for system readiness.

Table 4. System readiness checklist and considerations.

System Readiness Questions	System Readiness Considerations
Do you have a place to store large amounts of data?	Big-data predictive analytics offers the greatest potential value but requires the storage of large amounts of data (e.g., terabytes or more per year).
Do you have computing power and a GPU to read and process large amounts of data quickly?	Big-data predictive analytics requires that large amounts of data be analyzed—often in realtime or streaming, which requires large amounts of computational power that exceed the capabilities of most desktop computers and even large, on-premises servers.
Are power and/or communications bandwidth (roadside fiber) available for traditional edge devices and devices with advanced computing capabilities?	A basic CCTV camera uses 40–60 W. It is estimated that an additional 10–30 watts are needed for analytics on edge (an approximately 50-percent increase in power).
Is ATMS able to support data volumes for building, training, and iterating models? If not, consider cloud service analytics and predictive analytics in the loop.	While it may be possible to integrate a predictive model within an ATMS, the model may likely have to be trained externally. Use of the cloud will facilitate the development of predictive models.

DATA READINESS

Data readiness refers to data collection, quality, storage, and analytic capacity for big-data predictive analytics. Table 5 summarizes key questions and considerations for data readiness.

Table 5. Data readiness checklist and considerations.

Data Readiness Questions	Data Readiness Considerations
Does the storage of specific types of data raise issues?	For example, most agencies do not store CCTV video for more than 2 was a policy. Likewise, the storage of certain data that may contain personally identifiable information may not be possible. Some agencies choose not to access specific data (e.g., a pothole report) because they are liable if the agency does not take immediate action.
Does your agency have sufficiently high-resolution, disaggregated data?	Large volumes of high-resolution, disaggregated data are needed to develop predictive models. Often, only aggregate, 15-min or lower resolution data for long road segments may be available.
Does your agency have many years of data?	Large historical datasets are needed to develop predictive models that train for seasonality, time of day, and other inherent variabilities in traffic.
What percentage of data is labeled, and what is the quality of the labeling?	Labeled data are data that come with a tag—like a name, a type, or a number. The label is the target of interest in the prediction. Unlabeled data are data that come with no tag. For example, to detect overturned vehicles from video data, the video has to have tags that identify overturned vehicles. Much more can be done with a labeled dataset.
Does your agency have ground truth data?	Ground truth data form the target for training or validating the predictive model with a labeled dataset.
Does your agency have ancillary data to create labels?	Data labeling enables predictive analytics algorithms to build an accurate understanding of real-world environments and conditions.
Does your agency store raw, unprocessed, or unaltered data?	Archived data to be used in predictive analytics should not be imputed or modified per a schema; raw data provide the noise that could be picked up by the predictive model. If the archived data have been filtered or cleaned, they cannot be used effectively for model development.
Are data representative of the entire area of interest (e.g., are data more reliable in one area versus another)?	A model developed from 80 percent of the data or area will not be useful for the remaining 20 percent. Representative data are needed (e.g., winter versus summer months, weekdays versus weekends, a subset of the transportation network). For example, if cameras are in only a specific area, the model might work for that roadway but not necessarily for some other roadway.

ACQUISITION READINESS

Acquisition readiness refers to processes and practices that support the procurement of the tools, data, and technologies that in turn support predictive analytics. Table 6 summarizes key questions and considerations for acquisition readiness.

Table 6. Acquisition readiness checklist and considerations.

Acquisition Readiness Questions	Acquisition Readiness Considerations
Is your agency able to purchase cloud services?	Verify that acquisition policies allow cloud services.
Have you defined the capabilities rather than the processes for acquisition?	Traditionally, organizations specified requirements for use of specific software, hardware, or processes. Procurement should focus on desired capabilities rather than processes.
Has your agency considered what is owned and how it can be shared?	Whether procuring a dataset, an analytics platform, or a predictive model, an agency should consider the level of transparency, ownership, and sharing that may be needed and weigh that level against relative potential costs.
Do acquisition systems support monthly service purchases (e.g., cloud) with imprecise costs?	Costs of cloud services use a pay-as-you-go, or pay-for-what-you-use, model; therefore, the cost of data storage and processing may vary from month to month.
Will the time required to acquire the necessary hardware (servers) to support predictive analytics surpass the life of the hardware?	Technology is changing rapidly. If the time required to get approval and acquire the necessary hardware to support predictive analytics is longer than the life of the hardware required, alternative approaches have to be considered. With cloud services, hardware is managed by the service providers and is considered a disposable commodity. Servers are continuously decommissioned and updated by the service provider at the service provider's expense.
Is your agency able to outsource data analytics (e.g., consultant support)?	Expert skill sets, outside of those available at a transportation agency, may be required to develop predictive models.

MAINTENANCE READINESS

Incorporating predictive analytics into a TMS requires ongoing maintenance of hardware, data, staff, and the predictive models themselves. Some agencies have incorporated real-time descriptive and diagnostic analytics using big data. Few agencies also have acquired edge devices with computing capabilities to supplant or complement traditional devices; however, the maintenance of embedded predictive models is in the purview of the vendor. Thus, maintenance readiness is still a developing consideration. Table 7 summarizes key questions and considerations for system readiness that have been drawn from broader industries that have more mature predictive analytics pipelines.

Table 7. Maintenance readiness checklist and considerations.

Maintenance Readiness Questions	Maintenance Readiness Considerations
Does your agency have a replacement strategy for edge device obsolescence?	The rate of hardware obsolescence is a challenge from both cost and acquisition standpoints. Agencies should plan for the ways such edge devices will be upgraded or replaced. Such planning may be a relatively easy hurdle for agencies with mature processes for managing traditional edge devices such as CCTV cameras.
Does your agency have a plan and/or resources in place for continuous data preparation and maintenance?	Automated data source changes can affect data pipelines and predictive models. Data streams and pipelines have to be monitored to identify relevant changes and ensure they are working properly. Additionally, new sources of data are emerging frequently that could help improve prediction capabilities. Those data sources should be assessed and incorporated into the models as necessary.
Will protocols or automation be put in place to detect when your prediction models have to be retrained?	Predictive algorithms should not be developed as set-it-and-forget-it models like traditional models. They have to be monitored and updated to reflect changes in the data.
Will you have the resources to retrain the predictive models as needed?	See the considerations contained in table 4.

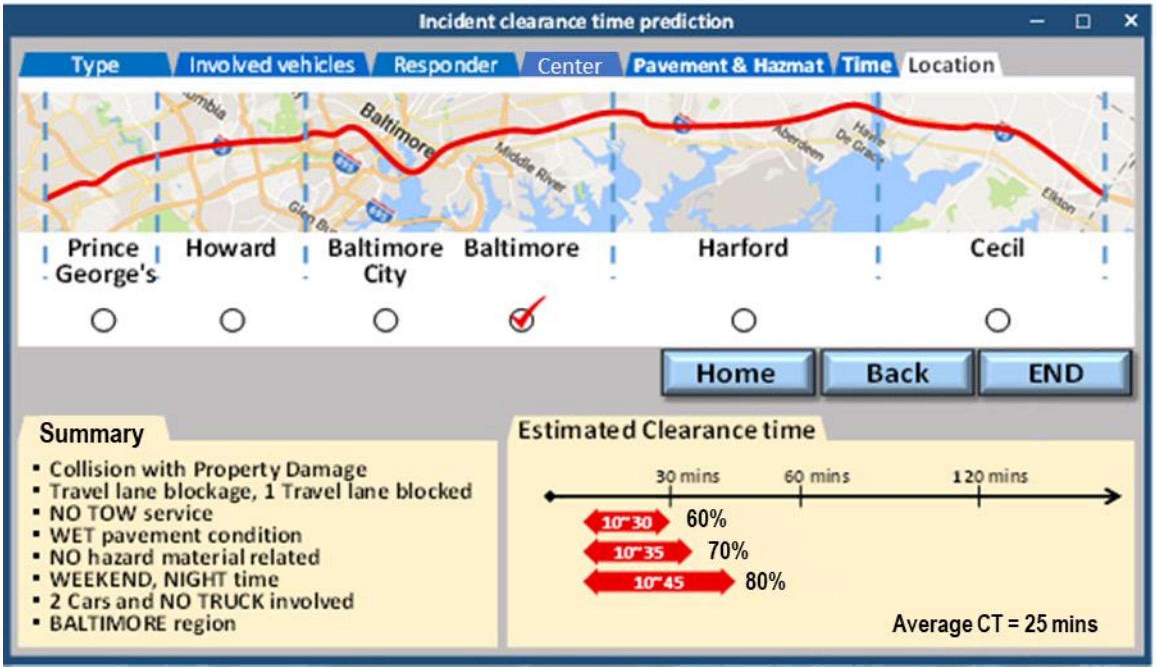
CHAPTER 6. CASE STUDIES: USING PREDICTIVE ANALYTICS TO MANAGE TRAFFIC

This chapter provides lessons learned with using predictive analytics from two transportation agencies and one law enforcement agency. The case studies describe the analytics application, stage of implementation, challenges to implementation, benefits, and lessons learned to the extent that information was available. In summary, real-time descriptive and diagnostic analytics for incident detection and response strategies are maturing. Some predictive models have begun to demonstrate value; however, they are typically not integrated with a TMS.

MARYLAND DEPARTMENT OF TRANSPORTATION

The MDOT Coordinated Highways Action Response Team (CHART) program, through a collaboration with the University of Maryland, developed in 2019 a prototype that predicts incident clearance times in four time ranges—less than 30 min, 30–60 min, 61–120 min, and more than 120 min—based on multiple years of historical crash data from the program's ATMS.(24) The researchers used traditional regression and classification analytics to develop the predictive model. The model requires such inputs as vehicle status (e.g., overturned), number of vehicles involved, number of responders involved, location, pavement condition, lanes blocked, and other data elements available through the CHART ATMS.

Figure 9 illustrates the first iteration of the tool's dashboard with the incident clearance time prediction model.(23) TMC operators can use the information to plan and select incident response strategies—from traveler information messages on DMSs to the field resources needed to reduce incident duration, to the consideration of providing alternate routes. Additionally, by knowing the likely duration of an incident and rightsizing the response, TMC operators can help reduce the likelihood of secondary crashes (e.g., by providing advance queue warning for drivers approaching the incident).



CT = clearance time.

Figure 9. Screenshot. MDOT I–95 incident clearance time prediction prototype interface.[27]

The first prototype was limited to incidents involving collisions on I–95 in Maryland between Exit 27 and Exit 109. The model was initially trained on data from 2012–15 and tested on data from 2016, wherein it correctly predicted the incident clearance time range for 74.3 percent of incidents. After a retraining of the model with data from the first 6 mo of 2017, the model's accuracy on the test set increased to 77.2 percent. For certain months, accuracy reached as high as 97 percent.[23] The updated model demonstrated an overall 85- to 90-percent reliability. Based on that success, the CHART program expanded the project to calibrate predictive models for I–495, I–695, and I–70 in Maryland, yielding a confidence level greater than 80 percent.

CHART included a third phase that developed and calibrated predictive models to estimate clearance duration by class of roadway. The tool also expanded to predict the queue length associated with the incident. That new capability requires additional data input: either the real-time data or the archived detector data (e.g., upstream flow rate and travel speed). The third phase is expected to conclude in early 2023. Figure 10 presents the queue prediction interface, which consists of three sequential tabs: data source selection, input of related data, and predicted queue length. The third tab summarizes inputs on the left and the mean queue length prediction on the right.[27]

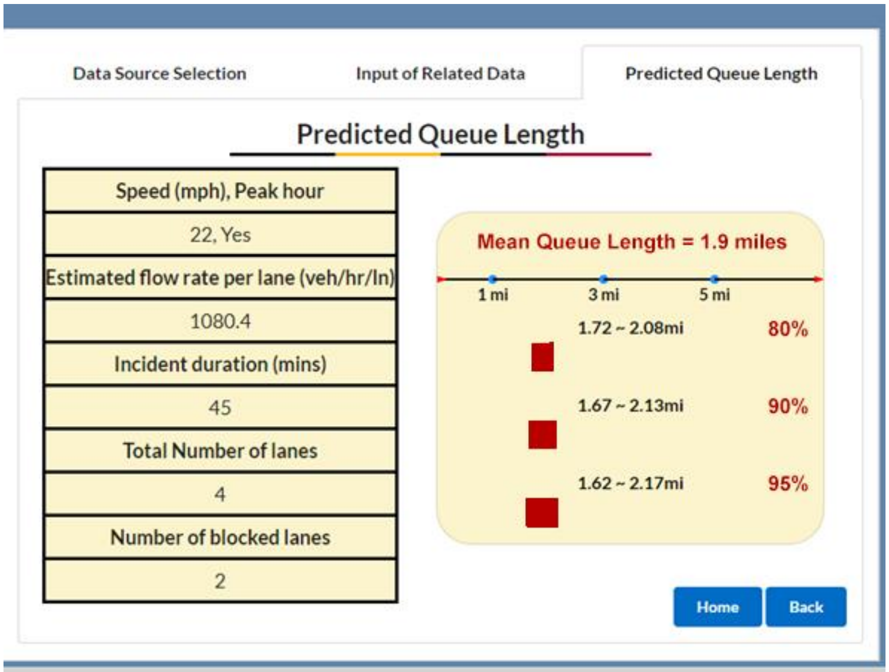


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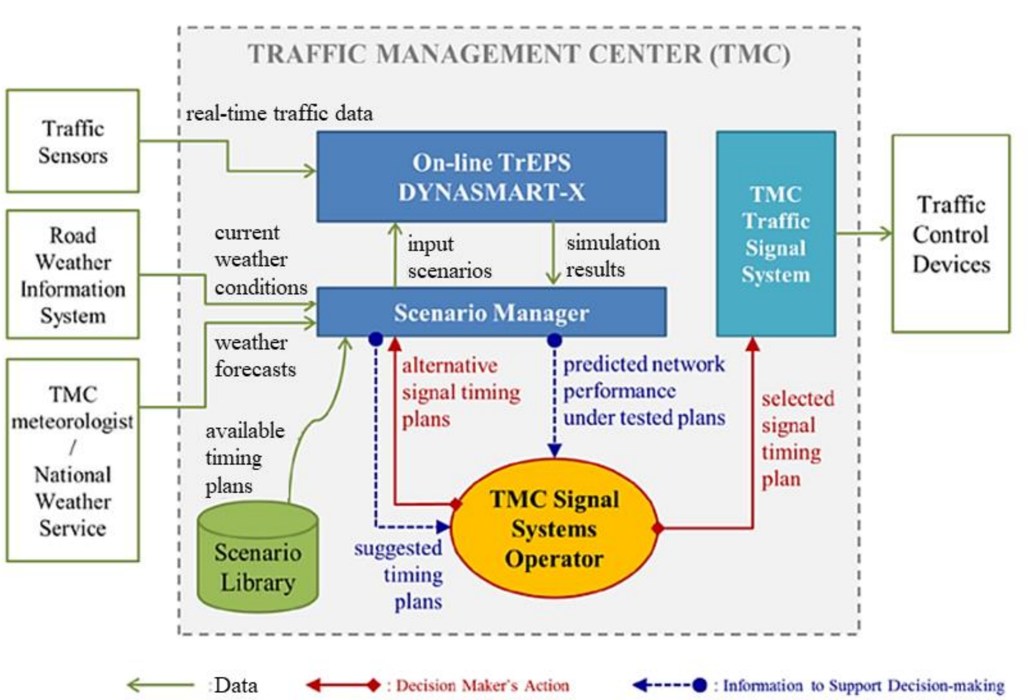
Figure 10. Screenshot. MDOT queue prediction interface.[27]

One of the key challenges limiting the use of this predictive capability is that the UI is not integrated with the CHART ATMS. Consequently, the tool requires operators to manually enter information (e.g., vehicle counts, county, number of responders, and number of lanes closed) that could readily be pulled from the operators' ATMS.[1] Thus, when considering the tool through the lens of the four architecture illustrations in Computer Service Options for use in Predictive Analytics, operators should be aware that the bidirectional arrows would generally lead only from the TMS and subsystems as well as from the edge devices to the core computing server. That challenge would be met by a planned integration of the predictive capability into the ATMS.

KANSAS CITY INTEGRATED MODELING FOR ROAD CONDITION PREDICTION

As part of the FHWA-funded Integrated Modeling for Road Condition Prediction (IMRCP) project, the Kansas City Scout Traffic Management Center (KC Scout) deployed a system based on the Traffic Estimation and Prediction System (TrEPS) platform.[28] Figure 11 presents the IMRCP phase 2 data collection, data storage, forecasting, notification, and reporting elements.

[1]Dicembre, J. 2022. Personal communication in preparation for FHWA Talking TIM Webinar, October 22, 2022. https://transportationops.org/ondemand-learning/talking-tim-october-2022.



Source: FHWA.

Figure 11. Flowchart. Traffic estimation and prediction system framework.[(29)]

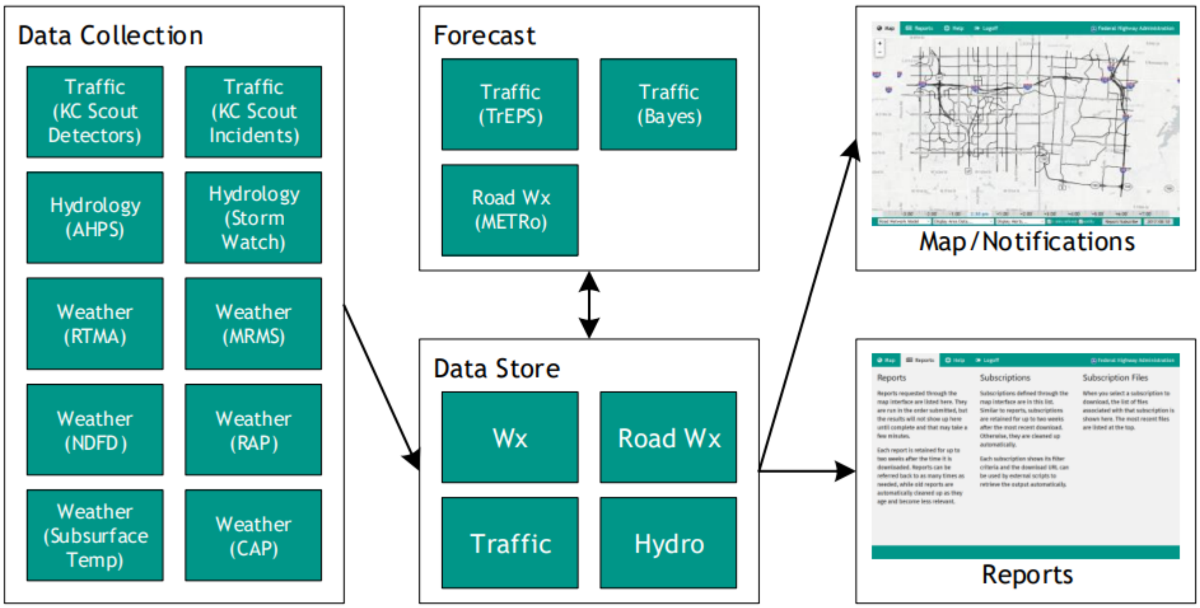
Researchers working with KC Scout's IMRCP system applied a similar predictive approach for Utah DOT, with advances in reporting and interface elements. KC Scout operators who used the system report did not receive prediction-based notifications from the tool during the test period due to two challenges:

- Weather data collected from May to December 2016 to calibrate the simulation model's weather adjustment factors did not contain sufficient adverse-weather conditions.
- Winter storms did not occur during the testing period (September through November 2017). The predictive model was not explicitly calibrated for night and weekend travel when other adverse-weather events occurred.

A phase 3 effort expanded the model to Kansas City metropolitan area highways, added a second machine-learning-based traffic model, and tested the system during the 2018/19 and 2019/20 winter seasons.[(28)] System functions are illustrated in figure 12. The system includes:

- TrEPS traffic demand prediction at zonal levels.
- Traffic network conditions based on weather, work zone, incident, and special events data.
- The Model of the Environment and Temperature of Roads predicts pavement conditions based on National Weather Service data.

The research team noted that data needs (e.g., inadequate number of reliable road weather sensors and traffic detection stations and difficulty with metadata management) and labor-intensive traffic model development needs were key gaps in the use of IMRCP.[(28)] KC Scout operators' periodic use of the IMRCP tool suggests that the IMRCP road weather data and weather forecast may be useful and inform maintenance decision support systems without providing an interface to incorporate data directly into the management and operations of specific operational strategies or other traffic management decisions.[(29)]



Source: FHWA.
AHPS = Advanced Hydrologic Prediction Service; CAP = Common Alerting Protocol; MRMS = Multi-Radar/Multi-Sensor System; NDFD = National Digital Forecast Database; RAP = Rapid Refresh; RTMA = Real-Time Mesoscale Analysis; Wx = weather.

Figure 12. Flowchart. IMRCP system functions.[(31)]

FHWA funded an evaluation of the IMRCP phase 3 system to ascertain whether IMRCP had an operational impact and whether users consider the IMRCP information useful. The study confirmed that while operators referred to IMRCP for weather forecast information—in particular during winter weather or rain—the system had a minimal operational impact during the 2018/19 and 2019/20 winter seasons. The study also noted that the TrEPS and machine-learning-based speed prediction models deviated by more than 20 mph and up to 20 mph from ground truth, respectively, as estimated using loop detector data. The research team cited missing, incomplete, and erroneous data as a factor contributing to the poor prediction capability.

The system and components are available on the ITS CodeHub.[(32)] The system authors also note that "the distributed nature of the system, data sources and services require consistent monitoring to assure a high quality of service."[(28)] IMRCP is a stand-alone system, which means it is not integrated with the KC Scout TMS. Thus, a manager or operator would have to open the IMRCP software to view map notifications or reports. The manager or operator would process and interpret information from the stand-alone system and compare it with other data systems' information and apply expert judgment to decide whether to implement a real-time action such as displaying a traveler information message or to support an offline action such as change or add staffing for a future shift.

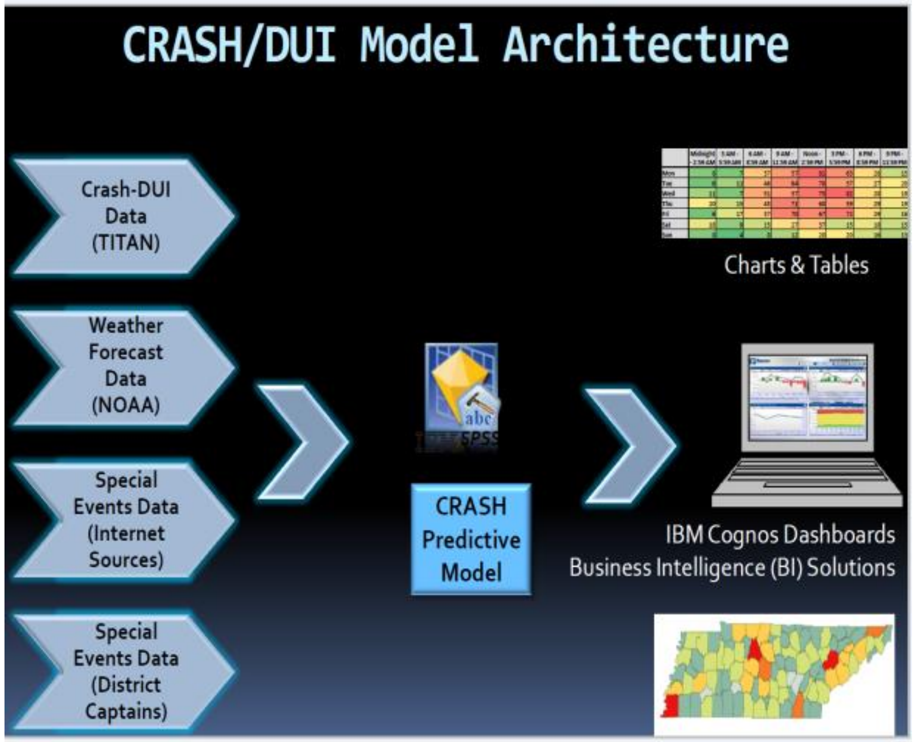
TENNESSEE PREDICTIVE ANALYTICS FOR RESOURCE ALLOCATION

The Tennessee Department of Transportation (TDOT) and various collaborators have developed a predictive analytics tool for resource allocation and emergency response planning that incorporates prediction.(33) The tool is not yet ready for TMS testing or integration. Nonetheless, the TDOT case study illustrates how tools with predictive capabilities could be applied to resource planning (how many staff for a given shift) and resource positioning (police beats, safety service patrol routes) to reflect situational circumstances such as high winds, snow, and planned special events.

A collaboration between TDOT, the Tennessee Department of Safety & Homeland Security, and Vanderbilt University called the Crash Reduction Analyzing Statistical History (CRASH) tool evaluated opportunities to improve highway safety patrol vehicles deployment by using a predictive model. (34) The Tennessee Highway Patrol (THP) Predictive Analytics program developed a model by using both commercially available statistical software to predict the likelihood of crashes and historical crash data from its Tennessee Integrated Traffic Analysis Network (TITAN), National Oceanic and Atmospheric Administration weather data, and special events data (e.g., sporting events, holidays, and festivals).(33) TITAN is a suite of tools developed for the electronic collection, submission, and management of all traffic-safety-related data in Tennessee, typically collected through the State's crash report. TITAN accepts reports submitted by law enforcement agencies, validates the data contained within reports for completion and accuracy, and then stores statistically valid information for use in safety analyses.

The predictive model generates crash forecasts by 4-h temporal, day, week, and 42-mi^2 geographic blocks. Figure 13 illustrates model inputs and outputs. Sheriffs' offices can use the information to allocate personnel for the greatest impact on traffic safety. The CRASH tool, which includes a predictive model, helps supervisors develop weekly enforcement plans and assign patrols to the times and places the model suggests the risks of serious crashes are highest.

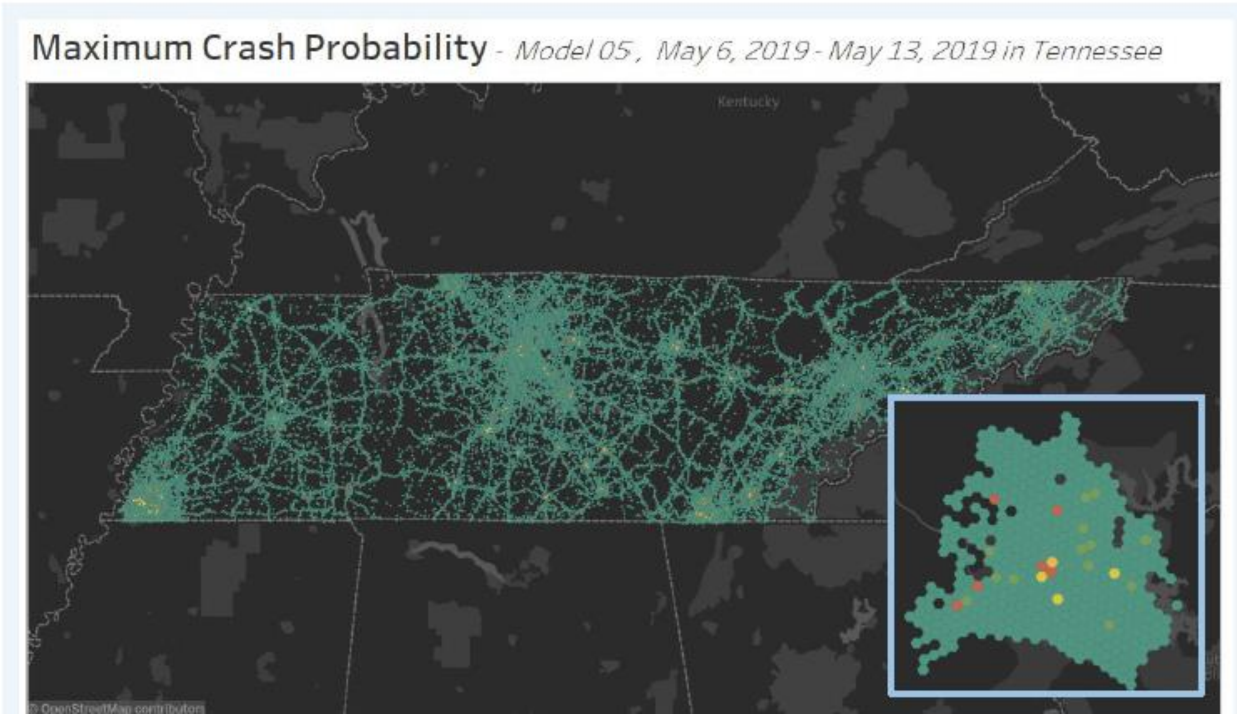
The predictive models are 70-percent accurate in identifying areas of concern for alcohol-, drug-, and crash-involved incidents. THP uses the information to allocate and geographically position law enforcement patrol resources. Key findings have included significant savings in response times, with a 19-percent average improvement when roadside assistance trucks were available. Emergency responders can be placed closer to accident-prone areas where first responders' travel times and the times first responders are not available due to attending accidents can be reduced.



Source: Volpe Center.
DUI = driving under the influence; GIS = geographic information system; NOAA = National Oceanic and Atmospheric Administration; TITAN = Tennessee Integrated Traffic Analysis Network.

Figure 13. Flowchart. TITAN CRASH predictive model.[35]

A more recent extension of the work between THP and the U.S. Department of Transportation (USDOT)/Volpe assessed the value of adding data from a free navigational application to the TITAN model.[35] Inclusion of the data was shown to improve geographic resolution from 42 mi^2 to 1 mi^2 and temporal resolution from 4 h to 1 h without reducing model accuracy. Figure 14 illustrates the higher resolution data and enhanced visualization interface the Volpe Center developed. Based on the validation and value of the higher resolution data, THP plans to ingest the new data into its commercial statistical software and thereby recalibrate its predictive models.



Source: USDOT/Volpe.

Figure 14. Illustration. Enhanced crash propensity model interface.[(35)]

CHAPTER 7. TRENDS, ISSUES TO CONSIDER, AND FUTURE DIRECTION

Predictive analytics generates statements about future events or the future state of a transportation system. Projections of the future have the potential to help managers and operators of TMSs reach decisions with greater confidence, timeliness, accuracy, and precision in support of making transportation operations safer, more reliable, and more efficient. Predictive analytics is a DST that offers agencies the potential to improve the active management and operation of TMSs as well as operational strategies and control plans used for managing traffic.

Many agencies have been moving toward actively managing and operating their TMSs and operational strategies. By proactively responding to predicted changes in events that might influence roadway conditions or traffic demand, transportation operators may be able to mitigate the implications of incidents, prevent delays, and avoid secondary crashes.

Most predictive efforts are stand-alone and yet to be integrated within agency TMSs. Prediction has to be integrated within TMS physical subsystems and components and be structured to support operational strategies, functions, actions, and services. Integrating predictive analytics within a TMS enables decisionmakers to use the information to improve operations.

Agencies can prepare to use predictive analytics in the future by considering the following:

- Supporting TMSs to proactively manage and control traffic—By moving toward proactive management and operation of their TMSs and the use of operational strategies, agencies position culture, policies, and procedures to support the adoption of predictive analytics in the future.

- Exploring opportunities to consider developing simpler predictive analytics—By applying data to develop regression or clustering models, an agency can grow its understanding of statistical methods and confidence with predictive model development and refinement processes.

- Embracing modern management practices for data systems—When focusing on real-time operations using multiple emerging data sources, data systems design has to be flexible and self-adjusting, support distributed storage and processing, decouple hardware and software, distribute data governance, and support broad data access and use. Core to modern practices for data systems is the ETL method for data storage. Implementing these and other modern management facets for data systems may lead agencies to consider cloud storage, management, software, and analytics services.

- Understanding data through the lens of descriptive and diagnostic analytics before pursuing predictive analytics—Predictive analytics is the third level in analytics advances, requiring mastery of descriptive and diagnostic analytics before its exploitation and confident use. An agency pursuing predictive analytics must first have confidence in and mastery of descriptive and diagnostic analytics with the intended data, whether that mastery is through in-house, contracted, or vendor offerings. As described in chapter 2, descriptive and diagnostic analytics align with the monitoring and calculation stages for active traffic management.

- Considering multiagency or multistate data sharing to facilitate model development—Given the data requirements for predictive model development—particularly the need for a large volume of well-labeled data—coupled with the cost of supporting such systems, multistate collaboration on archived data sharing may prove a viable pathway whereby agencies with a common predictive need can develop and test predictive models. For example, agencies may want to develop a model similar to that developed by MDOT to predict incident duration and queue length. Once models have met a specific confidence threshold, they can be implemented and tailored for each agency's operations and decision thresholds specific to deployment of resources and DMS messaging.

- Considering open-source tools and code—Agencies can find many reasons for turning to open-source tools and code. Having open-source or agency-owned software and DSTs gives agencies the opportunity to make and manage changes when applicable. The ability to modify software and supporting APIs in support of the operational strategies agencies may use provides agencies the opportunity to make changes in the future. That ability also enables agencies to test, evaluate, and make changes to improve those strategies and control plans in the future. While agencies may have different TMSs, certain logical functions and actions may be common among TMSs. Algorithms or predictive models developed by one agency may be used and further refined by another. By sharing methods and code, agencies can save resources, validate models, refine models to localized needs, and support more robust predictive modeling ecosystems.

A few other trends also will make predictive analytics more accessible and usable for transportation operations within the next decade—if not sooner. The following list describes some of the trends:

- Transportation agencies continue to modify the structures and architectures of their TMSs to become more modular. The changes offer the potential for agencies to make incremental changes to their TMSs' capabilities. The capabilities in turn may enable agencies to explore the potential for incorporating the use of predictive analytics in support of agencies use operational strategies, control plans, or operate TMSs.

- Agencies may have the ability to purchase or lease software and other products that can access and use proprietary black-box predictive and prescriptive capabilities. While black-box systems have significant transparency challenges and may deliver the prediction to the data subsystem in the form of an API, testing maturity and collaboration among agencies harks of the potential to validate the prediction—if not the model. An example of that approach is the Eastern Transportation Coalition data marketplace, which includes data validation processes and reports for vendor data.

- Cloud service providers are developing tools that make the process of developing and applying predictive analytics far simpler—a form of plug-and-play capabilities. Thus, even with only little expertise, agencies may be able to apply machine-learning and deep-learning algorithms to develop predictive models. While predictive models do represent an opportunity, that opportunity must be tempered by diligence with regard to the ways the model or algorithm will be implemented within the TMS software subsystem and whether the model has to live within a cloud environment due to the need for specific cloud functions.

Traffic incidents, road weather, work zone, and arterial management are four areas in which predictive capabilities show promise. Decisionmaking around freeway operations strategies such as ramp metering and VSLs also may benefit from incorporating predictive analytics into the algorithms and software used for supporting specific operational strategies and control plans. While vendors may be better positioned to offer predictive capabilities through the services they may provide, access to and use of those resources involve tradeoffs related to knowing what may be incorporated into the models and the basis of how they operate. Other tradeoffs in the use of vendor predictive capabilities are whether the capabilities offer the potential for future changes that would better support TMSs' management and operation. Thus, for agencies with access to or in-house expertise and with TMSs that have the ability to incorporate software and tools onto their software subsystems, addressing a need through in-house predictive model development affords agencies the opportunity to test and evaluate the use of predictive analytics and to improve the use of specific operational strategies and control plans.

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