Integrated Modeling for Road Condition Prediction Phase 3 Project Report

October 2020

FHWA-HOP-20-061

U.S. Department of Transportation
Federal Highway Administration

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. FHWA-HOP-20-061	2. Government Accession No.	3. Recipient's Catalog No.

4. Title and Subtitle Integrated Modeling for Road Condition Prediction Phase 3 Project Report	5. Report Date October 2020 6. Performing Organization Code
7. Author(s) J. Kyle Garrett; Jiaqi Ma; Hani Mahmassani; Michelle Neuner; Bob Sanchez	8. Performing Organization Report No.
9. Performing Organization Name and Address Leidos Inc. 11251 Roger Bacon Drive Reston, VA 20190 Synesis Partners LLC Northwestern University Transportation Center University of Cincinnati	10. Work Unit No. (TRAIS) 11. Contract or Grant No. DTFH6116DOOO53L
12. Sponsoring Agency Name and Address U.S. Department of Transportation Federal Highway Administration 1200 New Jersey Avenue, SE Washington, DC 20590	13. Type of Report and Period Covered Project Report 3/26/2018–9/25/2020 14. Sponsoring Agency Code

15. Supplementary Notes
Road Weather Management Program
Task Order Contracting Officer Representative (TOCOR): Jawad Paracha

16. Abstract
Transportation Systems Management and Operations (TSMO) is at a critical point in its development due to increased data availability and analytics. New approaches in road weather management are bringing together meteorology, traffic management, law enforcement, maintenance, and traveler information to support agency decision making and influence travel behavior. This convergence of opportunities has led the Federal Highway Administration's (FHWA) Road Weather Management Program (RWMP) to initiate research into Integrated Modeling for Road Condition Prediction (IMRCP) to investigate and capture that potential. Phase 1 of IMRCP developed the foundational concept of operations and requirements. The IMRCP phase 2 work specified, implemented, tested, and evaluated the IMRCP concept in a demonstration. The IMRCP phase 3 project builds on the prior work to investigate operations applications. Phase 3 has expanded geographical coverage to all Kansas City metropolitan area highways, enhanced the dynamic traffic assignment (DTA) model deployed in phase 2, added an alternative machine learning-based traffic model, and updated the system documentation. The project report describes the phase 3 development, demonstration, evaluation, and assessment of the IMRCP. It provides a summary description of the system design, the study area deployment and engagement, operations experience, evaluation, and recommendations for further study.

17. Key Words Prediction; Road Weather Management Program (RWMP); transportation system management and operations (TSMO); weather-responsive traffic management (WRTM); traffic modeling; road condition; weather; road weather; Integrated Modeling for Road Condition Prediction (IMRCP); METRo; TrEPS; MLP	18. Distribution Statement No restrictions.

19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 68	22. Price n/a

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized.

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 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 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 (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

AHPS	Advanced Hydrologic Prediction Service
ASOS	Automated Surface Observing Systems
ATMS	advanced transportation management system
CAP	common alerting protocol
CV	connected vehicle
DMS	dynamic message sign
DOT	department of transportation
DTA	dynamic traffic assignment
E–E	External–External
E–I	External–Internal
ESS	environmental sensor station
FHWA	Federal Highway Administration
h	hour
in.	inch
ID	identifier
I–E	Internal–External
I–I	Internal–Internal
IMRCP	Integrated Modeling for Road Condition Prediction
I–435	Interstate 435
I–470	Interstate 470
I–49	Interstate 49
IT	information technology
ITS	intelligent transportation system
KC	Kansas City
KC Scout	Kansas City Scout
KDOT	Kansas Department of Transportation
km	kilometer
LTL	less-than-truckload
MARC	Mid-America Regional Council
MDSS	maintenance decision support system
METRo	Model of the Environment and Temperature of Roads
min	minute
MLP	machine learning-based prediction
MODOT	Missouri Department of Transportation
mph	mile per hour
MPO	metropolitan planning organization
MRMS	Multiple Radar/Multiple Sensor
NCEP	National Centers for Environmental Research
NDFD	National Digital Forecast Database
NeXTA	Network EXplorer for Traffic Analysis
NOAA	National Oceanic and Atmospheric Administration
NOCoE	National Operations Center of Excellence
NSSL	National Severe Storms Laboratory
NWS	National Weather Service

OD	origin-destination
ODM	Online Demand Model
RAP	Rapid Refresh
RDBMS	Relational Database Management System
RTMA	Real-Time Mesoscale Analysis
RWIS	road weather information system
RWMP	Road Weather Management Program
TDOD	time-dependent origin-destination
TMC	transportation management center or traffic management system
TrEPS	Traffic Estimation and Prediction System
TS	time series
TSMO	transportation systems management and operations
US–69	U.S. Route 69
UDOT	Utah Department of Transportation
USDOT	U.S. Department of Transportation
VSL	variable speed limit
WAF	weather adjustment factor
WRMS	road weather-responsive management strategies
WRTM	weather responsive traffic management
WxDE	Weather Data Environment

EXECUTIVE SUMMARY

Transportation systems management and operations (TSMO) is at a critical point in its development due increased data availability and analytics. New approaches in road weather management are bringing together meteorology, traffic management, law enforcement, maintenance, and traveler information to support agency decision-making and influence travel behavior. Through these operational efforts and private sector innovations, travelers today have higher expectations for their travel experience. Travelers now participate in generating and validating information, as well as consuming it. This trend will accelerate with deployment of connected vehicle (CV) systems. Within this context, the role of prediction and forecasting will become more important to travelers' transportation and activity choices, as well as to agency decisions in transportation operations. Freight carriers and logistics providers will also benefit in planning routes, times, and delivery schedules.

Based on these opportunities, the Federal Highway Administration (FHWA) Road Weather Management Program (RWMP) has undertaken the investigation, development, and demonstration deployment of an Integrated Modeling for Road Condition Prediction (IMRCP) system. Phase 1 of IMRCP developed the foundational concept of operations and system requirements. The model envisioned is a practical tool that State departments of transportation (DOT) can use to support traveler advisories, as well as maintenance and operational decisions at both strategic and tactical levels. The IMRCP phase 2 work specified, implemented, tested, and evaluated the IMRCP concept in a demonstration deployment. The concept was vetted with a broad stakeholder group and then developed in a straightforward systems engineering process that continued to incorporate stakeholder feedback at key intervals. Working with local and State agencies, the demonstration system was deployed in part of the Kansas City metropolitan area. Performance of IMRCP models and interfaces was evaluated by the research team over a 4-month period of operations in late 2017 with the KC Scout (KC Scout) traffic management center (TMC).

IMRCP phase 3 builds on the prior work to investigate operations applications. The objectives of phase 3 are to:

- Redeploy the phase 2 model over the same area in Kansas City;
- Increase the geographical coverage to all Kansas City metropolitan area highways in the KC Scout areas of operation;
- Add an additional traffic model;
- Run the system for two winter seasons;
- Evaluate the system results;
- Update the system documentation.

The expanded deployment operated for 18 months with enhancements throughout the period. IMRCP system operations and the operations response with KC Scout were independently evaluated by team members not involved in the development of the IMRPC system.

IMRCP provides an interactive map and flexible reporting tools to meet its goal of providing information on predicted road conditions in support of transportation operations. The data that populate these user interface features are kept in a data store that contains both collected data and data generated through forecasting components. IMRCP generates forecasts for traffic and road weather conditions and obtains forecasts from sources outside the system for atmospheric weather, hydrology, work zone plans, and known special events. Current traffic and incident conditions come from the KC Scout advanced transportation management system (ATMS). Current environmental conditions are collected primarily from the National Weather Service (NWS) and other government agencies.

The IMRCP system forecasts traffic and road weather conditions using current and forecasted atmospheric and hydrologic condition data from the data store, collected from the sources previously described. The Traffic Estimation and Prediction System (TrEPS) model estimates and predicts the traffic demand and network states at the zone-to-zone (origin-destination) level. The machine learning-based prediction (MLP) package predicts traffic network conditions based on a given set of system variables, including weather, work zones, incidents, and special events. The Model of the Environment and Temperature of Roads (METRo) model estimates and predicts pavement conditions on roadways within the network of interest.

An evaluation of the IMRCP demonstration deployment was conducted by research team members with the staff of the KC Scout TMC. The evaluation explored what impact IMRCP had on KC Scout operations and assessed if the information was useful to the KC Scout operators/supervisors. The key questions guiding the evaluation data collection and analyses were: (1) Did IMRCP have an operational impact? and (2) Did the users consider IMRCP information useful? The analyses of IMRCP speeds data and operator/supervisor interviews provided insight into the actual and perceived operational impact and usefulness. The evaluation also provided perspectives on the accuracies of the traffic models relative to data provided by the KC Scout traffic management system.

The enhancements made to expand the regional view and traffic modeling capabilities have been integrated successfully into the system. The demonstration deployment provides real-time predictions of traffic and road conditions over the entire Kansas City metro area, which incorporate data on atmospheric and road weather conditions, traffic, incidents, hydrological conditions, work zones, winter maintenance operations, and special events, when such data are available. The predictions are available to system users, operators, and maintainers in user-friendly maps and reports. The underlying IMRCP system provides a scalable framework for deployment in other areas, is extensible to other types and sources of data, and can support additional application-specific user interfaces, as needed.

Lessons learned, deployment experience, potential applications, and conclusions from the IMRCP phase 3 deployment have identified both gaps and barriers to further deployments. Gaps discussed in this report are primarily technical, but barriers may be limited acceptance with operators and maintainers, ease of deployment, or operational benefits. The research team’s recommendations for further study are therefore intended to close gaps, reduce barriers, and develop new opportunities for applying predictive capabilities in solving transportation operations challenges. Key recommendations include automating the configuration processes for new deployments, improving data acquisition, adding quality checking to feed the prediction models, tightening the integration of hydrological models, and providing actionable recommendations for management strategies in response to weather and traffic predictions.

CHAPTER 1. INTRODUCTION

BACKGROUND

Transportation systems management and operations (TSMO) is at a critical point in its development due to increased data availability and analytics. New approaches in road weather management are bringing together meteorology, traffic management, law enforcement, maintenance, and traveler information to support agency decision-making and influence travel behavior. Through these operational efforts and private-sector innovations, travelers today have higher expectations for their travel experience. Travelers now participate in generating and validating information as well as consuming it. This trend will accelerate with deployment of connected vehicle (CV) systems. Within this context, the role of prediction and forecasting will become more important to the travel and activity choices made by travelers, as well as to agency decisions in transportation operations. Freight carriers and logistics providers will also benefit in planning routes, times, and delivery schedules.

Development and adoption of traffic prediction approaches by operating agencies have been limited, however, even with a growing body of research. While this is partly attributable to limited data, available predictive tools have been narrowly focused and have not taken full advantage of developments in related disciplines and domains. As a result, the use of predictive methods in support of operational decisions continues to be limited.

Recent efforts to incorporate forecasted weather conditions into traffic predictions have shown considerable promise. Factoring in reported conditions from environmental sensor stations, vehicle fleets, and citizen-reported conditions could improve estimation of the current system state from which predictions are developed. The utility of traffic predictions could be further enhanced by augmenting the forecast weather conditions with known and likely capacity constraints, such as work zones and incidents. Current and planned road treatment approaches, snowplow routing, parking restrictions, and maintenance decisions could be included as well.

Based on these opportunities, the Federal Highway Administration Road Weather Management Program (RWMP) has undertaken the investigation, development, and demonstration deployment of an Integrated Modeling for Road Condition Prediction (IMRCP) system. This effort has included a survey of available and imminent weather, hydrological, traffic, and related transportation management models; development of a concept of operations and fundamental system requirements; development of a system architecture and system design; implementation of a foundational system; and deployment of the system with an operating transportation agency to evaluate its effectiveness. Research, development, and operations stakeholders have been involved in every part of the IMRCP effort.

Phase 1 of the IMRCP initiative developed the foundational concept of operations and requirements. The model envisioned therein is a practical tool that State departments of transportation (DOT) can use to support traveler advisories and maintenance and operational decisions at both strategic and tactical levels. The IMRCP phase 2 work specified, implemented, tested, and evaluated the IMRCP concept in a demonstration. The concept was vetted with a broad stakeholder group and then developed in a straightforward systems engineering process that continued to incorporate stakeholder feedback at key intervals. Working with local and State agencies, the demonstration system was deployed in part of the Kansas City metropolitan area. Performance of IMRCP models and interfaces was evaluated over a 4-month period of operations in late 2017 with the Kansas City Scout (KC Scout) traffic management center (TMC).

IMRCP phase 3 builds on the prior work to investigate operations applications. The objectives of phase 3 are to redeploy the phase 2 model over the same area in Kansas City, increase the geographical coverage to all Kansas City metropolitan area highways in the KC Scout areas of operation, add an additional traffic model, run the system for two winter seasons, evaluate the system results, and update the system documentation. The expanded deployment operated for 18 months with enhancements throughout the period. IMRCP system operations and the operations response with KC Scout were independently evaluated.

PURPOSE

The purpose of the IMRCP is to integrate weather, traffic, and other operations data sources with analytical methods to effectively predict road and travel conditions. Identification of system functions and interfaces is driven by stakeholders in TSMO who also provide feedback on the usefulness of model results. The model could ultimately become a practical tool for transportation agencies to support traveler advisories, maintenance plans, and operational decisions at both strategic and tactical levels.

This project report describes the phase 3 development, demonstration, evaluation, and assessment of the IMRCP. It provides a summary description of the system design, the study area deployment and engagement, operations experience, and evaluation.

SCOPE

The IMRCP provides a framework for the integration of road condition monitoring and forecast data to support tactical and strategic decisions by travelers, transportation operators, and maintenance providers. The system:

- Collects and integrates environmental observations and transportation operations data.
- Collects forecast environmental and operations data when available.
- Initiates road weather and traffic forecasts based on the collected data.
- Generates travel and operational advisories and warnings from the collected real-time and forecast data.
- Provides the road condition data, forecasts, advisories, and warnings to other applications and systems.

Road condition and operations data and forecasts integrated into the prediction, as available, include:

- Atmospheric weather.
- Road (surface) weather.
- Small stream, river, and coastal water levels.
- Road network capacity.
- Road network demand.
- Traffic conditions and forecasts.
- Traffic control states.
- Work zones.
- Maintenance activities and plans.
- Emergency preparedness and operations.

DOCUMENT OVERVIEW

Chapter 1 provides an overview of the background, purpose, and scope of the project and this document.

Chapter 2 describes the overall IMRCP project, including the methodology and approach, project tasks and deliverables, and stakeholder engagement.

Chapter 3 describes the process of implementing and deploying IMRCP, including the vision and objectives, user needs, application scenarios, system description, study area description and modeling, traffic model calibration, system deployment and operations, and open-source work product.

Chapter 4 describes the evaluation of the IMRCP project.

Chapter 5 describes the end results of phase 3 of the IMRCP. This section includes case studies and applications; lessons learned and limitations; and deployment considerations, conclusions, and recommendations for further study.

CHAPTER 2. PROJECT DESCRIPTION

The multidisciplinary nature of transportation systems management and operations (TSMO) can be exemplified in road weather-responsive management strategies (WRMS) that bring together meteorology, traffic management, law enforcement, maintenance, and traveler information to support agency decision-making and influence travel behavior. Similar needs are present in work zone management, traffic incident management, and active traffic management strategies. All of these strategies seek to provide actionable information to travelers, enabling them to make better choices for safe and reliable travel, and to agencies, enabling them to minimize and mitigate the impact of disruptions. Initiatives across all of these disciplines have been working toward developing similar frameworks and methodologies.

Travelers today have higher expectations for their travel experiences because of these management strategies and private-sector innovations in gathering, processing, and disseminating of information. Travelers have moved from being passive consumers of information with unknown accuracy to being vital players in generating and validating information. This trend will accelerate with deployment of connected vehicle systems, which will create a powerful new platform for collecting and sharing information. Within this context, the role of prediction and forecasting will become more important to choices made by travelers, as well as to agency decisions in the active management of surface transportation operations. Economic imperatives require freight carriers and logistics providers to factor in a variety of traffic conditions for planning routes, times, and delivery schedules.

While a wide variety of approaches have been proposed in the scientific literature for predicting traffic conditions, the development, application, and adoption of these approaches by operating agencies have been limited. Part of the reason has been limited data availability, a situation that is changing rapidly. Another reason is that available tools have been too narrowly focused and have not taken full advantage of developments in related disciplines and domains. As a result, the use of predictive strategies in TSMO remains nascent, and decisions continue to largely be reactive.

To support proactive operations, higher-quality predictions are needed for incorporating factors beyond the fundamental traffic models into the analysis. Previous efforts incorporating forecast weather conditions in traffic predictions[1] have shown considerable promise in improving the relevance and usefulness of traffic predictions for agency decision-making related to incoming weather. However, the richness and usefulness of traffic predictions can be enhanced by augmenting the forecast weather condition during the prediction window with known and likely capacity constraints (such as planned work zones or snow route restrictions or incidents). Incorporating reported conditions from environmental sensor stations (ESS), mobile observations from fleets, and citizen reports may further improve the predictions. Current and planned road treatment approaches, snowplow routing, parking restrictions, and maintenance decisions might be factored in as well.

---

[1] Federal Highway Administration, *Implementation of a Weather Responsive Traffic Estimation and Prediction System (TrEPS) for Signal Timing at Utah DOT*, FHWA-JPO-14-140 (Washington, DC: U.S. Department of Transportation [USDOT], 2014), https://rosap.ntl.bts.gov/view/dot/3442.

Phase 3 of the Integrated Modeling for Road Condition Prediction (IMRCP) demonstration project has provided an opportunity to develop, deploy, and evaluate an integrated model for predicting road conditions that incorporates transportation and non-transportation data, deterministic and probabilistic data, and measured and reported data into a framework for agency decision-making and traveler information. The model provides a practical tool for transportation agencies to support traveler advisories and maintenance and operational decisions at both strategic and tactical levels.

METHODOLOGY AND APPROACH

One of the main challenges in deploying an integrated prediction model is accounting for the different latencies, qualities, and levels of certainty in source data and methods to generate consistent, accurate, and useful results. For example, in the Utah Department of Transportation (UDOT), citizen and maintenance personnel reports of road conditions are subjectively weighted in decision-making based on the timing of the report and nature of the decision. The in-house meteorologists weigh all observed conditions along with ensemble weather forecasts to make a call on the road condition forecast.[2] Creating methods and a framework to accommodate those considerations is a significant undertaking.

The model also needs to translate road-segment-based information into meaningful and actionable information within a corridor and across the network. This is where it is critical to understand the impact of road conditions on traffic. Being able to translate road weather conditions into traffic impacts can inform the route, mode, and time choices of travelers. This also calls for integrating recent developments in using probabilistic information and forecasts in decision-making processes as new information becomes available. For example, optimal routing for both individuals and service vehicles (package delivery, repair vehicles, etc.) requires different algorithms than are typically used in deterministic conditions.

The recommendations from predictive models need to be conveyed in simple, understandable terms to the end user and enable querying the system for additional information. For example, using probabilistic models may entail communicating probabilities to the traveler, a concept traditionally avoided by departments of transportation but commonly employed in meteorology.

The products of the phase 3 project are the IMRCP system software and documentation, a demonstration, an evaluation of the demonstration, and an analysis of the experience. To facilitate use by State and local transportation agencies, including those involved in the demonstration, the model has had to be easy to use, rely on available data sources, integrate with existing legacy systems, generate timely predictions, and ultimately provide decision support to operators in a useful manner.

PROJECT TASKS AND DELIVERABLES

Phase 1 identified user needs and set broad requirements for a demonstration of IMRCP capability. It surveyed the existing field of predictive models, engaged a broad stakeholder community, and developed a concept of operations and requirements for an integrated model for

[2] FHWA, *Connected Vehicle-Enabled Weather-Responsive Traffic Management Final Report*, FHWA-JPO-18-648 (Washington, DC: USDOT, April 2018), 23–24.

predicting road conditions that incorporates transportation and non-transportation data, deterministic and probabilistic data, and measured and reported data.

Phase 2 started with follow-on efforts to develop a system architecture and design with input from the IMRCP project stakeholders. A foundational system was then implemented and deployed in a suburban Kansas City study area in cooperation with the Kansas City Scout (KC Scout) transportation management center (TMC), which is operated cooperatively by the Missouri Department of Transportation (MODOT) and the Kansas Department of Transportation (KDOT). The effectiveness of the system's ability to incorporate real-time and archived data and results from an ensemble of forecast and probabilistic models to predict the current and future overall road/travel conditions was then evaluated.

Phase 3 builds on the prior work to more deeply investigate operations applications. The Kansas City study area was expanded from the congested commuting corridor used in phase 2 to include the entire metropolitan area monitored by the KC Scout TMC. The Traffic Estimation and Prediction System (TrEPS) dynamic traffic assignment (DTA) model deployed in phase 2 was enhanced with additional scenario management and calibrations. An alternative machine learning-based prediction (MLP) for traffic forecasting was added, based on several years of detailed traffic data from the TMC and other sources. System documentation was updated to reflect the enhancements and respond to prior user feedback, then reposted with the system code to the U.S. Department of Transportation's (USDOT) open-source application development portal on GitHub.[3] The system was operated for 18 months through two winter seasons, during which the system was enhanced to address operational challenges as they occurred. A formal evaluation was undertaken to identify achievements and challenges in system operations and in the operations response at KC Scout.

Taken together, phase 3 activities have formalized many of the modeling techniques, built operational experience with the IMRCP, and provided a more thorough understanding of the opportunities and limitations associated with the integrated model.

Phase 3 began with a review of documentation from the prior phases to uncover any gaps between the documentation and the deployed system capabilities. The review also identified opportunities for system and documentation improvements in the phase 3 development and deployment.

The IMRCP stakeholder engagement plan was updated in phase 3 to reflect the expansion plan and focus on operational rather than developmental activities. The engagement plan identified the stakeholders, schedule for engagement, webinar formats and approach, and main outcomes expected from each engagement with the group. The plan was used to guide stakeholder interactions throughout the project life cycle.

The system architecture and design description were updated in phase 3 to reflect the enhancement of the TrEPS model, addition of the MLP traffic forecast, and accommodations for expansion of the roadway network model. The map interface was significantly upgraded to improve performance and reliability when looking at broader views of the metro, regional, and

[3] "OSADP/IMRCP" application development portal, GitHub, accessed April 1, 2020, https://github.com/OSADP/IMRCP.

national weather conditions. Descriptions of each of these efforts are provided later in the document.

Deployment of the upgraded phase 3 IMRCP system required significant expansion of the roadway network configuration and data collectors. The study area expanded from a significant high-congestion corridor to the entire metro area monitored by the KC Scout TMC. Traffic and weather data for the entire metro area over several years were compiled and used in the training and calibration of the MLP traffic model. The system acceptance test plan was updated and executed against the expanded and completed system.

An evaluation of the IMRCP system and its use were conducted as part of the phase 3 deployment. The purpose of the evaluation was to explore what impact IMRCP had on KC Scout operations and assess whether or not the information was useful to the KC Scout operators and supervisors. The findings from the evaluation could be used to inform others who may be considering similar deployments, and provide the Federal Highway Administration with information to help determine next steps for IMRCP.

STAKEHOLDER ENGAGEMENT

Stakeholder involvement in the IMRCP project was needed to understand user needs and potential modeling and data constraints. Meteorologists helped in understanding forecast models and ensemble methods. Traffic researchers and modelers assisted in understanding current and emerging models and predictive capabilities. DOT maintenance workers and DOT traffic operations personnel were needed for gathering user needs, including use of modeling and prediction in operational decision-making. Third-party information provider and traveler needs were collected from DOT traveler information managers.

Staff at KC Scout TMC, Missouri Department of Transportation (MODOT), and Kansas Department of Transportation (KDOT) have been particularly supportive of the demonstration study area deployment in the Kansas City metropolitan area. They have participated in stakeholder engagement and activities with other IMRCP stakeholders, supported the development team with data and access to their transportation management systems, used the demonstration IMRCP alongside their TMC systems, and provided input to the evaluation.

Specific stakeholder meetings and webinars included:

- Presentation to ITS Heartland Annual Meeting – April 24, 2018.
    - ITS Heartland is the regional ITS America association including MODOT, KDOT, and three other States. The presentation provided an opportunity to describe the IMRCP efforts with KC Scout to a broader set of WRMS stakeholders.

- Stakeholder core working group kickoff – July 12, 2018.
    - Stakeholders were introduced to the phase 3 IMRCP project, scope, and objectives. The deployed and operating phase 2 system was demonstrated as a basis for soliciting input on opportunities for enhancement in phase 3. Stakeholder participation opportunities were also described.

- IMRCP phase 3 MODOT update – August 17, 2018.
    - An update and demonstration were provided to KC Scout and MODOT personnel to solicit renewed operations interest for the phase 3 enhancements.

- National Operations Center of Excellence (NOCoE) webinar – August 30, 2018.
    - An introductory presentation and demonstration were provided through a NOCoE webinar to a national audience interested in TSMO.

- Road Weather Management Program (RWMP) Stakeholder Meeting – September 18, 2018.
    - The project objectives, phase 2 system deployment and accomplishment, and phase 3 plans were presented with KC Scout to attendees at the RWMP meeting. Demonstrations were available to attendees in the technology vendor area.

- Stakeholder update – January 31, 2019.
    - The phase 3 objectives and progress were described with a system demonstration for a broad audience of interested stakeholders.

- Presentation to ITS Heartland Annual Meeting – April 30, 2019.
    - An update on the Kansas City model deployment was provided to the ITS Heartland Annual Meeting. Results from the 2018–2019 winter season of operations were summarized.

- Stakeholder core working group update – June 27, 2019.
    - An update on the Kansas City model deployment was provided to the IMRCP core working group. Results from the 2018–2019 winter season of operations were summarized and plans for the evaluation and next season of operations were provided.

- Stakeholder core working group update – August 21, 2019.
    - The project team met with the core working group to discuss the KC Scout operating experience, evaluation, broader potential applications for WRMS, and the upcoming season.

- RWMP Stakeholder Meeting – August 29, 2019.
    - Phase 3 objectives and results were presented to RWMP meeting attendees by the KC Scout representative. Demonstrations were available to attendees in the technology vendor area.

CHAPTER 3. IMPLEMENTATION AND DEPLOYMENT

Development of Integrated Modeling for Road Condition Prediction (IMRCP) capabilities presents diverse challenges. The interdisciplinary nature of the concept necessitates a broad group of stakeholders with particular operational needs, leading to an equally broad set of application scenarios. The variety of data types needed to support the scenarios requires identifying, accessing, and developing components for data collection from a wide variety of sources. The spectrum of data conditions, quality, and attributes across those sources then requires a flexible and extendable data repository and data processing capability to synthesize the input needed by all of the component forecast methods. The system and user interfaces should be able to represent the original data and forecast results in consistent, easy-to-use presentations that provide user-selectable geographical and past-present-future views.

As noted in the project description, previous phases of IMRCP have provided thorough analyses of the existing state of predictive methods in meteorology, traffic, hydrology, and operations planning. At the end of IMRCP phase 2, a prototype system integrating the data sources and methods needed to create predictions of system conditions was modeling part of the Kansas City metropolitan area and providing data to the Kansas City Scout transportation management center for evaluation. That deployment suggested certain enhanced capabilities that could improve the forecast results and user interfaces for operations and assessment. The resulting phase 3 deployment is described in this section.

USER NEEDS

User needs for IMRCP were thoroughly described in the phase 1 analysis and concept of operations. Potential users of the IMRCP range from travelers to transportation operators to maintenance managers to consulting meteorologists to emergency planners. The breadth of interested stakeholders prefigures the wide range of functions to be required of the IMRCP.

Users need information to help them make appropriate travel and traffic management decisions. Too much information outside a user’s context, however, may distract the user from more immediate and relevant information. Potential road condition predictions are useful only if they are relevant to the traveler’s temporal and spatial context. This has significant ramifications for predictive capabilities. Traffic information provided to managers and travelers has, to this point, been limited to observed conditions, but predictions have more dramatic decision implications. Information must be timely enough to facilitate effective decisions based on anticipated conditions. Telling someone in the middle of a 1-hour (h) commute that severe congestion is likely for the next 30 minutes (min) is much less effective than having issued the advisory 90 min earlier.

Users need to have road condition predictions expressed in clear terms consistent with other similar contexts that help their decision-making processes. Traffic information and signage already provides some information of this type; travelers understand what an icy road ahead or a deer crossing sign means. These signs are used to express likelihood and provide an advisory appropriate to the traveler’s immediate decision context. Predictive capabilities expand this concept to more specific times and conditions.

User needs for decision support are not, however, directly changed by the availability of road condition predictions. A traveler, for example, might look for routing information in travel planning. Road condition predictions are an input to this information, not the reason for initially seeking it. As such, the users of the predictions are, in this case, the routing system rather than the end user. The road weather maintenance decision support system (MDSS) demonstrates this in practice; the precipitation and icing forecasts are embedded in the analysis of decision-support planning.

APPLICATION SCENARIOS

The potential users of IMRCP face diverse challenges related to traffic, weather, and hydrology. The IMRCP system functions can conceptually assist users in meeting these challenges.

Variable Speed Limits

Transportation systems management and operations (TSMO) practitioners could use IMRCP to be proactive rather than reactive. Dynamic or variable speed limits (VSL) can enhance network performance during peak demand periods when congestion and delay are often exacerbated by adverse weather, reduce traffic shock waves and incidents, and delay or prevent flow breakdown, and thus maintain optimal throughput. The posted speed limit, which could also consider visibility, friction, and traffic conditions, may be adjusted based on a combination of prevailing and predicted weather conditions.

Enhanced Traveler Information

Road weather information, such as in-route weather warning and route conditions, can be disseminated through radio, Internet, mobile devices, roadside dynamic message signs (DMS), and other similar means. Travel time predictions for alternative routes and times would enable users to select the best route and departure time for their particular travel need, including the impact of work zones or inclement weather. Travelers could therefore choose their departure time and/or route based on the predictive information.

Enhanced Intelligent Signal Controls

IMRCP integrates weather forecasts with traffic predictions. The results could form a basis for selecting traffic signal control interventions systematically. To achieve this, the signal control interventions would be linked to the predicted weather and traffic conditions based on measured conditions. Real-time traffic data feeds are used as a basis for the traffic state estimation and prediction within the IMRCP and could be obtained directly from signal control sensors in a corridor.

Maintenance

IMRCP enhances the ability to support strategic and tactical maintenance decisions at an agency. The IMRCP could complement the current use of MDSS at an agency by integrating traffic and roadway characteristics into a single predictive view of conditions. Using this integrated forecast enables agencies to make better decisions relating to winter maintenance. Similarly, IMRCP would provide non-winter maintenance personnel the capability to include weather and traffic forecasting in day-to-day decisions on maintenance scheduling.

Freight

IMRCP capabilities can help freight managers, dispatchers, and operators/contractors make better decisions in pursuit of higher customer satisfaction, at an overall lower cost. Once a truck is on the road for a long-haul move, whether for a truckload delivery or as part of a less-than-truckload (LTL) network move, predictive IMRCP information could help drivers select routes that best meet their travel time and travel time reliability objectives. Better route planning with IMRCP could then improve load planning by operators. This scenario, however, would require IMRCP to be deployed over an area consistent with the desired route planning.

Work Zones

For work zone personnel, IMRCP provides segment-level alerts for monitoring work zones. The tool complements the ability of smart work zones and work zone intelligent transportation systems (ITS) to provide more actionable information to travelers. Potential scenarios include near-term work zone support and coordination, where the work zone impact can be assessed using current conditions and imminent operations plans.

Travelers

As end-user beneficiaries of IMRCP, commuters will have access to forecasts of traffic conditions that parallel their access to weather forecasts. Commuters will also have access to predicted conditions resulting from planned (forecast) work zones, special events, or localized flooding.

IMRCP applications could enable tourists to plan long trips on unfamiliar roadway networks. Tourists would have access to traffic forecasting services in IMRCP that provide data for the entire trip planning horizon, predicting likely conditions using archived and real-time traffic conditions, and atmospheric and road weather forecast conditions. As in the freight scenario, this would require IMRCP to be deployed over an area consistent with the desired route planning.

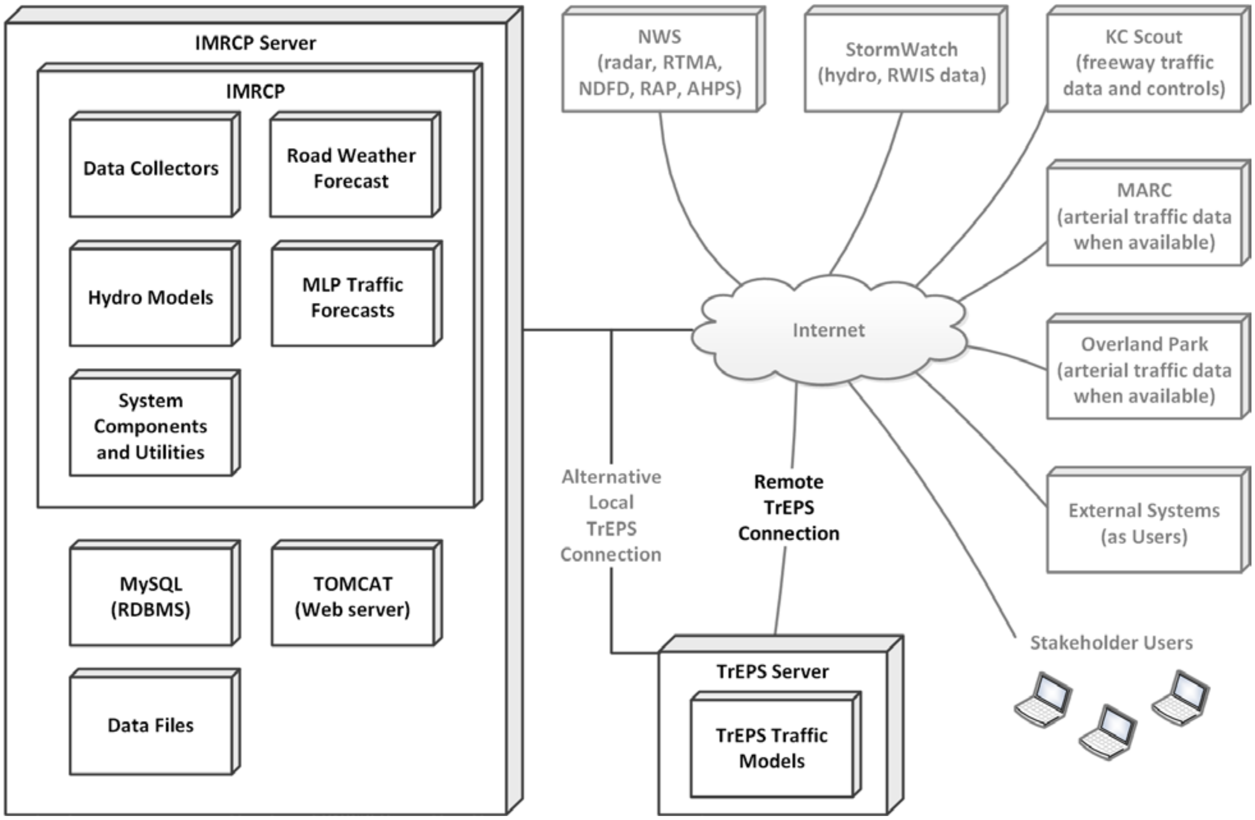
Emergency Response

Just as IMRCP can facilitate predictive route planning for freight and individual travelers, it could also assist emergency response planning for either responders or evacuees. The model’s predictions of traffic and roadway conditions, in consideration of weather and hydrology, could improve safety and mobility during incidents and, depending on severity, extreme weather events.

SYSTEM DESCRIPTION

Because the purpose of IMRCP is to provide information on predicted road conditions, the user interface is essential to providing that view. IMRCP provides flexible reporting tools and an interactive map to meet that need. The data that populate these user interface features are kept in a data store that contains collected data and data generated through forecasting components.

Forecast data are generated within the IMRCP context for traffic and road weather conditions and are obtained from sources outside the system for atmospheric weather, hydrology, work zone plans, and known special events. Current traffic and incident conditions come from the KC Scout advanced transportation management system (ATMS). Current environmental conditions are collected primarily from the National Weather Service (NWS) and other government agencies. The major system components and interfaces are illustrated in figure 1.



AHPS = Advanced Hydrologic Prediction Service. IMRCP = Integrated Modeling for Road Condition Prediction. KC = Kansas City. MARC = Mid-America Regional Council. MLP = machine learning-based prediction. NDFD = National Digital Forecast Database. NWS = National Weather Service. RAP = Rapid Refresh. RDBMS = Relational Database Management System. RTMA = Real-Time Mesoscale Analysis. RWIS = road weather information system. TrEPS = Traffic Estimation and Prediction System.
Source: Federal Highway Administration

Figure 1. Diagram. Components of the Integrated Modeling for Road Condition Prediction.

Data Collection

The integration of diverse sets of data requires a diverse set of data collectors. Traffic, hydrology, and weather data relevant to a deployment area are collected from numerous sources.

Current air temperature, wind speed, surface pressure, and humidity observations are collected from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Research (NCEP) Real-Time Mesoscale Analysis (RTMA). These weather observations are used as input to the traffic model for generating traffic predictions and to the road weather model for road weather predictions. They can be viewed on the map or through reports.

Atmospheric weather forecasts are collected from the NOAA NWS National Digital Forecast Database (NDFD). These forecasts are displayed on the user interface through the reporting and subscription features. They are also used in traffic and road weather predictions.

The NOAA/NCEP Rapid Refresh (RAP) is used as the source for forecast surface pressure, precipitation amount, and precipitation type. Forecast weather data are used for traffic and road weather predictions and providing information to users.

The NOAA National Severe Storms Laboratory (NSSL) Multiple Radar/Multiple Sensor System (MRMS) provides radar and precipitation rate and type observations for IMRCP. These weather data can be viewed on the map or through reports and are used as input for the traffic model and road weather prediction model.

Current hydrological conditions and forecasts are collected from the NOAA/NWS Advanced Hydrologic Prediction Service (AHPS) when new data become available at any of the AHPS stations in the study area. The values are used to determine the flood depth on road network links based on inundation mapping provided by AHPS. Additional hydrological conditions and forecasts for small streams can also be collected from other sources, when available.

The current pavement and subsurface temperatures can be collected from a road weather information system (RWIS) station or the Federal Highway Administration's Weather Data Environment (WxDE) for use in road weather predictions. These values are used in initiating road state and road temperature predictions with the Model of the Environment and Temperature of Roads (METRo).

Alerts, watches, and warnings are collected from NWS using the Common Alerting Protocol (CAP) and are available for IMRCP users to view.

Current traffic conditions are collected from traffic detectors maintained by the road network infrastructure owner/operator (in this case, KC Scout for the metro area highway network). Speed, volume, and occupancy data from these detectors are provided by an ATMS to the IMRCP system for predicting traffic across the network.

Incident and work zone data are also collected from an ATMS (again, KC Scout in this case). The location, estimated time frame, lane closures, and type of event are used to feed the traffic model for predictions and to display on the map.

Forecast Model Components

IMRCP forecasts traffic and road weather conditions using current and forecast atmospheric and hydrologic condition data from the data store, collected from the sources previously described.

The Traffic Estimation and Prediction System (TrEPS) model estimates and predicts the traffic demand and network states at the zone-to-zone (origin-destination) level. After an appropriate offline calibration based on traffic data archives for the network of interest, the TrEPS online component is capable of continuously interacting with multiple sources of current real-time traffic data, such as from loop detectors, roadside sensors, and vehicle probes, which it integrates with its own model-based representation of the network traffic state. TrEPS also considers and integrates current road weather conditions, incident status, and work zone plans into its estimation and prediction of network link speed, volume, occupancy, and travel times. For this IMRCP integration, detector, incident, work zone, and weather data input are provided from the core IMRCP data store.

The machine learning-based prediction (MLP) package predicts traffic network conditions given a set of system variables that include weather, work zones, incidents, and special events. MLP is a comprehensive, data-driven prediction module that uses a Markov process to explicitly characterize the probabilistic transition between traffic states under different external conditions (e.g., weather, incidents). For road network links without real-time traffic detectors, a neural network model is used for predictions if a detector can be matched within 5 miles downstream, and historical INRIX® data are used when no detector can be found downstream.

The METRo model estimates and predicts weather-related pavement conditions on roadways within the network of interest. The model computes pavement temperatures and surface conditions on network pavement segments and bridges using current condition data from RWIS and mobile sensors (when available), atmospheric weather forecasts, and pavement configuration data.

Data Store

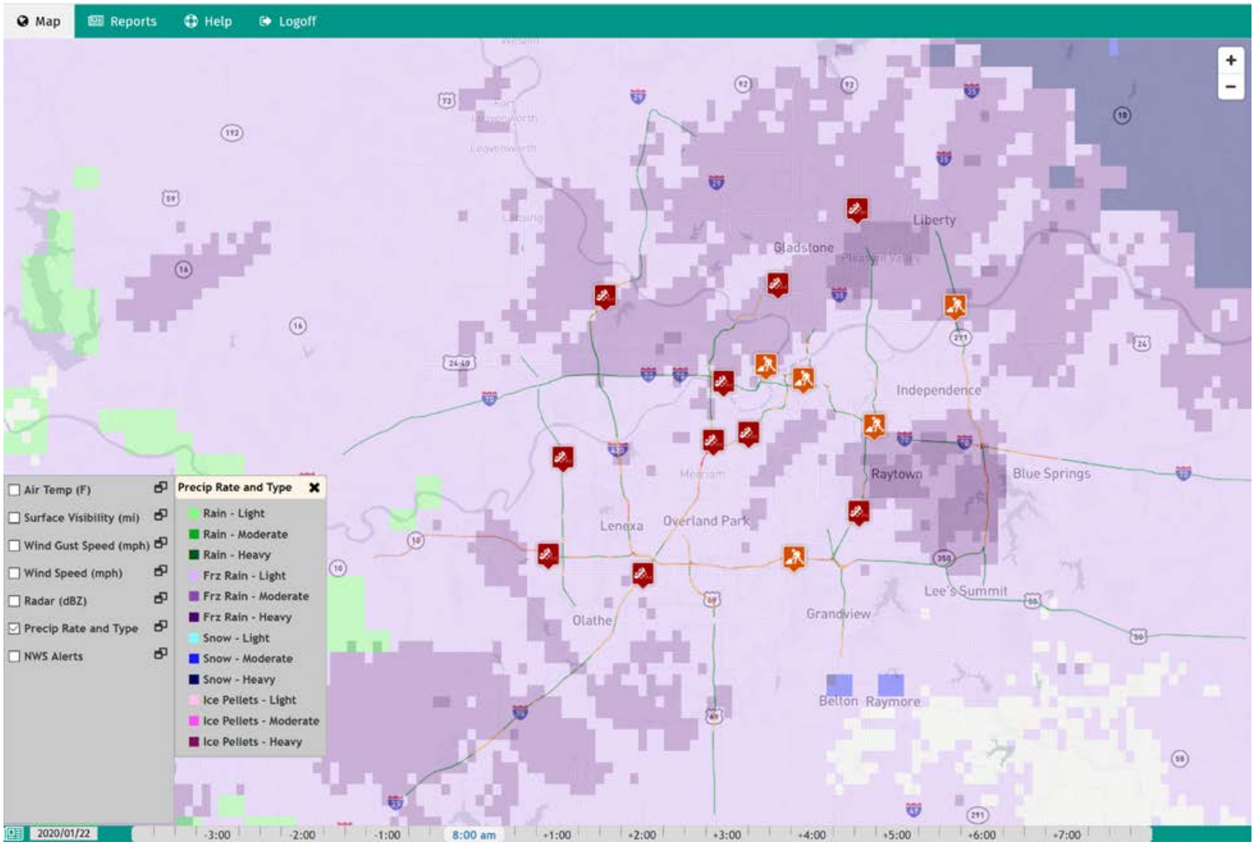
All data collected and computed by the system are kept in its integrated data store. Data collected by the system directly from external sources are kept in their original formats. Data generated by the system in data digest and forecasting components are stored in compatible file structures. All data kept by the system are indexed to location and temporal contexts. All other system components work from data within the store for forecasting, presentation, and reporting. The data store was enhanced in phase 3 to provide faster access to large data sets in support of broader geographical views.

User Interface

The IMRCP user interface provides forecast traffic and road weather conditions on maps, on-demand reports, and in subscriptions. The map interface can be used to view conditions on roadways, over regions of a deployment area for alerts, in combinations. As a live system, the map can be set to view a single point in time or to automatically refresh as new data become available. Notifications of current events and predicted conditions can be pushed to the user view over the map. Time controls on the map enable users to view forecasted and recent past conditions or to access archives and replay past events. Reports can be created from the map view and retrieved when complete.

The map interface has been substantially enhanced for phase 3 based on user evaluations. The desire to see larger geographical views led to more sophisticated rendering, storage, and presentation of the area (weather) layer data on the maps. The location of map view controls and legends was also updated from the phase 2 system with more display options and overlays.

A complete description of the system features and user interface is provided in the *Integrated Modeling for Road Condition Prediction System User Guide.*[4] Figure 2 shows the user interface features depicting traffic conditions across the demonstration area with mixed winter precipitation.



Source: Federal Highway Administration

Figure 2. Screenshot. User interface of an example map in the Integrated Modeling for Road Condition Prediction system.

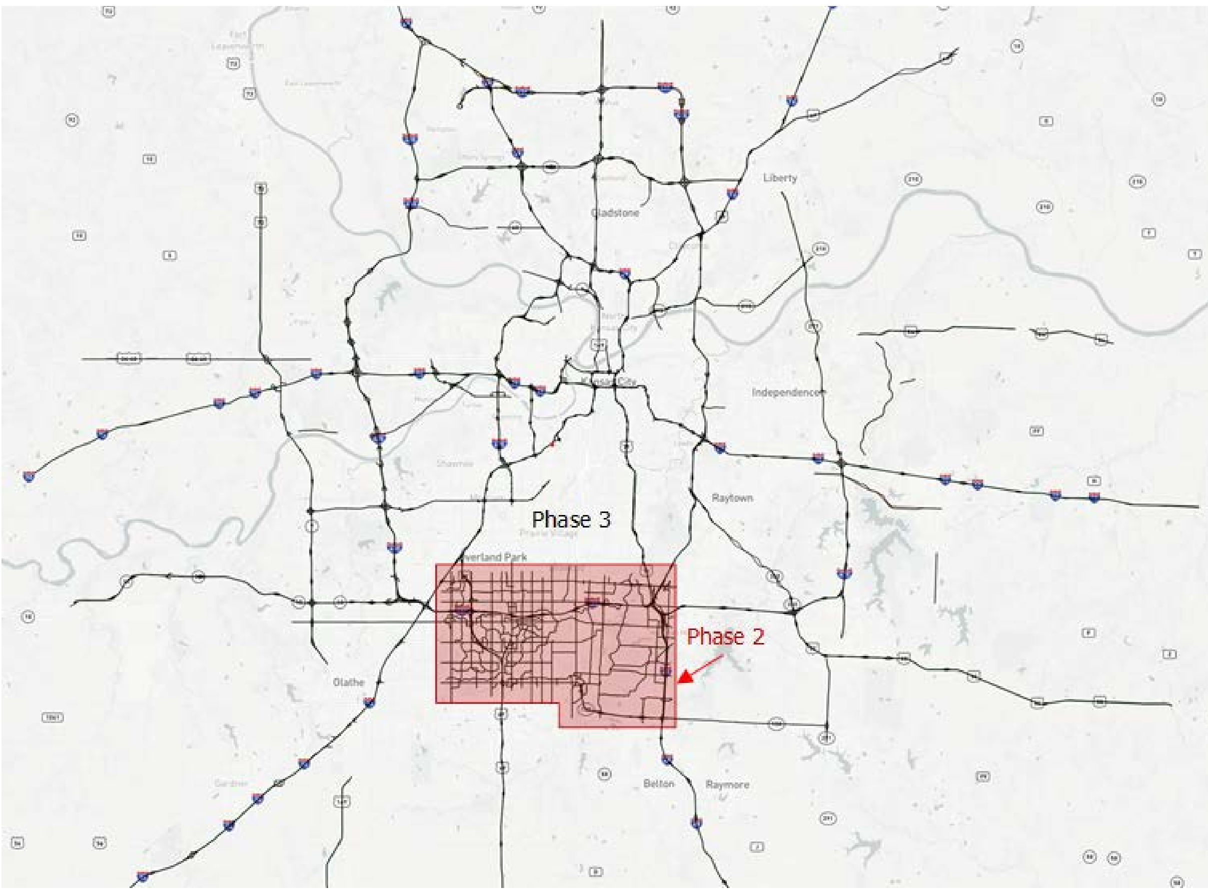
STUDY AREA DESCRIPTION AND MODELING

The IMRCP phase 2 study area was selected from among several candidate locations in the United States to demonstrate a broad range of capabilities. The Kansas City region is subject to highly variable weather conditions, typical urban congestion patterns, and interesting hydrological characteristics. The specific study area within the metro area was chosen based on a combination of characteristics, including congested traffic, alternative routes, weather sensors, and hydrologically challenging areas (several streams are subject to severe flooding within the study area). A planning model for the city, available from the Mid-America Regional Council

[4] USDOT, *Integrated Modeling for Road Condition Prediction System User Guide*, FHWA-JPO-18-747 (October 2019).

(MARC) metropolitan planning organization (MPO), was used as a basis for the phase 2 road network model.

KC Scout operator feedback in phase 2 indicated the IMRCP model needed to cover the entire metropolitan area to support TMC-based operations. KC Scout operators are accountable to the entire metro area and wanted a view of regional traffic and weather conditions rather than just a preselected subnetwork. As shown in figure 3, the IMRCP phase 3 study area greatly extends the phase 2 model (shown in red) to include all of the freeways monitored by KC Scout. Traffic modeling on the extended freeway network is provided by MLP. The TrEPS dynamic traffic assignment (DTA) model continues to be deployed in phase 3 only on the phase 2 freeway and arterial network.



Source: Federal Highway Administration; OpenStreetMap® contributors

Figure 3. Map. Kansas City metropolitan study area of the Integrated Modeling for Road Condition Prediction.

This extension greatly increases the number of data sources for traffic, weather, and hydrology data. The phase 3 study area is made up of 5,936 roadway model links, 1,892 nodes, and 928 bridges. Data in the study area are collected from 205 traffic signals, 670 traffic detectors on the mainline freeway links, 332 ramp detectors, 178 StormWatch hydrological observing sites, 25 AHPS stations, and a NOAA Automated Surface Observing System (ASOS) station.

KC Scout is the primary operational stakeholder for the IMRCP demonstration deployment. Staff from KC Scout TMC, Missouri Department of Transportation (MODOT), and Kansas Department of Transportation (KDOT) supported the modeling effort and provided evaluation input for IMRCP after it was deployed. Real-time and archive data for the highway network were provided through KC Scout's TransSuite® data portals. Incident and work zone data were collected from KC Scout's event feed once per min, and traffic detector data consisting of speed, volume, and lane occupancy were collected from KC Scout's detector feed, also once per min.

Weather and hydrological data for the study area were gathered primarily from the NOAA sources described earlier but were supplemented with local sources such as the StormWatch system operated by the City of Overland Park, Kansas. Atmospheric weather forecasts are updated and retrieved once per hour. Hydrological systems generally update their data feeds only when the data change, but the IMRCP is configured to check those feeds at least once every 10 min to capture potential flash-flooding events. Based on these data availabilities, METRo road weather condition forecasts are recomputed once per hour. Weather conditions are provided with the 1-min traffic data updates to the TrEPS and MLP traffic models, which then recompute 2-h traffic condition forecasts once every 15 min.

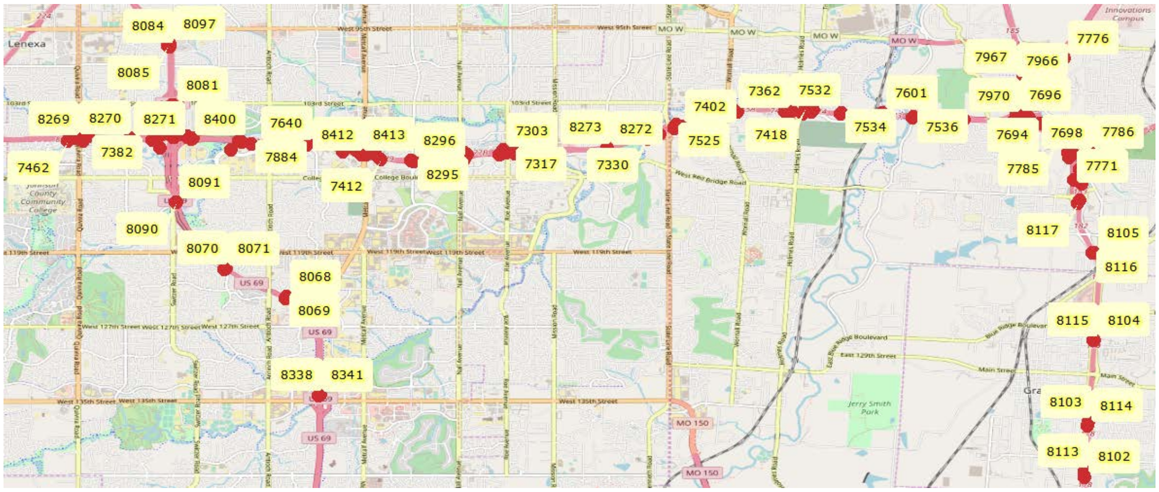
TRAFFIC ESTIMATION AND PREDICTION SYSTEM TRAFFIC MODEL

Calibration of the TrEPS traffic model is a critical and significant component of the integrated model deployment. This section summarizes the results of the model calibration effort. It provides a comparison between the model estimation results and the corresponding real-world observations.

Traffic Flow Model

The primary sources of traffic information were radar-based detectors installed along each of the three freeways (i.e., Interstate 435 [I–435], U.S. Route 69 [US–69], and Interstate 49 [I–49]) in the TrEPS study area (figure 4). Initial traffic flow model calibration was based on the 2018–2019 archived detector data provided by KC Scout. Detector-retrieved traffic parameters—including volume, speed, and occupancy—defined freeway traffic conditions in 1-minintervals. The daily 24-h traffic flow demand profile was described in a vector, which included 288 intervals of 5 min each of flow volume, speed, and occupancy. One-min aggregated values were used to estimate link-level speed-density relationships for each available detector.

Due to reliability, consistency, and availability issues, 69 detectors were adopted for the traffic flow model calibration. The archived data used to verify the relationship between speed and density consisted of 5- and 1-min aggregated historical detector data collected during 2017. Speed-density relationships were calibrated using the time-varying traffic data records: density and speed at 5-min measurement intervals. A two-regime traffic flow model form is used for traffic flow on freeways, while a single regime model form is used for arterials. Traffic flow model parameters include breakpoint density (k_{bp}), speed-intercept (v_f), minimum speed (v_0), jam density (k_{jam}), and the shape parameter (α).



Source: Federal Highway Administration; OpenStreetMap® contributors

Figure 4. Map. Selected detectors for traffic flow model calibration by identifier code.

Freeway traffic flow models were divided into sections, depending on the freeway type of facility (i.e., mainline, on-ramp, off-ramp, or freeway-to-freeway ramp), direction of traffic, and free-flow speed characteristics. The calibrated speed-density curves for the network are documented in the *Integrated Modeling for Road Condition Prediction [Phase 2] Final Report*.[5] The graphs therein represent typical example freeway links for which the observations were available, grouped by type of section they belong to.

Weather Adjustment Factors

Relevant literature findings[6,7] have shown that the traffic flow model parameters—the maximum service flow rate (qmax), shape parameter (α), and free-flow speed (uf)—are sensitive to both rain and snow intensities. As the rain or snow intensity increases, maximum flow rate, speed intercept, and free-flow speed are reduced.

A historical weather data set obtained from KC Scout and NWS sources from May to December, 2016, provided sufficient detail relative to visibility and precipitation intensity levels for calibration. However, since heavy rain and snow conditions appeared very rarely (i.e., were not recorded in the archived data set with great enough detail for weather adjustment factors [WAF] to be calibrated), the detectors did not provide enough data for traffic flow model calibration for heavy rain and snow weather conditions. Lack of adverse weather data within the archived data set, particularly a representative number of rain and snow days with associated parameters, coupled with the necessity of examining the traffic model's prediction quality for adverse

[5] USDOT, *Integrated Modeling for Road Condition Prediction Final Report*, FHWA-JPO-18-631 (December 31, 2017), figure 5 and figure 6.

[6] Ibrahim, A. T., and Hall, F.L. (1994) Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationships. *Transportation Research Record* 1457, Washington, D.C., pp. 184–191.

[7] Rakha, H. A., Farzaneh, M., Arafeh, M., and Sterzin. E. (2008). Inclement Weather Impacts on Freeway Traffic Stream Behavior. *Transportation Research Record: Journal of the Transportation Research Board* 2071, Washington, D.C., pp. 8–18.

weather conditions motivated the use of previously-calibrated WAF from a greater Chicago area network.[8]

Online Traffic Flow Model Update

The parameters of the traffic flow models embedded in the TrEPS platform are considered to be random variables with probability distribution due to inherent stochasticity of traffic behavior associated with flow breakdown during congested periods. This distribution can be shifted by external factors such as weather, variable speed limits (VSL), and nearby roadworks. To capture this time-variant traffic behavior, TrEPS updates the parameters of the traffic flow models online. The update process is initiated by speed deviation between predicted and observed detector values, which is continuously monitored in the consistency checking module. If a speed deviation on an observed link exceeds a predefined threshold, the traffic flow model assigned to the specific link is updated with the most recent detector data extracted from the IMRCP server. In adverse weather, the weather-adjusted traffic flow model is updated by adjusting the parameters of the base traffic flow model while pre-calibrated WAF remain intact.

Time-Dependent Origin-Destination Matrix

Joint estimation of the entire 24-h time-dependent origin-destination (TDOD) demand pattern was used in this study. Most previous DTA applications are limited to estimating peak-period demands. The 24-h demand was generated by extrapolating the estimated origin-destination (OD) demand from the peak period to an overall daily pattern. The static/historical demand matrix retrieved from the 2010 MARC transportation planning model, along with time-dependent traffic counts on selected observation links, was used to develop TDOD matrices over the time horizon with a chosen time interval (5 min).

The static/historical OD demand matrix for the Kansas City subnetwork was retrieved from a much larger 2010 MARC transportation planning model, which consisted of 981 zones and was developed for a peak period. To estimate the demand, the study area subnetwork (69 zones) demand was first extracted and then calibrated based on the detector data available.

For the OD extraction for the subarea under study, four types of trips relative to the subarea were observed: Internal–Internal (I–I), External–Internal (E–I), Internal–External (I–E), and External–External (E–E). I–I trips could be easily extracted from the original OD matrix. However, the effects of E–I and I–E on the subarea network also needed to be considered. To do so, a simulation of the entire network in Network EXplorer for Traffic Analysis (NeXTA) had been performed to retrieve vehicles' trajectory, and the number of vehicles entering or exiting the subarea had been added to the I–I trips with their corresponding zones. After the procedure was completed, total demand for the subarea was 1,438,515 trips per day.

---

[8] FHWA, *Analysis, Modeling, and Simulation (AMS) Testbed Development and Evaluation to Support Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Programs. Calibration Report – Chicago,* FHWA-JPO-16-381 (Washington, DC: USDOT, October 2016).

Offline Calibration of the Origin-Destination Matrix

The demand extracted in the previous section needed to be calibrated based on the archived detector data. This section discusses the detector data, demand calibration, and the results.

Data Sources

The time-dependent link counts on selected observation links within the Kansas City phase 2 network were used with DTA models for calibrating time-dependent OD matrix. The characteristics of traffic count data used in this project are shown in Table 1. Out of 148 detectors available in archive data, 79 were excluded for reasons such as unreliable daily counts, inconsistencies in mass balance, or uncharacteristic speed-density relationships. The remaining 69 detectors were used for offline demand calibration.

Table 1. Characteristics of traffic count data.

Facility Type	Freeway (Interstate 435, Interstate 49, and U.S. Route 69)
Data Source	Kansas City Scout
Resolution	5 minutes
Data Contents	Flow, speed, occupancy

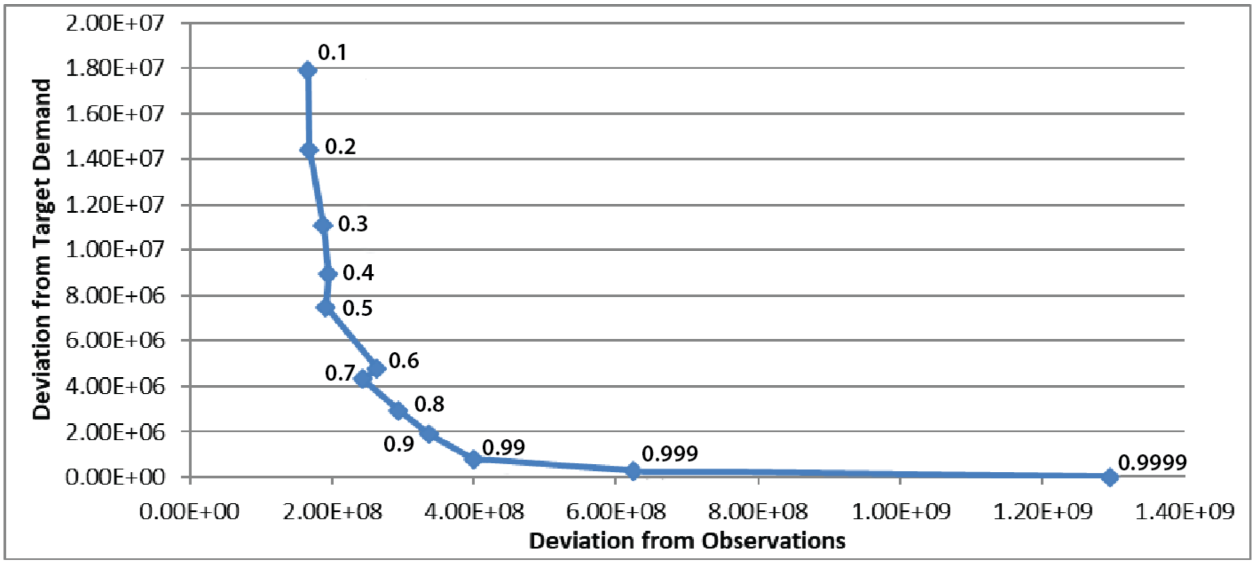
Source: Federal Highway Administration

Demand Calibration

The demand calibration was based on minimizing the weighted distance between historical OD and detectors values, with weights of *w* and (*1–w*), respectively. Additionally, time weights and links weights were devised to impose more control over time and individual link calibration.

In each DTA simulation, a number of iterations of the user equilibrium algorithm were applied to reach an equilibrium state in the network. Initially, a sensitivity analysis on parameter *w* was conducted to select the optimal weights in the objective function corresponding to the deviation from historical demand and link counts. The sensitivity analysis includes two ranges of values for parameter *w*. The first range includes 0.1–0.9, with increments of 0.1, for the deviation from historical demand. The second range includes the following values: 0.99, 0.999, and 0.9999.

Figure 5 shows deviations from observations and the deviation from the target demand under different weight selections in the first iteration of the basic solution method. By comparison, *w* = 0.9 gives a decent compromise between two deviation terms in the objective function and is selected for numerical experiments. The link weights have been carefully selected so the simulation better matches the observation. The time weights of the 288 intervals (total of 24 h) of demand may vary from period to period.



Source: Federal Highway Administration

Figure 5. Graph. Sensitivity analysis of different weights.

Calibration Results Evaluation/Validation

The TDOD estimation was first validated on a link-level basis, and then the overall calibration results, including the traffic flow model, WAF, and TDOD, were taken into DYNASMART-X and verified by the comparison between simulation data and historical observation data.

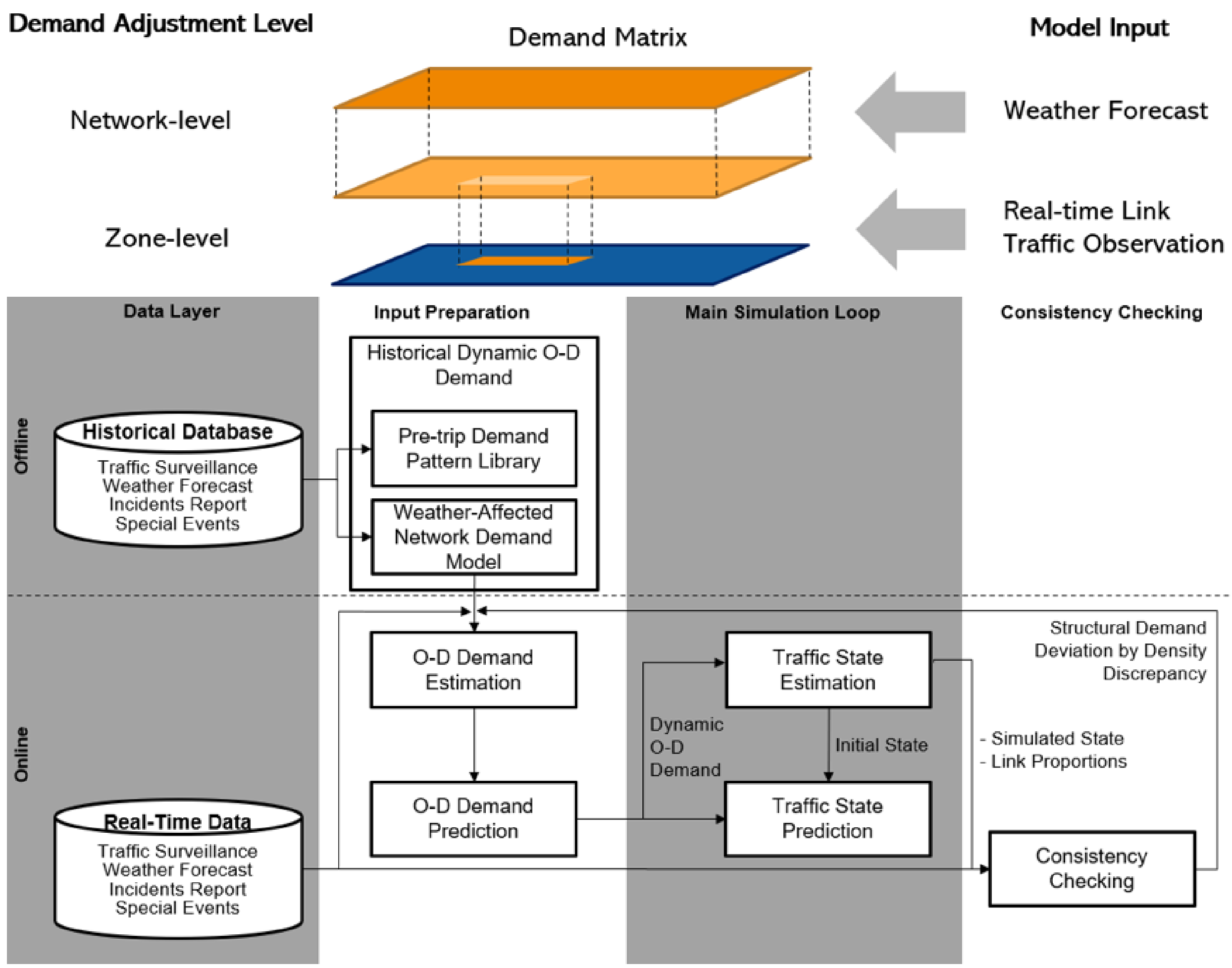
First, the simulated and observed link counts are compared for each link. Simulation results based on the estimated time-dependent OD matrix are compared with the actual observations. Results showing the 5-min and cumulative vehicle counts for three selected links before and after calibration are documented in the *Integrated Modeling for Road Condition Prediction [Phase 2] Final Report*.[9] The graphs therein represent typical example freeway links for which the observations were available, grouped by type of section they belong to.

Online Calibration of the Origin-Destination Matrix

Due to the variety of weather patterns, lack of data, and the time-consuming calibration process, it is not feasible to prepare demand input in regard of all possible weather situations. In IMRCP phase 3, the research team modified the OD demand estimation/prediction module in TrEPS to combine the knowledge learned from correlation analysis between weather factors and observed traffic volume into an online demand estimation and prediction framework. Two levels of weather-sensitive demand adjustment are considered in this framework: (1) the weather-affected demand factors can reflect the network-wide demand reduction into *a priori* demand, while (2) the regional difference of weather impact would be addressed in a demand estimation/prediction module that executes zonal demand adjustment based on traffic states discrepancy between link

[9] USDOT, *Integrated Modeling for Road Condition Prediction Final Report*, FHWA-JPO-18-631 (December 31, 2017), figure 9 and figure 10.

traffic measurement and simulated link traffic states. The framework of online traffic demand calibration in TrEPS is shown in figure 6.



OD = origin-destination.
Source: Federal Highway Administration

Figure 6. Diagram. Framework of online traffic demand calibration in Traffic Estimation and Prediction System.

MACHINE LEARNING-BASED TRAFFIC PREDICTION

The MLP package predicts traffic network conditions given a set of system variables including weather, work zones, incidents, and special events. MLP is a comprehensive data-driven prediction module and considers a Markov process to explicitly characterize the probabilistic transition between traffic states under different external conditions (e.g., weather, incidents). It is able to accurately capture the recurring and non-recurring traffic congestion. MLP provides a reliable prediction of traffic speeds for traffic management centers to efficiently deploy proactive traffic management strategies.

Model

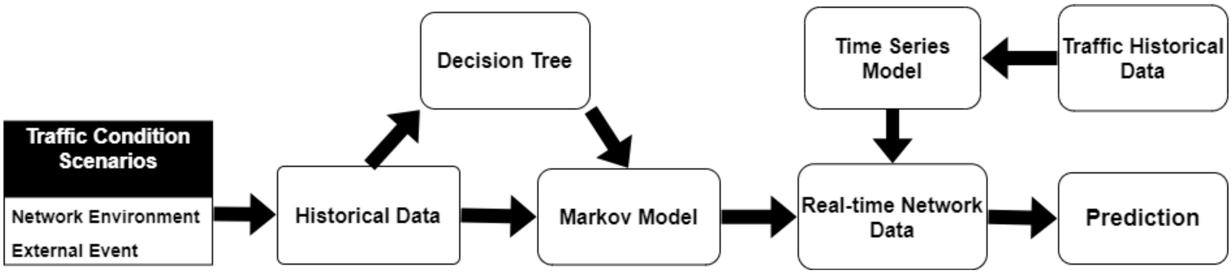
The MLP package contains three classes: MLP scenario identifier, MLP traffic predictor, and MLP update manager.

The scenario identifier identifies what specific scenario the current traffic condition belongs to and then selects/generates corresponding models for traffic state prediction. It contains three parts: a traffic state cluster, a Markov model generator, and a decision tree model. All three parts use the archived data as input and provide established models for the future use. The traffic state cluster defines the traffic states based on the levels of traffic speeds. The Markov model is developed based on historical traffic state transitions and is used to explain the stochastic evolutions of traffic states for each link. The decision tree model identifies the conditions regarding whether a certain external event will influence the traffic condition.

The traffic predictor predicts likely future network traffic states for a specified prediction horizon (such as 15 min, 30 min, 1 h, or 2 h) under specific network external conditions. The traffic predictor uses information on current network link traffic states and other system variables, such as work zones and incidents, as model inputs to predict future network states. The traffic predictor considers different transition probabilities between traffic states under different external conditions (e.g., weather, incident) and uses a time series model to account for the latest trends and observations from the field. Therefore, it is able to accurately predict traffic state evolution under different external conditions and can adjust the prediction based on real-time field observations.

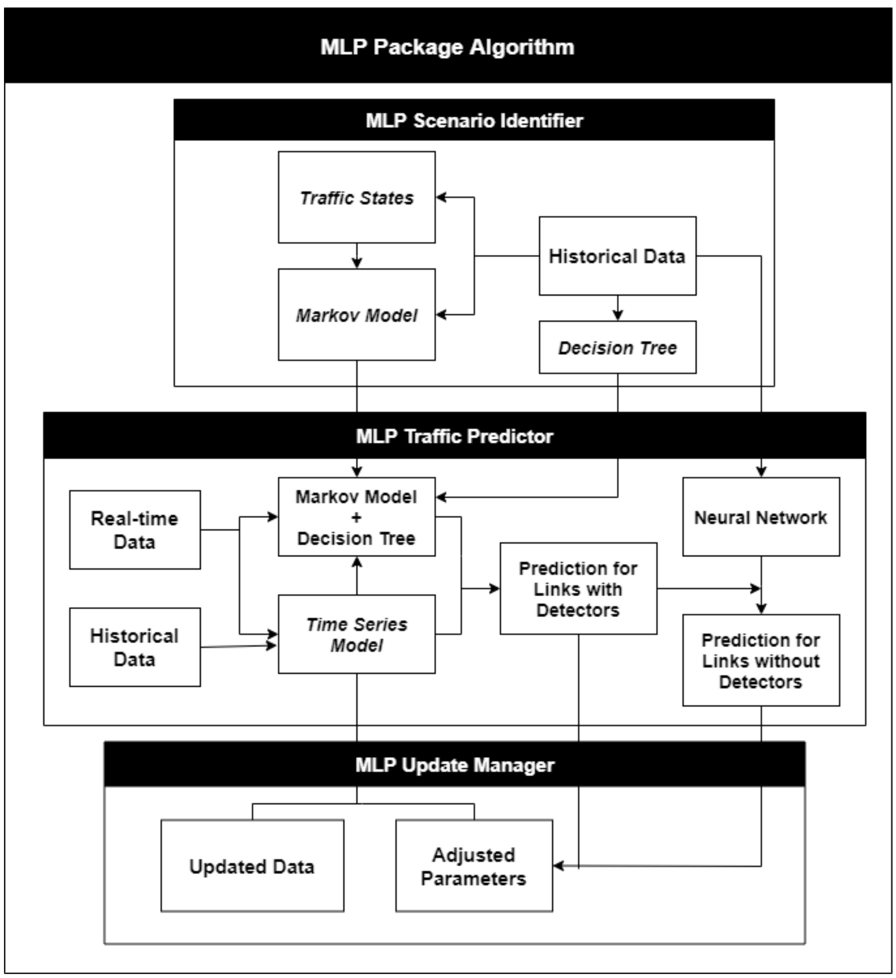
The update manager is built as a part of the prediction process that maintains and updates the latest MLP parameters. The purpose of the online update is to use both the empirical and real-time distribution of travel speed/time for different traffic conditions to enhance prediction accuracy and robustness. The update manager has two tasks. First, it updates the distribution of key traffic variables using the updated data store (e.g., traffic speed, volume) and prepares them for use by the traffic predictor. Second, it schedules periodic updates to the traffic predictor through a recalibration process using new data collected from the previous period.

To be specific, figure 7 illustrates the main components of the MLP models. The algorithm considers that the environment variables (e.g., weather) and external event variables (e.g., incidents) affect the transition probability matrices between different traffic states. A decision tree model based on the historical data determines if the external events are influential to the traffic condition and whether the Markov model will be applied. The time series model takes online data as input to reflect the most current traffic conditions observed in the field. This makes the prediction model robust, particularly during special conditions that have different traffic patterns from regular scenarios.



Source: Federal Highway Administration

Figure 7. Diagram. Proposed machine learning-based prediction model algorithm.



Source: Federal Highway Administration

Figure 8. Diagram. Representation of the Integrated Modeling for Road Condition Prediction machine learning-based prediction (MLP) process.

Data

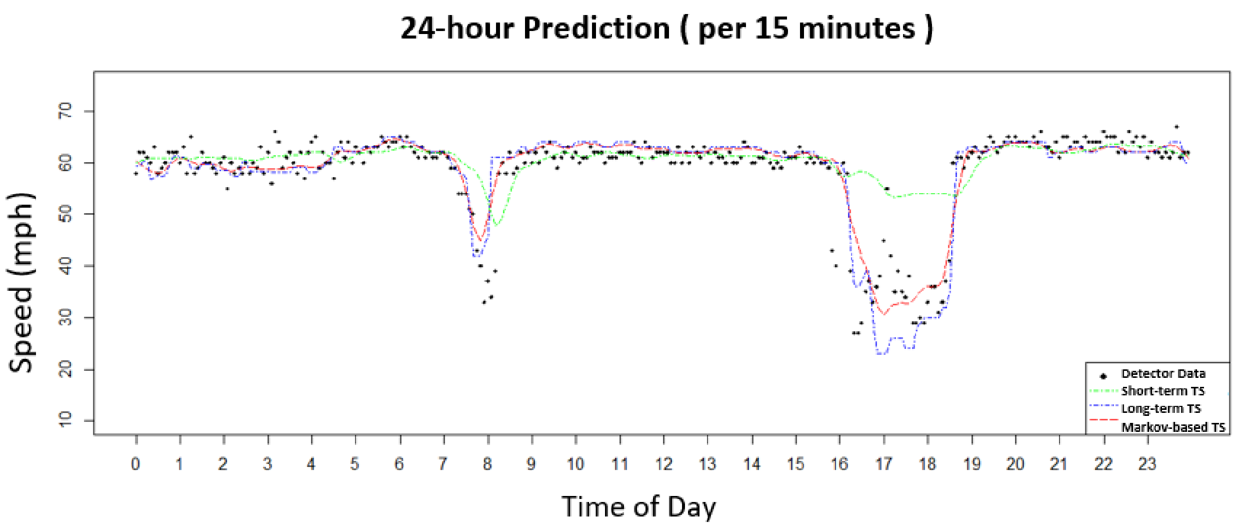
A total of 14 variables are categorized into three groups, including network environment, external event, and traffic states. The traffic states are collected by detectors and the weather data are collected from NWS modeling and forecast systems for use within the IMRCP system.

Model Calibration

Figure 8 shows a graphical representation of the IMRCP MLP algorithmic flow. First, MLP understands which facility group (e.g., functional type) the link belongs to and extracts data about network external condition scenarios (e.g., system variables, such as weather and incidents). Then, it pulls the most relevant historical data and calculates inputs for the Markov and time series models. Online detector data feeds are also used as inputs to ensure predicted traffic conditions can best reflect real-time conditions. In the MLP software, to predict traffic for links without detectors, a neural network model is constructed by fusing data of different sources (i.e., detector observation and real-time prediction data from nearby links). Predicted values from the nearest downstream links with detectors (within 10 miles) for normal conditions are used for the prediction of links without online data. This extends the predictability of most of the links on the network. For remote links without detectors nearby, it is recommended to use either online or historical private sector data (e.g., INRIX, HERE) for prediction.

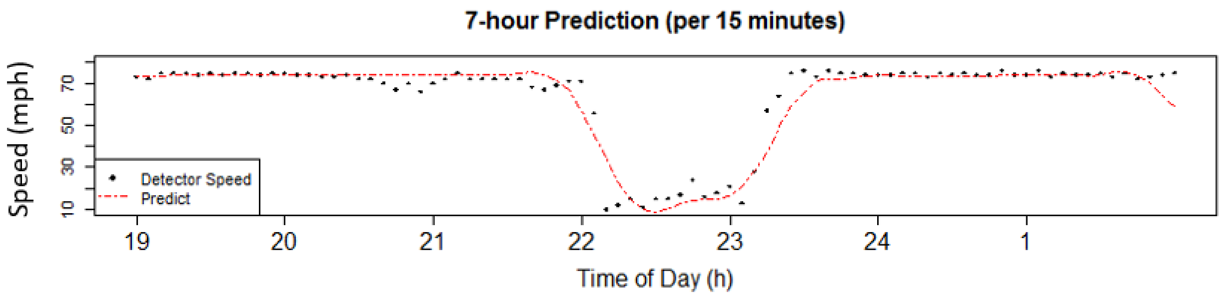
Results

The prediction results of the normal case are shown in figure 9; cases with incidents are shown in figure 10. The Markov-based model is compared with a weighted time series model without Markov processes. Figure 11 shows the predictions of light and heavy rain conditions and light and heavy snow conditions. For all cases, the model can capture the drops and turning-backs well.

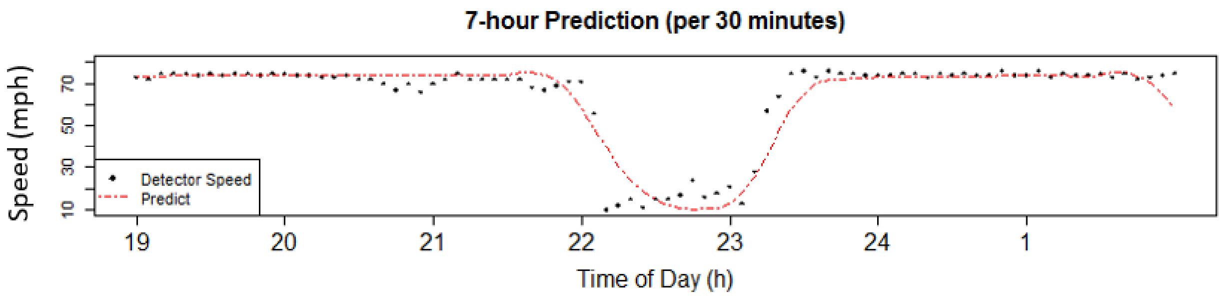


mph = mile per hour. TS = time series.
Source: Federal Highway Administration

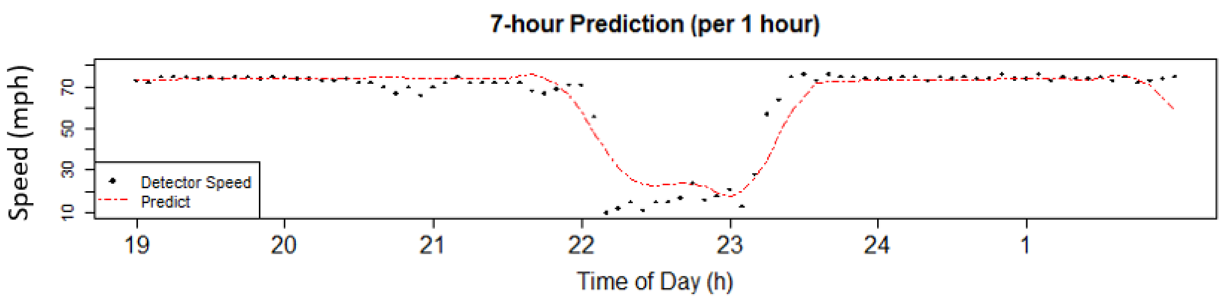
Figure 9. Graph. Prediction of normal case with daily traffic patterns.



A. Graph. Predictions of speeds with incident (per 15 minutes).



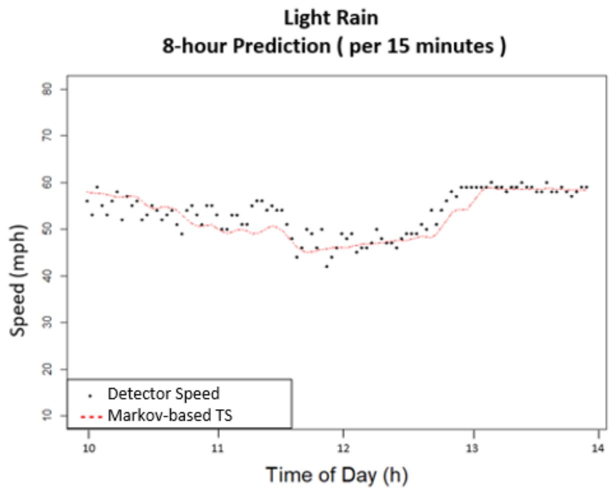
B. Graph. Predictions of speeds with incident (per 30 minutes).



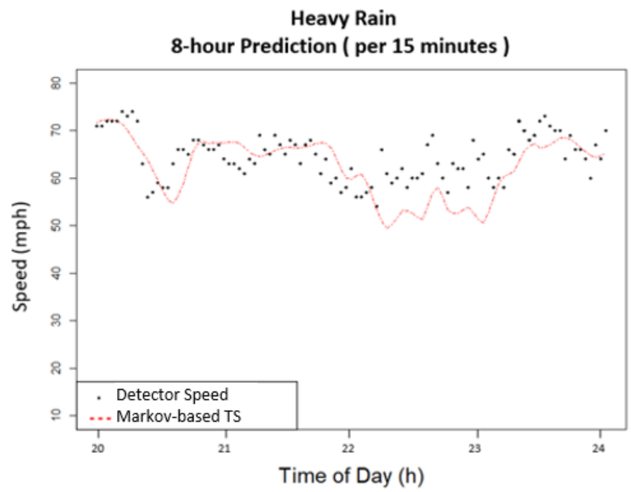
C. Graph. Predictions of speeds with incident (per 1 hour).

h = hour. mph = mile per hour.
Source: Federal Highway Administration

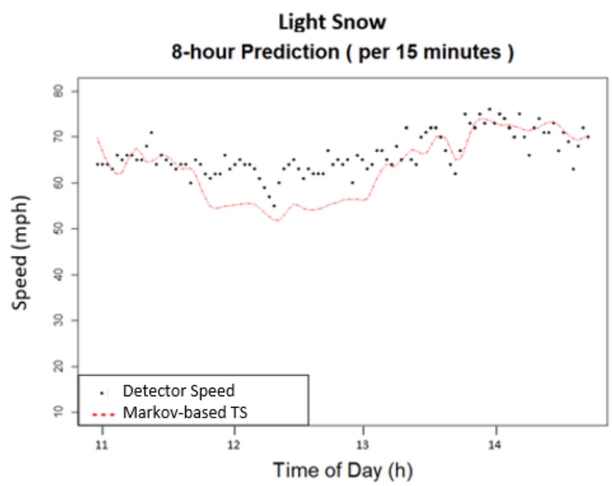
Figure 10. Graphs. Predictions of speeds with incident on link.



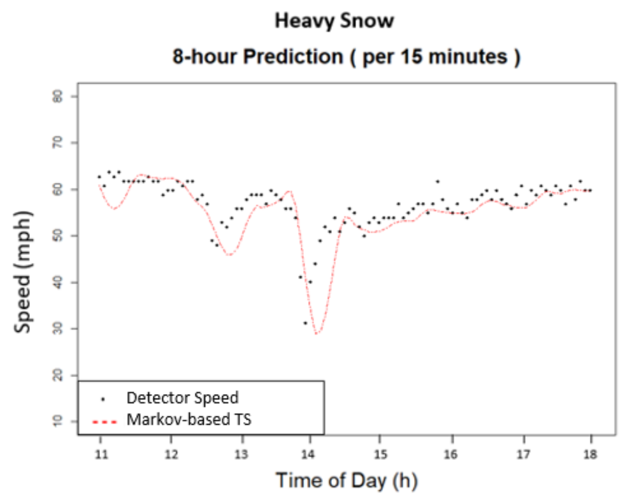
A. Graph. Speed Predictions (Light Rain)



B. Graph. Speed Predictions (Heavy Rain)



C. Graph. Speed Predictions (Light Snow)



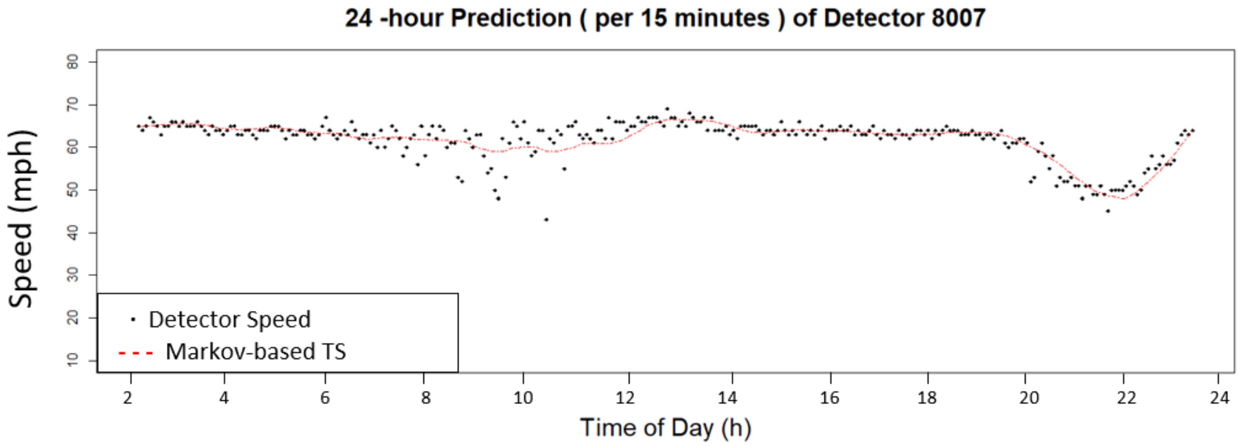
D. Graph. Speed Predictions (Heavy Snow)

h = hour. mph = mile per hour. TS = time series.
Source: Federal Highway Administration

Figure 11. Graphs. Predictions of speeds with rain and snow weather condition.

Error rates, root mean square error, and mean absolute error are used to evaluate the performance of the proposed model. The error rates of the normal case are between 5 and 9 percent. For the cases with an incident on the link or downstream of the link, the error rates of the predictions for the Markov-based model are between 9 and 18 percent, while the error rates of the time series model, without the Markov process, is between 53 and 60 percent. It shows that the MLP package using the Markov-based time series model is significantly more accurate than the traditional time series model. The prediction of weather events shows that the model can generally capture the drops and trends of speeds during the weather conditions. The error rates are below 10 percent and the root mean square errors are below 6 percent.

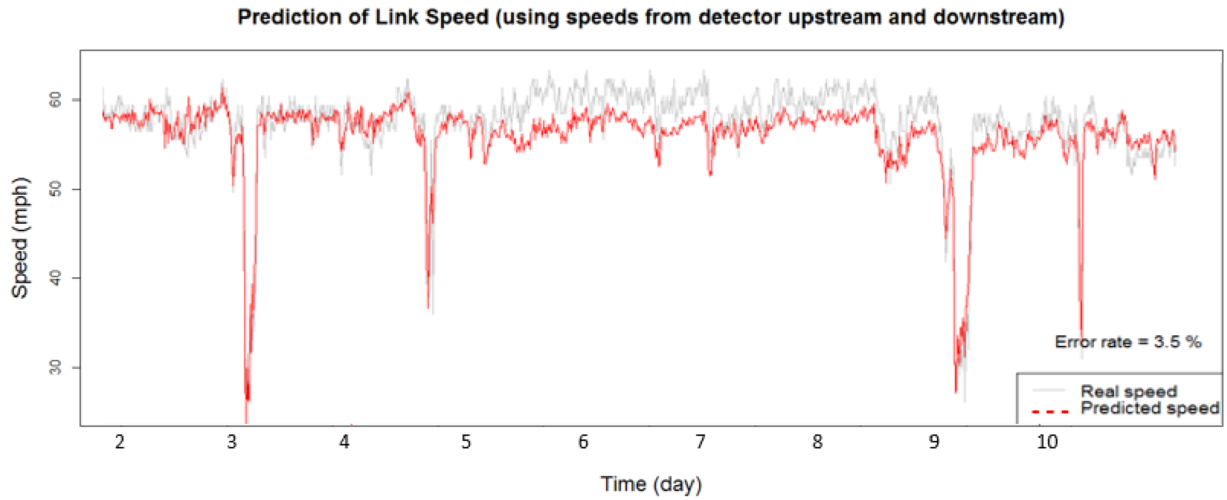
Predictions of special events are conducted. Links are selected based on the observation of historical data sets. Examples for game days of the Kansas City Royals are shown in figure 12. Generally, the predictions of the model can capture the congestion patterns caused by special events well.



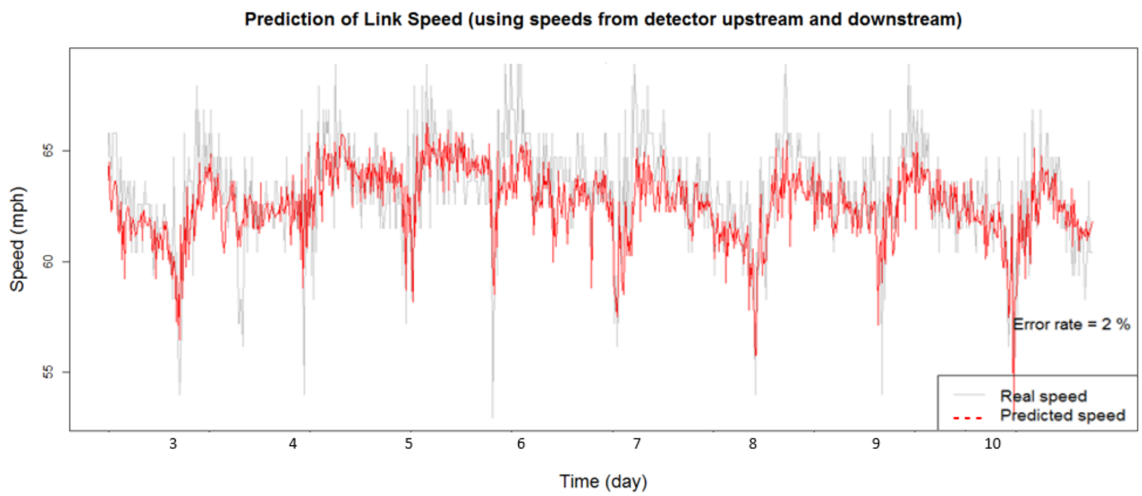
h = hour. mph = mile per hour. TS = time series.
Source: Federal Highway Administration

Figure 12. Graph. Examples of predictions for special events.

For links with no detectors providing real-time traffic data, data from the downstream detectors will be utilized to predict the future speed values. A neural network model is built to predict the link traffic speed under normal cases based on the downstream detector data. If there are external conditions, the same transition matrices are applied. Predictions of traffic speed during 10 days on two detectors are show in figure 13. The predicted values can detect recurrent patterns and speed drops, including congestions caused by incidents. The error rates are about 3.5 percent and 2 percent, which are satisfactory.



A. Graph. Predictions for detector with incidents.



B. Graph. Predictions for detector with recurrent patterns.

mph = mile per hour.
Source: Federal Highway Administration

Figure 13. Graphs. Examples of predictions for links without detectors.

Generally, the results show a relatively accurate prediction under the conditions of incidents and bad weather conditions, with error rates between 4 and 18 percent. Compared to the benchmark models, the MLP model can capture the most potential changes in traffic states and can provide a reliable prediction using the Markov transition matrices. The performance of the MLP package is superior to the benchmark model for both cases with and without external conditions. The MLP package is able to accurately capture the recurring and non-recurring traffic congestion.

CHAPTER 4. EVALUATION

INTRODUCTION

This chapter provides a summary of the Integrated Modeling for Road Condition Prediction (IMRPC) evaluation effort. The complete details and results of the evaluation are documented within the evaluation report.

SUMMARY OF FINDINGS

The evaluation explored whether or not IMRCP had an impact on the Kansas City Scout (KC Scout) operations and to assess whether the information was useful to the KC Scout operators and supervisors. The key questions guiding the evaluation data collection and analyses are: (1) Did IMRCP have an operational impact? and (2) Did the users consider the IMRCP information useful? To explore whether IMRCP had an impact, the evaluation investigated the accuracy of IMRCP speeds and speed forecasts. To investigate whether IMRCP information was useful, KC Scout operators and supervisors were interviewed to obtain their insights and perspectives. The findings in this section describe the outcomes of investigating speed and speed forecast accuracy and operator and supervisor perceptions of IMRCP's operational impact and usefulness.

Did Integrated Modeling for Road Condition Prediction Have an Operational Impact?

This evaluation found that IMRCP had minimal operational impact during the 2018–2019 and 2019–2020 winter driving seasons. However, operators did report that they often referred to IMRCP for weather forecast information prior to weather events. They stated that during normal day operations, they relied on existing KC Scout tools, applications, and information sources to monitor real-time traffic operations. Consequently, IMRCP speeds and speed forecasts were basically unused by the operators.

Analysis of the Traffic Estimation and Prediction System (TrEPS) and machine learning-based prediction (MLP) speeds and speed forecasts at three locations during seven winter days revealed that the two IMRCP models produced speeds and speed forecasts of varying accuracy. Three types of analyses for each location and date were completed:

- Analysis of historical predicted speeds.
- Analysis of forecast speeds for 15-, 30-, 45-, 60-, 75-, 90-, 105-, and 115-minute (min) predictions.
- Analysis of speed forecast errors (absolute, relative absolute, and root mean square errors).

Looking at the accuracy of historical predicted speeds, TrEPS speed data were found to be problematic on several dates, sometimes with several hours of predicted speeds considerably different (over 20 miles per hour [mph]) from the detector speeds. The TrEPS model predicts speeds using several input parameters, such as changes to posted speed limit, roadway construction (or blockage) information, and detector data. If any of these inputs are inaccurate or missing, it may affect TrEPS ability to predict accurate speeds. For example, it appeared that speeds reported by TrEPS at Interstate 435 (I–435) eastbound at State Line Road were affected by a construction work zone that was not reported by KC Scout. The MLP speed data often appeared to be within about 5 mph of the detector speeds and were much less affected by the I–435 at State Line Road construction work zone changes, but occasionally had periods with large deviations (up to 20 mph) above or below the detector speeds.

Analysis of forecast speeds found that MLP and TrEPS speed forecasts both showed periods where the forecasts appeared to have large deviations (up to 20 mph) above and below the detector speeds. The deviations appeared to grow larger and for longer periods of time with longer-term forecasts. The MLP forecast speeds tended to more closely match the detector speeds than the TrEPS forecasts and the errors were examined in the forecast speed error analysis.

The analysis of speed forecast errors used three formulas to calculate and compare the speed forecast errors: absolute, relative absolute, and root mean square error.

The absolute error analysis measured the difference between the forecast speed and the actual detector speed. In general, when examining the 15–115-min speed forecasts:

- The MLP absolute error showed that shorter-term forecasts tended to be more accurate than longer-term forecasts. The results at the three detector locations (I–435 at State Line Road, I–435 at East Stadium Drive, and I–435 at East Antioch Road) showed the 15-min forecasts were from 3 to 8 mph more accurate than the 115-min forecasts.
- The TrEPS absolute errors showed mixed results for speed forecasts. At I–435 and State Line Road, the absolute errors were relatively consistent across all forecast times. On January 29, 2020, the absolute error was relatively consistent, ranging from about 35 to 42 mph. However, on February 12, 2020, the absolute error was about 40 mph for the 15-min forecast, decreased to about 11 mph for the 75-min forecast, then increased to about 21 mph for the 105-min forecast.
- The TrEPS absolute errors for speed forecasts tended to be larger than the MLP absolute errors. At I–435 and State Line Road, the average TrEPS error across all forecast times was about 26 mph versus about 10.6 mph for MLP. At I–435 at East Antioch Road, the average TrEPS error across all forecast times was about 33 mph versus about 7 mph for MLP.

The relative absolute error measured how large the absolute error was compared to the actual speed and provided the percent size of the error. In general, when examining the 15–115-min speed forecasts:

- The MLP relative absolute error also showed that shorter-term forecasts tended to be more accurate than longer-term forecasts, in that the error as a percentage of the speed was smaller for shorter-term forecasts. The results at the three detector locations showed the 15-min forecasts were from 7 to 18 percent versus from 13 to 41 percent for the 115-min forecasts.
- The TrEPS relative absolute errors generally showed mixed results. At I–435 and State Line Road, the relative absolute errors were relatively large (ranging from 40 to over 100 percent) and mostly consistent across all forecast times. The average relative absolute error was about 73 percent for all forecast times. On January 29, 2020, the relative

absolute error was about 66 percent for the 15-min forecast, steadily decreased to about 18 percent for the 75-min forecast, then increased to about 48 percent for the 105-min forecast.
- Comparing TrEPS to MLP, the TrEPS relative absolute errors were generally larger. At I–435 and State Line Road, the average TrEPS error across all forecast times was about 73 percent versus about 29 percent for MLP. At I–435 at East Antioch Road, the average TrEPS error across all forecast times was about 56 percent versus about 12 percent for MLP.

The root mean square error measured the spread (or concentration) between forecasts and actual speeds. In general, when examining the 15–115-min forecasts:

- The MLP root mean square error showed that shorter-term forecasts errors tended to be smaller than longer-term forecasts. The root mean square error ranged from 3 to 12 mph.
- For TrEPS, the root mean square errors were relatively consistent across all forecast times. The root mean square error ranged from 19 to 32 mph.
- Comparing the root mean square errors of TrEPS to MLP, the TrEPS root mean square errors were found to be two to three times larger than the MLP root mean square errors. At I–435 and East Antioch Road, the average TrEPS error across all forecast times was about 27 mph versus about 9 mph for MLP.

Did Users Consider Integrated Modeling for Road Condition Prediction Information as Useful?

This evaluation found that KC Scout operators and supervisors liked the weather-related prediction components of IMRCP, but preferred to use existing tools for obtaining information about real-time traffic conditions and incidents. Although road and weather information were sometimes helpful, the operators did not rely on IMRCP to select more relevant operational strategies. A KC Scout representative stated that IMRCP might be a helpful tool for planning and assessing winter maintenance response efforts and emergency operation staffing decisions.

The operators stated they accessed IMRCP when weather events were approaching, and found the weather information helpful. They mentioned that IMRCP was useful for both rain and winter weather, but more so for when winter weather was expected. The operators used it less during heavy rain or flooding events. Otherwise, the operators tended to not use IMRCP as part of their normal daily routines. In general, the operators did not use the traffic predictions capability. The operators said they liked the precipitation/weather predictions and the pavement status predictions because they can provide some insight into what locations to monitor more closely as the weather moves in. The operators used this feature to find areas with potential issues affected by the incoming weather. They reported it helped them prioritize and focus attention on particular roadway sections or areas, which in turn may improve their communication and decisions relating to motorist assist deployments. One user reported that IMRCP has been informally used to help inform transportation management center (TMC) staffing decisions during a weather event (e.g., should additional staff be called in, or can staff be sent home?).

The operators reported using IMRCP during the weather event in a more limited capacity. They are often busy during the weather events performing priority duties and responsibilities, such as entering, monitoring, and updating incidents into their system.

The operators typically do not use IMRCP to assess an event that has already passed; however, they acknowledge it may be helpful for data analysis and evaluation to determine lessons learned. One user believed there was a benefit to using IMRCP capabilities and its weather event data to look back and assess winter maintenance response efforts and emergency operation staffing decisions. Insight gained could potentially help save the agency staffing and monetary resources.

Overall, the users reported a fair confidence in the weather-related prediction components of IMRCP. As mentioned earlier, the operators did not use the traffic prediction components. The operators also indicated that periods of IMRCP downtime negatively affected the usage of IMRCP in their daily routines, especially in the 2019–2020 winter season. The operators' responses from the interviews seemed to indicate a more frequent use of IMRCP in the 2018–2019 winter season.

The evaluation has resulted in a better understanding of the impact the IMRCP phase 3 had on KC Scout operations, the accuracy of the speed predictions and forecasts, and the usefulness of the information to KC Scout operators and supervisors.

CHAPTER 5. ANALYSIS, CONCLUSIONS, AND RECOMMENDATIONS FOR FURTHER STUDY

The Integrated Modeling for Road Condition Prediction (IMRCP) demonstration in the Kansas City area has generated a significant body of operations data and experience. This section summarizes lessons learned and deployment considerations, describes some potential applications for IMRCP, draws conclusions from the demonstration, and recommends topics for further study.

LESSONS LEARNED

Accessing and maintaining data services needed to feed IMRCP are significant challenges. Weather forecast data are voluminous but manageable due to the well-documented National Oceanic and Atmospheric Administration (NOAA) and National Weather Service (NWS) interfaces. These apply nationally and can be reused in any IMRCP deployment within the continental United States. Even so, NOAA has changed some interfaces during the course of this project that required recoding some data collections components. Collection of weather data from NOAA sources is not easily configured by non-information technology (IT) or non-meteorological staff.

Access to traffic data is problematic. Real-time access to agency data is preferred but may be difficult to maintain. Advanced transportation management system (ATMS) software is not typically focused on sustained data provision beyond the transportation management center (TMC), and those data feeds are generally less important to an agency than its own internal operations users. In addition, historical data archives needed for training the traffic models may not be in the same data formats or be as accessible as the real-time data. Third-party and commercial data (e.g., from probes) may not be any more accurate, and may not be available in real time for IMRCP integration (depending on contracts with agencies and their terms of service). Many of these concerns would be mitigated by an IMRCP deployment within a transportation agency’s own TMC, where tighter configuration control over system metadata and fewer potential network access issues.

Hydrological data may be available, but not necessarily through a transportation agency. NOAA/NWS has made great strides in this area during the course of this project and has advanced data availability from its own hydrological networks and those of partner agencies. Data for small streams are less available, but increasingly important for more extreme severe weather systems. Hydrological data are also still difficult to relate to the transportation network. Flood stages are generally identified with particular stations, and do not necessarily relate to geodetic references enabling reference to nearby roadways.

Geographical and time references of data are essential to data integration across such disparately sourced data sets. While weather data are well referenced in space and time, that is not necessarily the case with traffic data, which are more typically associated with a road network link. IMRCP needs to know the applicable location of the sensed traffic data rather than the location of the sensor, mast, or cabinet. In this context, using sensor identifiers (ID) is difficult to manage. Even within a particular system context, IDs may vary in time for a fixed set of assets—

for example, in assigning a new one, or moving/revising an old one. Managing IDs across applications or systems is more difficult since each component may prefer or need its own IDs for a common set of objects. Time references for data have issues with determining their extents, meaning to the range of times over which the values are valid. When does the value become relevant or age out? Sometimes references assume an equally spaced series of data values (for example, in traffic detection) whereas others create new data points only when the value changes (for example, in the hydrological data feeds). Both models suffer from difficulty in handling gaps in the series of time-based observations.

IMRCP traffic forecasts demonstrated their capability and value, particularly in filling the field of near real-time views and very short-term predictions (fewer than 30 minutes [min]). The accuracy and reliability of the predictions are, nonetheless, somewhat limited by data availability. Accuracy and reliability affect the confidence with which operators and other users view the predictions, and their applications, in weather-responsive management strategies (WRMS). The solution likely has multiple facets, some of which are not directly under the control of the IMRCP models or deployments. Improving the maintenance, calibration, and reliability of agency fixed traffic detectors to provide a “ground truth” view would greatly improve model accuracy. Sections of the roadway network with sparse traffic data would benefit from using real-time probe data to supplement the fixed detectors. Adding traffic data quality checking to isolate detectors that may be out of calibration would improve the reliability of the forecast models.

Based on the project experience, operators are very focused on the here and now, monitoring known problem areas and incidents. They do not necessarily have the time or means to address the overall network conditions or to ask what might be about to happen. As such, it may be hard for operators in such environments to appreciate the potential of a traffic forecast, particularly when it requires monitoring yet another application or screen in a TMC. There seems to be a strong preference for having outputs integrated into existing TMC interfaces.

Maintenance personnel are focused almost exclusively on the weather forecasts. Traffic is not a first-order consideration in treatment plans, other than generally identifying priority routes. They may be unclear on how IMRCP fits with other road weather tools like maintenance decision support systems (MDSS). They generally want a long view of weather conditions commensurate with the duration of a storm, which may need forecasts 24–48 hours (h) in advance. That time horizon is inconsistent with the 2-h window available with the traffic forecasting tools used in this demonstration deployment.

IMRCP, as deployed for this demonstration, has not been able to demonstrate the feedback of treatment and observed conditions into the forecast models. This is primarily an issue of having insufficient winter maintenance reporting in the study area (although the Missouri Department of Transportation [MODOT] is now addressing that opportunity) and would also require road condition model updates to accommodate the treatment data. It has not been an issue in the Kansas City deployment due to the type and extent of winter weather conditions encountered during the demonstration interval, but it would be a bigger issue in hard winter areas where snow and ice are on roads for an extended multi-storm period.

Success in IMRCP applications will depend, to some extent, on building awareness of WRMS and their benefits. This may be the exception rather than the rule among agencies that would be candidates for IMRCP deployments. That awareness greatly facilitates discussions of the potential value and application of IMRCP in operations. This phase 3 deployment was unable to identify or implement any specific strategies.

Although the current IMRCP deployment provides extensive data resources, it is difficult to evaluate the forecast results. This is partially just the volume and temporal/spatial complexity of the data sets, but also identifies a need for more robust forecast performance measures. Once those are identified, they could facilitate inline performance monitoring as events move from initial conditions through the forecast periods. This would further support a performance dashboard for the roadway network and the IMRCP system itself.

DEPLOYMENT CONSIDERATIONS

An emphasis in phase 3 was to investigate the potential for interested agencies to develop their own deployments of an IMRCP system. This section summarizes the relevant considerations in a localized IMRCP deployment. A description of deployment needs and processes is detailed in the non-binding user manual, *Integrated Modeling for Road Condition Prediction Installation and Administration Guide*.[10]

Any agency intending to deploy a predictive capability, such as IMRCP, should have a collective institutional interest in the opportunity. The upper-management levels will need to have a vision of the potential of predictive analytics to prepare for and support its implementation. Technical champions will be needed to provide expertise and direction in its intended applications. And invested users will be essential in application of the system to operations strategies. Deployments without these institutional stakeholders will be challenged to develop and support sustained effective operations.

Building and deploying an IMRCP instance is detailed in the non-binding user manual, *Installation and Administration Guide*.[11] The IMRCP system and its components and documentation have been developed under U.S. Department of Transportation (USDOT) sponsorship and are available to interested parties on the Intelligent Transportation Systems (ITS) CodeHub.[12] Software components are open-source licensed, except for some TrEPS components that are available for download as executables. Other server components used in the phase 3 IMRCP demonstration have also used open-source software. The database server is an open-source MariaDB Server, and Apache Tomcat® 8 software is used for the application/web server. Other commercial databases and web servers could be used if administratively required for a particular environment. Java™ Runtime Environment 1.8 should also be installed on the server.

---

[10] USDOT, *Integrated Modeling for Road Condition Prediction Installation and Administration Guide*, FHWA-JPO-18-746 (October 2019).

[11] USDOT, *Integrated Modeling for Road Condition Prediction Installation and Administration Guide*.

[12] "Explore ITS CodeHub," USDOT Intelligent Transportation Systems Joint Program Office (ITS–JPO), accessed June 8, 2020, https://its.dot.gov/code/.

In practice, deploying an IMRCP system generally requires setting and configuring the server environment and the application components, identifying and configuring the data access components needed for model localization, configuring the models to use the localized data, and monitoring and maintaining the system. Although the computational components have been designed to accommodate some irregularities in data access and quality, the distributed nature of the system data sources and services requires consistent monitoring to assure a high quality of service.

Much of the data presented to users through the IMRCP interfaces are associated with the road network of the study area. The definition of the area to be modeled needs to consider the potential applications, extent of the network, availability of data from traffic monitoring and control systems, and effort needed to acquire the data and model the network. For example, creating the road network for the IMRCP study area is a critical and potentially time-consuming process. As described earlier, the Kansas City metro deployment in phase 3 modeled almost 6,000 road network links. The link data, though generally available from agency and third-party systems, have to be configured for the specific traffic and road condition models to be used in the deployment. The phase 3 demonstration did not completely automate that process, and significant manual quality checking of the underlying data was needed to assure consistency across two traffic models and the road weather model.

IMRCP uses many local data sources specific to the study area. Ease of access to and quality of data available for the area are important considerations that may not, themselves, determine the relative value of a deployment, but nonetheless affect the deployment’s applications and utility. Relative to the demonstration deployment, the study area uses data from traffic detectors maintained by the KC Scout TMC, but the traffic model calibration found that data availability from some detectors for calibration was not reliable enough to use in training and operating the system. System metadata (such as the location of the traffic sensors on the network links) presented similar challenges with availability and precision.

The accuracy of IMRCP predictions is directly related not just to the physical model of the road network, weather, and hydrology, but also to the operations and event data within the modeled region. TMC operators and ATMS software generally excel at identification and management of incidents and ITS traffic controls. Work zone management and winter maintenance operations may not, however, be integrated with those ATMS systems. Operational awareness of special events may be similarly limited. This is especially challenging in an area like the Kansas City study area, which has multiple State and local operating agencies. Identifying and entering data for work zones in the area, beyond those directly provided by the automated ATMS data feed, involved going to two State and multiple county/municipal data sources for work zone locations and schedules, with an IMRCP system manager entering the work zone data manually.

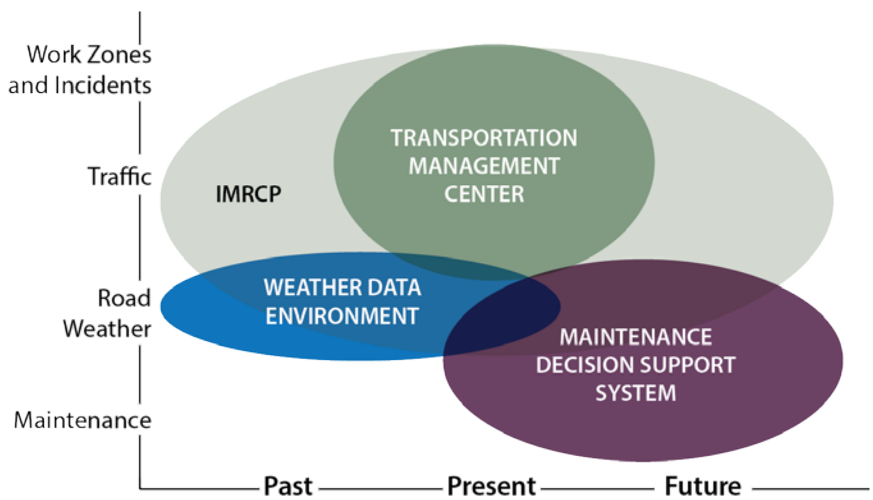
POTENTIAL APPLICATIONS

IMRCP and its predictive analytics have potential benefits and applications across transportation management and operations. At a high level, IMRCP may offer agencies operational awareness, informed planning and response, and improved safety and mobility.

IMRCP can offer TMC staff, winter maintenance staff, and other decision makers improved insight and overall awareness of the effect of impending weather on traffic. Agencies can monitor condition information, such as traffic, pavement state, pavement and air temperatures, precipitation, wind, and flooding, that is more typically distributed across multiple systems.

With the enhanced operational awareness and predictive analytics, agencies can better plan and make strategic decisions. For example, the capability of viewing future impacts may prompt the agency to issue news releases or social media alerts, update the staffing plans for incident responders or snowplow drivers, change work zone plans, arrange for alternate traffic routes, enact traffic controls (e.g., variable speed limits [VSL], variable message signs, ramp metering, road closure gates), or activate other response scenario plans. Agencies can use IMRCP and the collected data to analyze past events, determine lessons learned, measure performance, and guide future strategic decisions.

These IMRCP benefits to transportation agency operations may be further extended in complementing other tools using similar data sets. As shown in figure 14, IMRCP extends user awareness of traffic and road conditions from the past into the present and future, beyond the capabilities of typical TMC tools and road weather information systems (RWIS) like the Weather Data Environment (WxDE). IMRCP shares road weather data and forecasts with MDSS while adding the traffic forecast perspective, but it does not provide the direct winter maintenance recommendations of an MDSS.



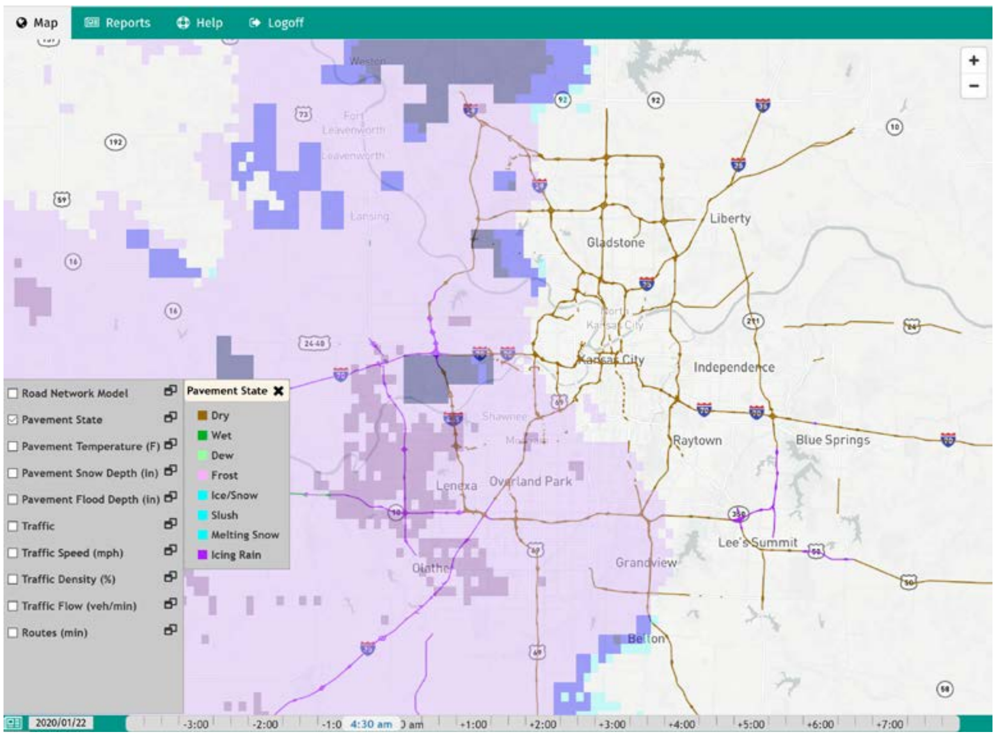
Source: Federal Highway Administration

Figure 14. Illustration. Integrated Modeling for Road Condition Prediction relationship to other weather-responsive management strategy tools.

Pavement State Prediction

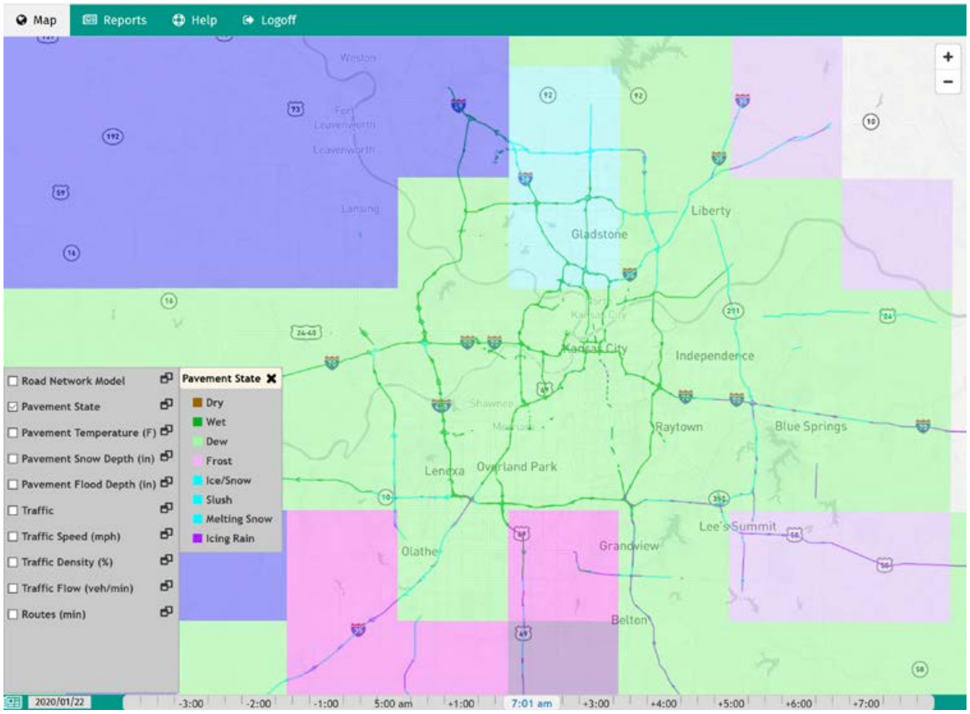
It may be beneficial for operators to view pavement state predictions as a weather event approaches, especially if the event will occur immediately prior to or during peak traffic hours. Predictions that indicate wet or icy roads may enable operators to better prepare for such events by focusing attention on those particular segments of the road network. Operations staff can provide more timely and accurate traveler information for travelers dealing with the inclement conditions. Maintenance staff otherwise without access to an MDSS may still be able to anticipate and make more informed plans for anti-icing and snow removal operations.

Figure 15 illustrates conditions as a winter storm was arriving from the west of the Kansas City area prior to morning rush hour. An operator can see on the Pavement State and Precip Type layers on the map that pavements are largely dry on the eastern part of the metro, but subject to mixed precipitation on the western part. To view pavement state predictions for the rush hour, the operator moves the time function ahead to 7 a.m. The forecast conditions in figure 16 indicate that the mixed precipitation is expected to continue with spotty wet, snowy, and icy pavement conditions all across the metro.



Source: Federal Highway Administration

Figure 15. Screenshot. Pavement state example – 4:30 a.m., January 22, 2020.



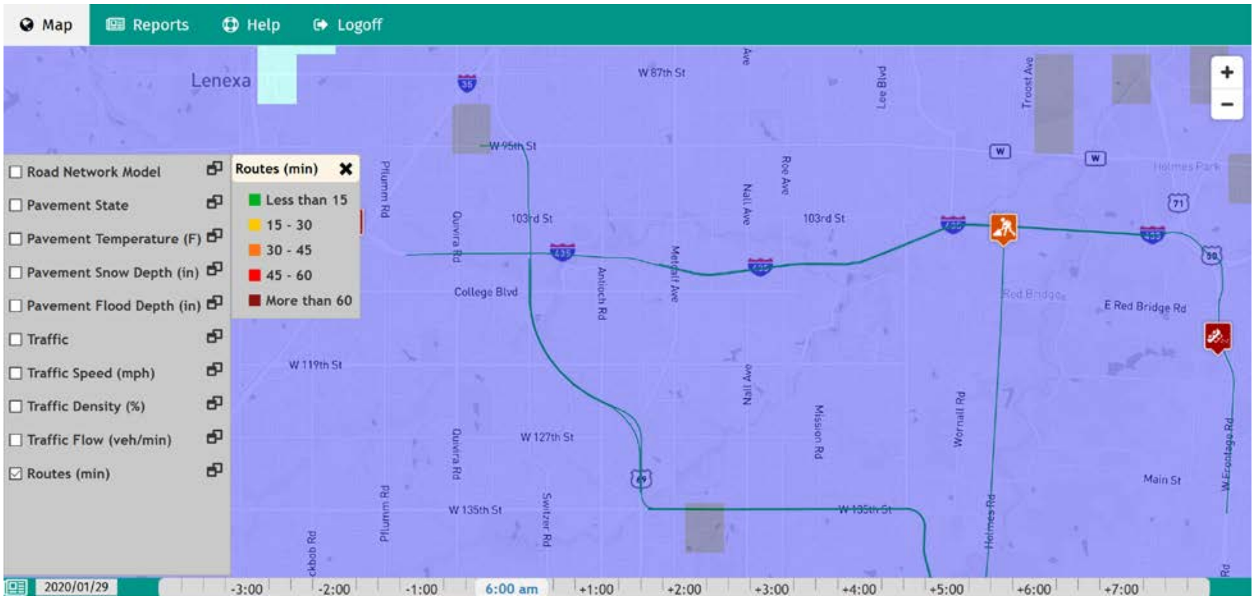
Source: Federal Highway Administration

Figure 16. Screenshot. Pavement state prediction example – 7 a.m., January 22, 2020.

Travel Time Predictions

Operators and travelers may find the route travel times produced by IMRCP useful for monitoring congestion and commute times. During inclement weather events, users can use the IMRCP predictions to adjust the departure time for their daily commutes.[13] As illustrated in figure 17, a user who lives near Interstate 435 (I–435) and Quivira and works at an office near the interchange between I–435 and Interstate 470 (I–470) could check to see the extent to which a passing winter storm will affect the usual morning commute. The user would find the routes layer from the road data layer tab on the map interface. This layer shows routes with available travel times displayed on the map. At 6 a.m., the travel time is still within reason, even with snow coming down (the blue shading across the map).

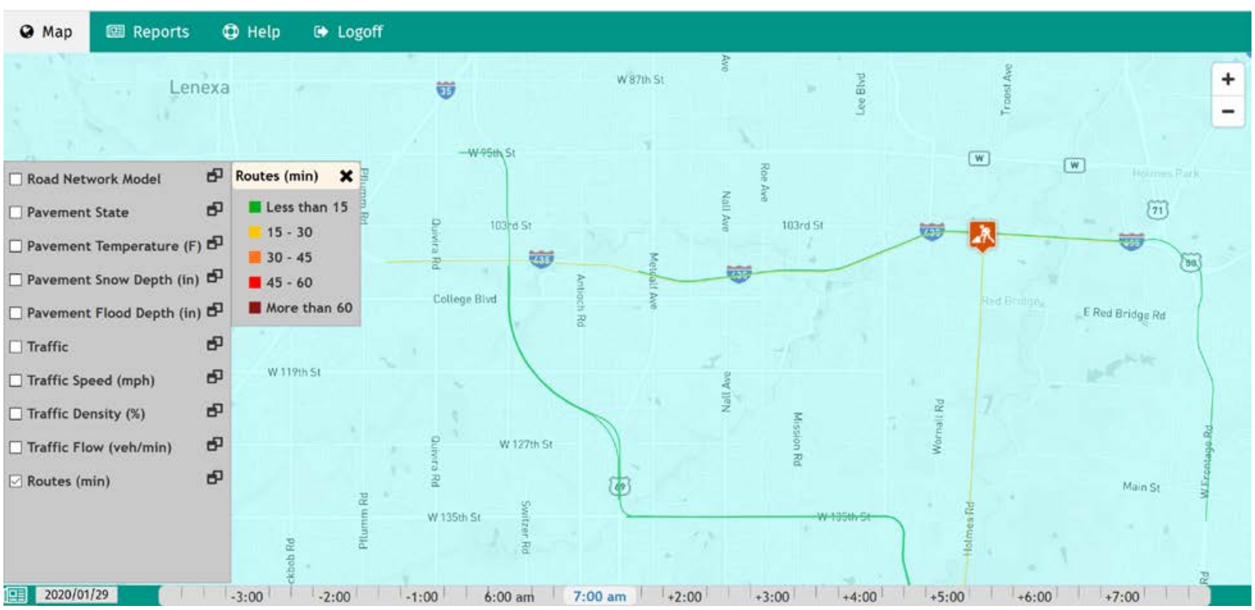
[13] Travel time predictions are available for only a limited set of routes in the demonstration Kansas City deployment.



Source: Federal Highway Administration

Figure 17. Screenshot. Route travel time early in a winter storm.

As these things go, waiting for the normal 7 a.m. commute time might have its consequences. On the one hand, the snow might be over by then. On the other, traffic is likely to be much worse. Moving the slider on the time scale 1 h into the future shows predicted conditions consistent with that expectation (figure 18). Even though the snow is forecast to be decreasing, travel time for that route increases from fewer than 15 min to as much as a half hour. Predicted travel times could be incorporated into traveler information messages to encourage leaving earlier or later than normal to avoid and lessen the impact of weather events on travel times.



Source: Federal Highway Administration

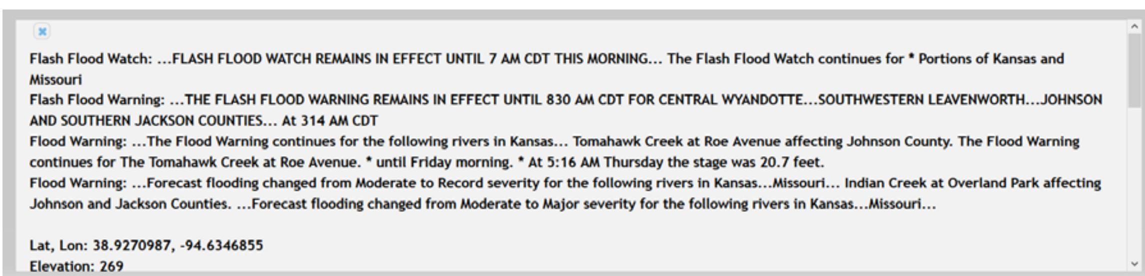
Figure 18. Screenshot. Route travel time prediction for a winter storm.

Flooding Events

The IMRCP system may be able to monitor hydrological data during flooding events for potential impacts on transportation infrastructure. The Kansas City demonstration study area was chosen, in part, because of its urban small-stream, flash-flood challenges. Transportation system operators and emergency services personnel can use the IMRCP system to view predictions for flooded roads or to look back at the behaviors of a hydrological event.

As a historical example, the small-stream flooding of July 27, 2017, proved to be a challenging hydrological event for the Kansas City study area. Several roads in the study area experienced flooding and closures. The NWS warning captured by IMRCP on July 27, 2017, at 6 a.m. in figure 19 is indicated graphically on the map in figure 20. The NWS alerts layer has been selected and the pavement flood depth layer displays the roads that registered as flooded based on the NWS inundation models. The overlays are darker in some areas as an indication of multiple watches and warnings overlaid on one another. Flood forecast depths, to the extent that they are available from NOAA/NWS, would be captured and viewable on the map. Closures for inundated roadways are included in the IMRCP traffic forecast models.

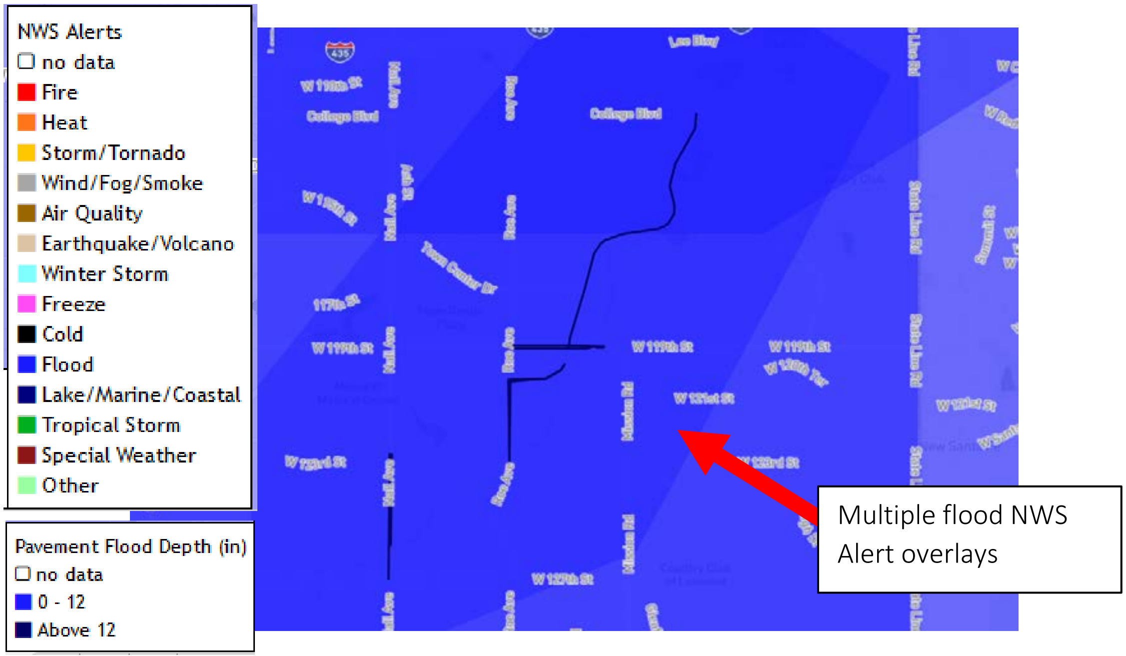
Providing hydrological data in an interface with traffic and weather data provides an integrated predictive perspective for transportation operations. Although these events are historically infrequent, recent industry interest in transportation resiliency suggests that they will become more of a concern to transportation operations in the near future. Providing an integrated view of conditions would enable operators to provide more specific and complete traveler information, or to anticipate and dispatch driver assistance and maintenance crews.


Flash Flood Watch: ...FLASH FLOOD WATCH REMAINS IN EFFECT UNTIL 7 AM CDT THIS MORNING... The Flash Flood Watch continues for * Portions of Kansas and Missouri
Flash Flood Warning: ...THE FLASH FLOOD WARNING REMAINS IN EFFECT UNTIL 830 AM CDT FOR CENTRAL WYANDOTTE...SOUTHWESTERN LEAVENWORTH...JOHNSON AND SOUTHERN JACKSON COUNTIES... At 314 AM CDT
Flood Warning: ...The Flood Warning continues for the following rivers in Kansas... Tomahawk Creek at Roe Avenue affecting Johnson County. The Flood Warning continues for The Tomahawk Creek at Roe Avenue. * until Friday morning. * At 5:16 AM Thursday the stage was 20.7 feet.
Flood Warning: ...Forecast flooding changed from Moderate to Record severity for the following rivers in Kansas...Missouri... Indian Creek at Overland Park affecting Johnson and Jackson Counties. ...Forecast flooding changed from Moderate to Major severity for the following rivers in Kansas...Missouri...

Lat, Lon: 38.9270987, -94.6346855
Elevation: 269

Source: Federal Highway Administration

Figure 19. Screenshot. Hydrological event alert for July 27, 2017.



Source: Federal Highway Administration

Figure 20. Screenshot. Local hydrological event map for July 27, 2017.

CONCLUSIONS

The objectives for IMRCP phase 3 development and deployment have been met. The enhancements made to expand the regional view and traffic modeling capabilities have been integrated successfully into the system. The deployment provides real-time predictions of traffic and road conditions over the entire KC metro area, which incorporate data on atmospheric and road weather conditions, traffic, incidents, hydrological conditions, work zones, winter maintenance operations, and special events, when such data are available. The predictions are available to system users, operators, and maintainers in user-friendly maps and reports. The underlying IMRCP system provides a scalable framework for deployment in other areas, is extensible to other types and sources of data, and can support additional application-specific user interfaces as needed.

Accurate and complete traffic and weather models depend on available and accurate data to drive the models. Incorporating available data may furthermore depend on available and accurate metadata that describe the data sources and their qualification. Traffic data sources for phase 3, for example, were challenged by scarcity (not enough data in some parts of the roadway network), reliability (data intermittently unavailable), and uncertainty in metadata (precise location of the measured data relative to the roadway). Taken together, these limitations may constrain the accuracy of model outputs and their utility in practical applications.

As was noted in the phase 2 report, atmospheric weather forecast models are mature and reliable for large-scale events, but are less accurate for very near-term needs at road network link levels. Current atmospheric forecast products from the NWS used in this demonstration provide 1-h temporal resolution and 3-kilometer (km), or greater, spatial resolution. This temporal resolution, in particular, leads to operational uncertainty as to when weather fronts might have an impact on particular links. Higher-resolution forecast models could improve the accuracy of forecasts for key points on the road network.

IMRCP phase 3 has used two very different traffic models to provide predictions for the study area road network. The Traffic Estimation and Prediction System (TrEPS) dynamic traffic assignment (DTA) approach is intended to predict flows and traffic conditions on all facilities in a network, including arterials. In many networks, such as this phase 3 study area, detectors are present only on freeways, with limited deployment on major arterials. By contrast, the machine learning and time series techniques used in the demonstration machine learning-based prediction (MLP) model are based on local approaches to speed prediction.

The TrEPS approach was motivated by the need to support development of intelligent traffic management solutions that consider flows not only on freeways, but also on the surrounding arterials. Accordingly, the TrEPS approach has a structural representation (simulation) of the flow patterns through the network, and provides predictions of flow (volumes), density (or occupancy), and speeds that are consistent with these values. Accordingly, the approach is predicated first on getting the flows (the demand) right across the entire network and predicting the associated congestion through a traffic model. IMRCP phase 3 has further resulted in two methodological improvements to the TrEPS approach by implementing an adaptive flow model on those links that have detectors, and a method to adjust the overall network demand in response to weather events, based on the detector data.

Machine learning techniques and time series models, such as those used in the MLP, have generally been successful in predicting speeds over the near term. They will tend to do quite well when there is a sufficiently rich data archive to support training the models. These methods are relatively simple to implement and offer a lot of flexibility, as they do not require a full network representation or modeling the flow patterns through the different parts of the network. As such, they can be deployed and scaled effectively, from a computational standpoint, to all links in a network with sufficient sensor data. IMRCP phase 3 demonstrated the strong potential of machine learning methods for speed prediction on freeway links with and near existing detectors.

Discussions with KC Scout TMC personnel indicated that the potential of the predictive information was not being fully realized. There was, instead, a reliance on the real-time model data as a primary gauge for traffic and road conditions. This is consistent with previous experiences whereby predictions alone are not sufficient in a real-time setting to affect operator actions. An awareness of the potential operational improvements associated with WRMS would facilitate, and may be a prerequisite for, seeing potential value of the integrated road condition predictions. Where that understanding is in place, system operators and maintainers will likely be more open to recommendations for what to do on the basis of these predictions—for example, recommendations on speed advisories under predicted weather events, or routes under incidents or construction. Research has shown the effectiveness of interventions predicated on predicted conditions rather than simply reacting to prevailing ones. Going forward, the value of the kind of predictions that IMRCP is capable of producing lies in developing applications that build upon these predictions to recommend weather-responsive transportation management strategies.

RECOMMENDATIONS FOR FURTHER STUDY, DEVELOPMENT, AND APPLICATION

The lessons learned, deployment experiences, potential applications, and conclusions from the IMRCP phase 3 deployment have identified both gaps and barriers to further deployments. Gaps discussed in this report are primarily technical, but barriers may be limited acceptance with operators and maintainers, ease of deployment, or operational benefits. The research team's recommendations for further study are intended to close gaps, reduce barriers, and develop new opportunities for applying predictive capabilities in solving transportation operations challenges.

Developing the physical road network model has required significant resources in IMRCP phase 2 and phase 3. A significant barrier to deployment would be lowered by considering automation of the road network modeling process in support of road condition and traffic forecasting.

The Kansas City area deployment did not have a significant number of reliable local road weather observations from which to initiate forecasts. A future deployment should make more effective use of weather observations from mobile and fixed-road weather sources to improve the road condition model fidelity.

Significant gaps in traffic detection stations on the road network have created challenges for calibration of the traffic models. Adding traffic probe data sources would improve the basis for both traffic model calibration and prediction.

Traffic model configuration and calibration have required significant resources in phase 2 and phase 3. Barriers to future deployment could be considerably reduced by at least partial automation of traffic model configuration and calibration.

Management of road network, traffic detection, hydrological station, and road condition sensor metadata was challenging throughout the project. Standardizing metadata management and providing an IMRCP system management interface would reduce barriers to deployment and improve prediction accuracy.

Traffic data quality was found to be highly variable across the demonstration deployment network and through its duration. Implementing traffic data quality checking could significantly reduce modeling errors and improve model reliability and accuracy.

The spatial accuracy of road condition predictions is hampered by the relatively coarse atmospheric forecast grids. That limitation can be addressed, and predictions improved, by developing or acquiring higher-resolution weather forecasts to feed the road weather condition models.

As noted among the lessons learned, hydrological stations tend to provide stream levels relative to local flood stages, which may or may not be correlated with local roadways. A more complete integration of hydrological forecasts with road conditions and closures would acquire or develop inundation models for any risk-prone areas to be included in the deployment region.

Although it was not the primary focus of the phase 3 demonstration deployment, supporting winter maintenance strategies was identified as a potential IMRCP application by KC Scout staff. Those applications would suggest providing winter maintenance modeling and tools more in line with current agency practice. A first potential enhancement would be to extend weather and road condition forecasts to encompass more typical storm durations (24–48 h). Integrating winter maintenance and road treatment data into the road condition modeling would improve forecast model fidelity for longer events with maintenance interactions.

The MLP traffic model developed in phase 3 showed significant promise as an extensible and efficient means of providing traffic speed predictions. It was nonetheless limited in this text deployment by the range and availability of data to train and calibrate the model. Its accuracy and applicability to this and other networks could be extended to a broader range of road and weather conditions.

The extension of MLP to predict other traffic parameters, such as traffic volume and density, is possible with additional data sources. These data sources include ubiquitous travel time data from private sector providers, such as INRIX and HERE, crowdsourced probe vehicle trajectory data, and continuous count station volumes and information on annual average daily traffic from conventional sources. MLP can also be used, in combination with simulation, to provide predictions of traffic under various traffic and weather management strategies.

The volume and complexity of the data sets used and generated by the IMRCP system create challenges in data analysis and reduction. Developing WRMS-oriented performance measures and a dashboard for IMRCP predictive capabilities would reduce barriers to acceptance and deployment and potentially enhance its operational impact by focusing operator and analyst attention on key performance indicators, locations, and notifications.

IMRCP phase 2 and phase 3 have focused on the development and evaluation of integrated predictive methods. Providing actionable WRMS recommendations from the system based on predicted conditions would remove a potential barrier to deployment and enhance its potential impact in an operational setting.

Future IMRCP deployments may want to prioritize opportunities to cooperate with agencies that would be willing to more fully integrate the IMRCP models with their TMC systems and operations. These opportunities would then identify specific weather-responsive management goals and strategies to be considered in their operations. Traffic, weather, hydrological, work zone, and other operations data sources would then be identified and acquired to support those particular goals and strategies. Models and interfaces could then be tailored to support implementation in those settings and with those users.

BIBLIOGRAPHY

Ibrahim, A. T., and Hall, F.L. (1994) *Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationships*. Transportation Research Record 1457, Washington, D.C., pp. 184–191.

Rakha, H. A., Farzaneh, M., Arafeh, M., and Sterzin. E. (2008*)*. *Inclement Weather Impacts on Freeway Traffic Stream Behavior*. Transportation Research Record: Journal of the Transportation Research Board 2071, Washington, D.C., pp. 8–18.

U.S. Department of Transportation. *Integrated Modeling for Road Condition Prediction Model Analysis* (unpublished). May 10, 2015.

U.S. Department of Transportation. *Integrated Modeling for Road Condition Prediction Concept of Operations* (unpublished). November 25, 2015.

Federal Highway Administration. *Integrated Modeling for Road Condition Prediction (IMRCP) – Phase 3 Evaluation Report*. FHWA-HOP-20-062. July 2020.

U.S. Department of Transportation. *Integrated Modeling for Road Condition Prediction Final Report*. FHWA-JPO-18-631. December 31, 2017.

U.S. Department of Transportation. *Integrated Modeling for Road Condition Prediction (IMRCP) – Phase 3 Final System Architecture Document*. FHWA-JPO-18-688. July 31, 2018.

U.S. Department of Transportation. *Integrated Modeling for Road Condition Prediction (IMRCP) System Design Description*. FHWA-JPO-18-727. June 1, 2019.

U.S. Department of Transportation. *Integrated Modeling for Road Condition Prediction Installation and Administration Guide*. FHWA-JPO-18-746. October 2019.

U.S. Department of Transportation. *Integrated Modeling for Road Condition Prediction System User Guide*. FHWA-JPO-18-747. October 2019.

U.S. Department of Transportation
Federal Highway Administration
Office of Operations
1200 New Jersey Avenue, SE
Washington, DC 20590

ops.fhwa.dot.gov

October 2020

FHWA-HOP-20-061

U.S. Department of Transportation
Federal Highway Administration