Multiresolution Modeling for Traffic Analysis: Guidebook

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FOREWORD

The *Multiresolution Modeling* (MRM) *for Traffic Analysis Guidebook* (*MRM Guidebook*) fills a prominent void in the transportation industry by providing essential MRM information. In MRM, the analyst simultaneously assesses traffic performance at multiple resolutions: macroscopic, mesoscopic, and microscopic. MRM's relevance increases with each passing year due to evolving computer capabilities, traffic analysis tool capabilities, and transportation system complexities. The *MRM Guidebook* provides an introduction to MRM, a methodology for MRM application by analysts, and a set of real-world MRM case studies. The *MRM Guidebook* will interest transportation modelers, traffic analysts, and transportation agencies. The following companion publications are also available: *Multiresolution Modeling for Traffic Analysis: State-of-Practice and Gap Analysis Report* (*SOPAGA Report*) and *Multiresolution Modeling for Traffic Analysis: Case Studies Report* (*MRM Case Studies Report*)[1] (Zhou, Hadi and Hale 2021). Although the *MRM Guidebook* provides high-level information in these areas, the *MRM SOPAGA Report* and *MRM Case Studies Report* offer additional low-level detail that may interest the reader.

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[1]Hadi, M., X. Zhou, and D. Hale. Forthcoming. *Multiresolution Modeling for Traffic Analysis: Case Studies Report.* Washington, DC: Federal Highway Administration.

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16. Abstract

The Federal Highway Administration (FHWA) and the Traffic Analysis and Simulation Pooled Fund Study sponsored a research project on multiresolution modeling (MRM). The project intended to develop consistent definitions and a unified modeling framework for MRM to help transportation professionals better understand opportunities and challenges associated with MRM. This guidebook assists agencies with developing a fully integrated MRM analysis. The guidebook summarizes MRM terminology and definitions, provides a methodology for MRM analysis, and illustrates in three case studies the benefits of applying MRM. The proposed MRM methodology extends the seven-step methodology provided for simulation analysis in FHWA's *Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software* (Wunderlich, Vasudevan, and Wang 2019). This guidebook will help transportation professionals assess the level of effort needed and benefits of developing multiresolution models for their analyses and provide guidance for model development.

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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or “metric ton”)	Mg (or “t”)
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or “t”)	megagrams (or “metric ton”)	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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

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LIST OF ABBREVIATIONS

α	coefficient volume on link *i*
β	Bureau of Public Roads exponential coefficient
ABM	activity-based model
AMS	analysis, modeling, and simulation
AT	area type
ATDM	active transportation and demand management
BPR	Bureau of Public Roads
c	link capacity
CAV	connected and automated vehicle
CBD	central business district
CBI	congestion and bottleneck identification
CMF	capability maturity framework
CMM	capability maturity model
CSV	comma-separated values
D	total volume
D_h	volume within the peak hour
D/C	demand-over-capacity
DBM	density-based method
DOT	department of transportation
DTA	dynamic traffic assignment
FHWA	Federal Highway Administration
FT	facility type
GMNS	General Modeling Network Specification
GPS	Global Positioning System
HCM	*Highway Capacity Manual*
HCS	Highway Capacity Software™
ICM	integrated corridor management
ITE	Institute of Transportation Engineers
ITS	intelligent transportation systems
LOE	level of effort
LOS	level of service
m	observed point
MaaS	mobility as a service
MAG	Maricopa Association of Governments
MAZ	microanalysis zones
MPO	metropolitan planning organization
MRM	multiresolution modeling
n	derived point
O-D	origin-destination
ODME	origin-destination matrix estimation
OSM	OpenStreetMap®
PHF	peak hour factor
POI	point of interest
QBM	queue-based method

QDF	queue demand factor
QEM	quick estimation method
SBA	simulation-based assignment
SERPM	Southeast Florida Regional Planning Model
SOP	standard operating procedure
SOPAGA	State-of-Practice and Gap Analysis
STA	static traffic assignment
STM	*Signal Timing Manual*
t_0	start of congestion period
t_3	end of congestion period
t_i	congested travel time for link *i*
TAZ	traffic analysis zone
TSMO	transportation system management and operations
u	speed
u_c	speed at capacity
u_{min}	minimum speed during the assignment period
v	traffic volume on link *i*
v/c	volume-to-capacity
VBM	volume-based method
VC&V	verification, calibration, and validation
VDF	volume-delay function
VHT	vehicle hours traveled

CHAPTER 1. INTRODUCTION

In the United States and many parts of the world, the increasing rate of surface traffic congestion is outpacing the available roadway infrastructure in urban areas. Agencies and governments are pursuing intelligent transportation system (ITS) solutions, active transportation and demand management (ATDM) strategies, connected vehicle technologies, and alternative intersection/interchange designs that significantly improve traffic flow without constructing additional lanes. Given the expenses and complexities associated with advanced traffic management, analysis, modeling, and simulation (AMS) tools are increasingly important for evaluating potential solutions and strategies prior to implementation. AMS tools have become indispensable for justifying future roadway improvements, analyzing traffic control strategy alternatives, and forecasting emerging technology impacts.

AMS tools exist at various resolutions, including microscopic, mesoscopic, and macroscopic. Each resolution has specific advantages and disadvantages and can provide a different function in the modeling process. Analysts generally use demand forecasting models that rely on macroscopic traffic models and static traffic assignment (STA) to assess regional transportation demand patterns involving large spatial scopes. Analysts often use microscopic models to study the operations and localized issues with limited spatial scopes. In multiresolution modeling (MRM), an agency starts from a developed regional macroscopic model, performs a more detailed (e.g., mesoscopic simulation-based dynamic traffic assignment (DTA)) analysis of a subregional area, and then performs an even more detailed (e.g., microscopic simulation) analysis of a corridor or facility. Figure 1 illustrates such a process.

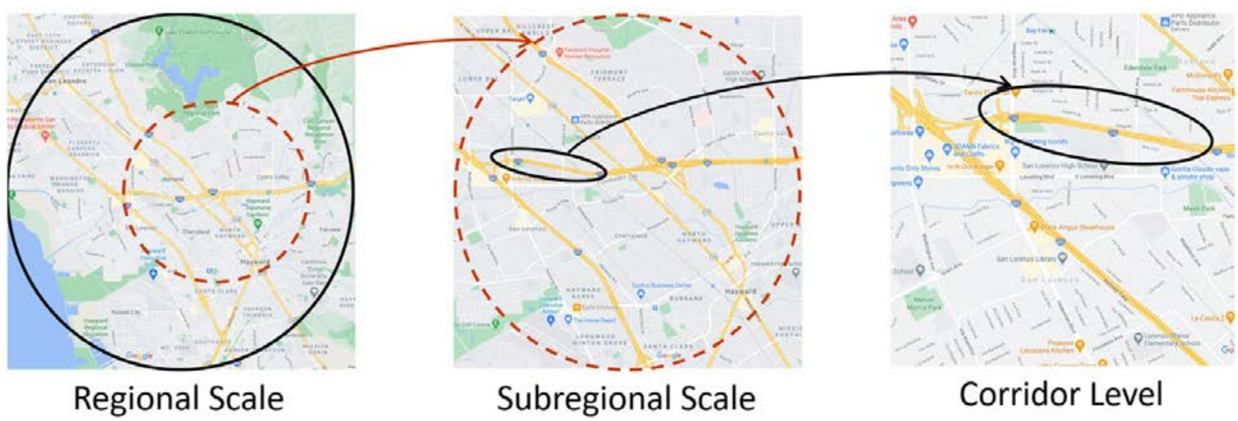


Figure 1. Maps. Different levels of road networks (Zhou, Hadi, and Hale 2021).

For more than a decade, there has been a slow but inexorable move toward the complementary use of multiple resolutions of AMS tools to comprehensively assess transportation deficiencies and improvement strategies at the lane, link, corridor, subarea, and regional network levels. The opportunity for this kind of an approach comes from the fact that today's practitioner has an ever-widening range of analysis tools to draw upon, each with its own set of strengths and focus areas. No single resolution model can purport to be best for all situations. The benefit of using two or more resolution models in conjunction with one another is that a broader understanding of the impacts of optional improvement strategies is achieved, resulting in more informed decisionmaking.

As such, an increasing number of transportation researchers and traffic software vendors are now advocating for wider application of MRM, in which the analyst applies multiple modeling tools at different resolutions toward answering a single question or set of questions. Ideally, the various tools and resolutions could consistently provide richer sets of output information, more frequent identification of modeling errors, and increased understanding of interaction effects among traffic network characteristics. However, in practice, certain challenges prevent the wider adoption of MRM tools and business practices. Including multiple tools and resolutions on a project tends to increase project duration, needed staff expertise and training, data requirements, and software license fees. If practitioners could better understand the tradeoffs and, to some extent, overcome the challenges, the industry could potentially benefit from improved decisionmaking in situations that warrant MRM.

BACKGROUND INFORMATION

Multiresolution Model Applications

MRM analyses can provide unique insights into the strategic driver behavior that microscopic simulation by itself cannot evaluate. Assessment of strategic behavior will consider the dynamic nature of the congestion and the impacts of alternative changes to the network and traffic management activities. Although figure 1 implies a one-way progression from coarse to fine-grained analysis, the authors recommend modelers pursue a feedback, iteration, and convergence process. This process helps ensure consistency between the different levels of modeling and should improve the modeling results. MRM models strategic traveler behaviors more effectively because MRM allows realistic representations of traffic dynamics for a larger-sized network. MRM can capture changes in behavior due to traffic and demand management policies and strategies, such as managed lanes, congestion pricing, and bus rapid transit. Interest in capturing the behavioral capability will increase with the need for modeling emerging technologies, such as connected and automated vehicle (CAV) technology, multimodal operations, micromobility, mobility as a service (MaaS), and ride hailing.

Some modelers believe that MRM analyses produce results that make more sense, and are more defendable, than traditional practices. Current modeling practices use demand forecasting model results to produce inputs to microscopic simulation models without using a simulation-based DTA model. However, some modelers use a more refined network in static assignment as a step between the demand forecasting model and microscopic simulation. MRM users expect that including a mesoscopic simulation-based step will better estimate demands. There has also been an increasing interest in using data from multiple sources, including emerging data sources, for better MRM. For example, agencies find value from using probe data to provide origin-destination (O-D) estimates to improve the models. In many cases, the additional costs of MRM and more detailed data may be justified because these costs are still a small fraction of the costs of the evaluated construction projects. One may recognize that without using MRM, there may be a large cost associated with using the wrong tool, leading to the wrong decision.

Although there may be an additional cost of using MRM, the cost is still a small fraction of a big project construction cost. Agencies may need to justify using MRM on a case-by-case basis. Agencies can consider MRM primarily when the area has traffic operation conditions and projects that justify advanced modeling and when the agency has adequate resources for this effort. Such modeling can significantly improve the decisionmaking process associated with the project. In particular, simulation-based DTA is useful when assessing express lanes, toll/pricing strategies, transit improvements, and other strategies that affect the strategic behavior of travelers. Simulation-based DTA is also useful in evaluating the impacts of transportation system management and operations (TSMO) strategies, such as incident management, integrated corridor management (ICM), and the impacts of emerging CAV technologies and applications. Simulation-based DTA focuses on the strategic behavior of route selection. However, analysts can combine such tools with other models to estimate other behavior parameters, like trip time-shift and mode shift.

Barriers to Adoption

Given the apparent benefits of MRM, the adoption rate of MRM throughout the United States and the world has been disproportionately slow. Some obstacles to MRM adoption by transportation agencies are technical (e.g., lack of common data standards, streamlined workflows, traffic analysis tool maturity, agency expertise, resources, and data). Other obstacles to adoption may be political or logistical (e.g., inertia, absence of a champion, lack of pilot projects, and a large learning curve). The authors have separately published the *Multiresolution Modeling for Traffic Analysis State-of-Practice and Gap Analysis Report* (*SOPAGA Report*) (Zhou, Hadi, and Hale 2021). The *SOPAGA Report* assesses barriers to MRM adoption based on extensive literature reviews and agency outreach.

Terminology and Definitions

A common understanding of basic terms and definitions associated with MRM may be important for understanding and accepting MRM. Although the *SOPAGA Report* comprehensively discusses such terms and definitions, this section summarizes the key MRM terms and definitions.

Travel Demand Models

Analysts have traditionally used demand models to forecast demands for future years and thus provide inputs to models that estimate future system performance. Analysts can further use demand models as sophisticated tools to forecast future multimodal demand and patterns. Demand forecasting models predict the impacts of infrastructure improvements; transportation policies; and socioeconomic, demographic, and land-use changes on transportation system performance (Patriksson 2015; Wisconsin Department of Transportation 2018). The input data of demand forecasting models include current socioeconomic data, network attributes, trip rates, and other factors to calculate current and future travel patterns in a transportation system. Combined with other planning tools, travel demand models can output a variety of information, including roadway traffic forecast information and deficiency characteristics.

The demand modeling community has used trip-based models, also referred to as four-step models. The four steps refer to trip generation, trip distribution, mode split, and traffic assignment. Analysts are increasingly using activity-based models (ABMs) in practice to replace the four-step travel demand models. ABMs generate activities, identify driver destinations, estimate the travel mode, and predict the network facilities or routes, similar to what trip-based models accomplish. However, ABMs have important modeling features not available in trip-based models. These features include considering realistic time and space constraints and the linkages among activities and travel. ABMs contain a set of discrete analytical models for household travel. Thus, ABMs work at a disaggregate person level rather than at the more aggregate zone level as in the trip-based models. This approach can more effectively account for various person-level and household-level attributes. For example, ABMs can provide better capabilities and sensitivities for evaluating pricing scenarios because they function at the person level. Thus, in the United States, conventional travel demand models are slowly moving forward to the new generation of behaviorally realistic ABMs. ABMs can become even more powerful when combined with simulation-based DTA to estimate network performance under the forecasted demands.

Demand forecasting tools generally use STA based on macroscopic traffic models, reflecting an assumed static behavior and instantaneous travel time estimation. Macroscopic traffic models use deterministic analytical relationships to estimate the speed of the traffic stream. Outputs from these static models include path and link volumes as well as the path travel times for each O-D pair, which are constant values for the whole analysis period. Macroscopic models apply volume-delay functions (VDFs) to estimate speeds based on the volume-to-capacity (v/c) ratio. These functions allow modeled traffic volume and demand to exceed the link capacity, which misrepresents traffic flows on over-capacity segments (Branston 1976). Widely used link capacity functions, such as the Bureau of Public Roads (BPR) (1964), Davidson's, Akçelik (1991), and conical functions, share similar characteristics as follows: They treat each roadway segment as independent without considering the dynamic nature of traffic flow and without considering queue spillback (Tisato 1991; Spiess 1984). From the perspective of MRM, if the analyst obtains inaccurate inputs for microsimulation models (e.g., overestimated traffic demand on saturated links) from the macroscopic models (which generally have less restrictive discharge rate constraints at bottlenecks), this might lead to flawed outputs.

Macroscopic Traffic Analysis Tools

Analysts can also use macroscopic traffic models to analyze traffic flow. The advantage of macroscopic models is that they are less complicated and have considerably lower computer requirements than microscopic models. Examples include those implemented in the freeway facility procedure of the *Highway Capacity Manual* (*HCM*) (Transportation Research Board (TRB) 2016). Macroscopic analytical and simulation tools are best suited for four types of analyses: large spatial and temporal resolutions, initial assessment of improvement alternatives, analyses that do not require a high level of accuracy, and low congestion levels with alternatives that can be adequately assessed with such tools. Macroscopic models also have less demanding computer requirements than microscopic models.

Mesoscopic Models

Mesoscopic models describe traffic facilities at a higher level of resolution compared with macroscopic models, but the behavior and interactions of vehicles exhibit a lower level of fidelity compared with microscopic models. Mesoscopic simulation models aim to fill the gaps between the aggregate-level approach of macroscopic models and the individual interactions of microscopic models. Outputs from mesoscopic models include time-varying traffic flow dynamics and traveler path choice behavior.

Mesoscopic models such as Jayakrishnan (1994), Ben-Akiva et al. (2002), and Zhou and Taylor (2014) can generate and track more precise individual vehicles or packets of vehicles than macroscopic models, especially the movements within intersections. Although the movements of vehicles (or packets) still follow the macroscopic representation of traffic flow, mesoscopic models have the advantage of considering queuing and spillback due to the subject link capacity and the downstream link queuing capacity.

Although mesoscopic models provide less fidelity than microscopic models, they offer better computational and modeling efficiency. As with microscopic models, the mesoscopic models' unit of traffic flow is the individual vehicle. Notably, analysts have mainly used these mesoscopic models in conjunction with DTA, which requires iterating between the assignment and loading (performance estimation) steps (Banister 1995).

Microscopic Models

Analysts use microscopic simulations for projects that require detailed operational analysis. Microscopic models simulate the movement of individual vehicles and vehicle-to-vehicle interactions based on car-following, gap acceptance, and lane-changing theories (Banister 1995). The simulations track vehicles through the network over small time intervals, generally at a resolution of a fraction of a second (e.g., every tenth of a second). Vehicles enter a transportation network using a statistical distribution of arrivals (a stochastic process). Then the simulation assigns a destination, vehicle type, and driver type to each vehicle upon entry. The outputs are the trajectories of individual vehicles.

Microscopic models call for more computer time and storage than macroscopic and mesoscopic models, thereby usually limiting the network size and number of simulation runs that can be completed (Sbayti and Roden 2010). On the other hand, microscopic models can represent vehicles more realistically than models at lower levels of resolution. Microscopic models are theoretically more responsive to different traffic control strategies and can produce more accurate measures of effectiveness. Microscopic models can provide enough flexibility to test various combinations of supply and demand for roadway management strategies.

Multiresolution Models

MRM is an integrated modeling approach. Analysts jointly apply multiple transportation analysis tools with varying temporal and spatial resolutions (i.e., macroscopic, mesoscopic, and microscopic simulation) to solve a single question or set of questions. Existing transportation analysis models vary widely in their implementations and data requirements. Each type of model has its advantages and disadvantages and represents a tradeoff between scales and levels of resolutions (Sloboden et al. 2012). Microscopic models effectively model behaviors of different user classes and analyze control policies (e.g., freeway ramp metering and arterial traffic signal coordination) (Sbayti and Roden 2010). Macroscopic traffic demand forecasting models are better at estimating the spatial distribution of travelers and mode shifts (Zhang et al. 2011). Mesoscopic models can estimate regional dynamic route shifts considering traffic dynamics and queuing phenomena (Zhou and Taylor 2014). Depending on network size and the types of analyses required, all kinds of models are potentially valuable for transportation analysis.

Traffic Assignment Methods

An important component of MRM is traffic assignment that can use macroscopic, mesoscopic, and microscopic simulation models in the loading step. This step loads traffic demands onto the network and estimates the traffic flow performance measures, such as travel times. Within the MRM framework, analysts can perform assignments and feed results from one model to another while maintaining consistency between the model assumptions. Analysts typically take the following steps, as shown in figure 1, when implementing MRM:

1. Use demand forecasting models to determine overall trip patterns in a regional network, including trip generation, trip distribution, mode split, and initial O-D matrices.
2. Use mesoscopic simulation-based DTA to realistically assign traffic to the network by accounting for strategic traveler behavior. In this step, some users have used a refined static assignment model based on a more detailed subarea network.
3. Use microscopic analysis of traffic at the corridor level or subnetwork level.

Macroscopic demand forecasting models use STA to assign traffic to paths between O-Ds in the network. STA assumes that link flows and link travel times remain constant over the modeling horizon, which normally covers all hours of the peak periods and even the entire day in some models. In comparison, DTA aims to capture travelers' time-dependent path choices as they traverse from their origins to destinations. The resulting time-varying link flows and travel times can capture more realistic traffic flow and driver responses compared to STA. DTA technologies are widely used in mesoscopic models. Microscopic models also incorporate DTA to estimate link demand inputs.

Some DTA models require input O-D matrices (outputs of trip-based demand models). Others also accept individual vehicle activities from ABMs as inputs. The major benefit of using DTA is the capability to account for spatial and temporal effects of congestion and costs in determining route choice. DTA can also predict the time-of-departure choice and mode choice when combined with other models. DTA is particularly suitable for analyses involving incidents, construction zones, ATDM strategies, ICM strategies, ITS, and other operational strategies, as well as capacity-building strategies. Analysts could potentially use any resolution of traffic analysis tools within DTA, but the mesoscopic scale is used most often. Industry experts have also recognized the following DTA model limitations:

- Subarea O-D matrices required for the assignment come from macroscopic travel demand models or user input; the accuracy of the DTA models depends on these matrices.
- DTA models have an overly simplistic representation of traffic signal control in some tools.

- DTA models may be unable to model intersection turning movements realistically in some tools.

Analytical and Simulation Models

Analytical and simulation methods are analysis approaches that attempt to estimate complex system performance under different conditions. Practitioners also refer to analytical models as deterministic models. These models allow the estimation of traffic parameters and performance, such as capacity, density, speed, delay, number of stops, queuing, and level of service (LOS), without conducting simulation analysis. Examples of such tools are those that implement *HCM* procedures (TRB 2010). These tools are suitable for analyzing the performance of isolated segments or intersections, particularly under lower congestion levels. In addition, these tools can quickly predict capacity, density, speed, delay, and queuing on a variety of transportation facilities.

Analysts use simulation models when an analytical formulation cannot be derived (e.g., when the model's size is too large or when no analytical solution can be derived). Simulation models provide results for a specific case study and should run a long time to achieve accurate numerical calculations. Analysts can use simulation models to measure the performance of transportation systems under different complex scenarios and alternative improvements to support decisionmaking.

Analytical and simulation approaches have a notable role in transportation network modeling. Analysts should carefully select the right approach and tool (or combination of tools) using guidance such as the Federal Highway Administration's (FHWA's) *Traffic Analysis Toolbox Volume II: Decision Support Methodology for Selecting Traffic Analysis Tools*, *Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software 2019 Update to the 2004 Version*, and *Scoping and Conducting Data-Driven 21st Century Transportation System Analyses* (Jeannotte et al. 2004; Wunderlich, Vasudevan, and Wang 2019; Wunderlich, Alexiadis, and Wang 2017).

The decision to use analytical traffic models versus simulation models also applies to DTA. There are two major types of DTA models: analytical and simulation-based DTA. Vendors built most of the existing commercially available models on a simulation-based framework because traffic flow simulators are generally more flexible for network flow loading than analytical DTA models in accounting for various network traffic conditions, such as traffic signals, incidents, or driver routing behaviors.

GUIDEBOOK OBJECTIVES

This guidebook aims to enable consistent and robust adoption of MRM for traffic analysis across State and local agencies. It also intends to assist agencies with developing a fully integrated MRM analysis and provide case studies to illustrate the benefits of applying MRM. This guidebook will help transportation professionals assess the level of effort (LOE) needed and benefits of developing MRM networks for their analyses and provide them with guidance for model development.

CHAPTER 2. METHODOLOGY

The MRM methodology seeks to enhance and fill the gaps of the seven-step microsimulation analysis methodology from *Traffic Analysis Toolbox Volume III*, as illustrated in figure 2 (Wunderlich, Vasudevan, and Wang 2019). The primary enhancements occur within step 1 (analysis planning), step 2 (data collection), step 3 (model development), and step 5 (calibration). The MRM methodology also aligns with the methodology presented in *Scoping and Conducting Data-Driven 21st Century Transportation System Analyses* (Wunderlich, Alexiadis, and Wang 2017). When working on MRM projects, analysts should use the methodology presented in this chapter in combination with Wunderlich, Alexiadis, and Wang (2017) and Wunderlich, Vasudevan, and Wang (2019).

Following is a summary of the proposed methodology, in relation to the steps in figure 2:

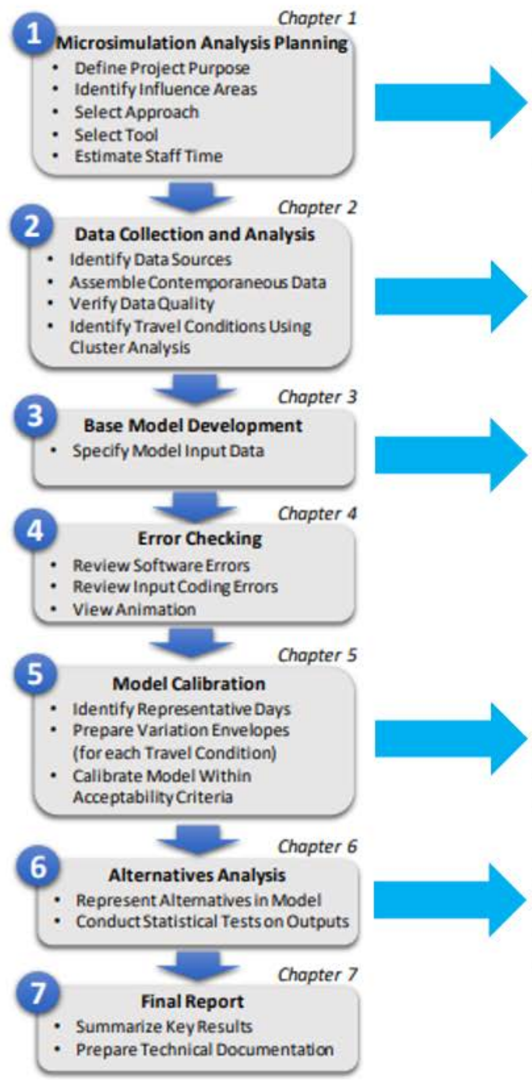
- Step 1 Microsimulation Analysis Planning: The methodology starts with MRM-specific project planning and scoping considerations. These considerations include evaluating project needs and objectives, specifying and defining performance measures to be estimated using different resolutions of MRM, determining additional data requirements that affect scoping due to the use of MRM, establishing data availability, and identifying the geographic and temporal scope for each resolution. Project planning and scoping also include identifying the analysis approach representing the transportation network geometry, control, demand, and multimodal system supply at each resolution level (and the associated interfaces). In addition, planning and scoping address resource allocation and estimating the LOE required for MRM.

- Step 2 Data Collection and Analysis: Next, the methodology discusses data collection and processing, considering that the required data (and associated details and resolutions) vary between the different analysis levels and resolutions. Different tools of the same resolution may also have variations in the data inputs.

- Step 3 Base Model Development and Step 4 Error Checking: Next, the methodology addresses the additional effort required for MRM model development. This includes interfacing or integrating the MRM tools, disaggregating zones and modifying connectors imported from demand forecasting models, creating demand estimation and control modeling in MRM, modeling of advanced technologies and strategies in MRM, and conducting multiscenario analysis.

- Step 5 Model Calibration: This chapter’s calibration, validation, and convergence section discusses additional steps to enhance MRM performance. These steps include bottleneck identification and calibration, macroscopic and mesoscopic (in addition to microscopic) traffic flow model calibration, and travel demand calibration. An important aspect of MRM calibration is ensuring consistency between different levels by applying feedback from higher resolution models to lower resolution models. The additional effort also involves ensuring the convergence of traffic assignment and DTA and ABMs.

- Step 6 Alternatives Analysis: Next, the methodology discusses alternatives analysis based on model results. This step includes accounting for model stochasticity, estimating future-year demands, estimating and optimizing signal timing, and conducting sensitivity analysis to account for uncertainty in model inputs. Finally, this chapter provides recommendations to improve the agencies' organizational and technical capabilities and improve their analysis capabilities. The recommended improvements are in business processes, performance estimation, data collection and management, development of standard operating guidance, tool utilization, workforce development, collaboration, and culture.



1. Justify the use of MRM.
2. Engage a large number of stakeholders.
3. Identify spatiotemporal scope for all modeling resolutions.
4. Select analysis approach and tools – assess MRM risks and costs.
5. Identify performance measures.
6. Determine data requirements and availability.
7. Estimate level of effort.

8. Provide required input data for different resolutions.
9. Collect data to increase the quality for O-D demand estimation and path assignment validation.
10. Collect data for bottleneck analysis.
11. Ensure that counts reflect demands and not capacities under oversaturated conditions.

12. Develop workflow for data importing and conversion, utilize model and data integration tools.
13. Disaggregate trips from larger to smaller zones.
14. Improve quality of O-D demand matrix estimation and traffic assignment.
15. Model traffic control.
16. Model transportation management and operations and emerging technologies.
17. Develop multiscenario datasets if possible.

18. Calibrate bottleneck attributes.
19. Calibrate macroscopic, mesoscopic, and microscopic traffic flow models.
20. Calibrate travel demands.
21. Assess convergence to ensure quality of traffic assignment.
22. Ensure convergence between ABM and DTA.
23. Ensure consistency between resolutions.

24. Account for model stochasticity.
25. Estimate future year demands.
26. Estimate signal timing for alternatives.
27. Perform sensitivity analysis.

Source: FHWA (adapted from Wunderlich et al. 2019).

Figure 2. Flowchart. Additional steps for the MRM methodology.

STEP 1: PROJECT PLANNING AND SCOPING

Multiresolution simulation can increase the budget and time needed to perform AMS within a project. Thus, additional efforts can be helpful during the planning and scoping stage, in which analysts or the agency will identify the needs and make a case for MRM. They will identify additional data and activities for successful use of the modeling process to ensure a cost-effective outcome of the study. The planning of a simulation project involves identifying objectives, hypotheses, data types, data quality requirements, performance measures, parties responsible for various parts of the analysis, geographic and temporal scopes, studied alternatives, technical approaches, appropriate analysis tools, and resources estimates. The resource estimates include the expected cost, schedule, and responsibilities for the analysis (Wunderlich, Alexiadis, and Wang 2017; Wunderlich, Vasudevan, and Wang 2019). This section discusses MRM consideration within key components of the planning and scoping process.

The planning and scoping activities will determine whether to use MRM and all aspects of such modeling. Key stakeholders who will impact (or will be impacted by) the analysis should be involved in project planning and remain involved until the end of the project. MRM will increase the need to integrate models developed by different entities and the spatial limits of the modeling and data needs. Implementing MRM will increase the number of stakeholders involved in the planning and scoping process.

Relationship to Project Needs and Objectives

Analysts should examine the project objectives to determine the need for MRM since study objectives reflect the system needs and potential alternatives to address those needs. Analysts use objectives as the basis for formulating hypotheses for a project, and MRM is suited to problems and alternative solutions that impact strategic traveler behaviors, such as shifts in routes, destinations, modes, times of travel, and even land use. Currently available tools to support MRM provide better alternative route traffic assignments to alternative routes. However, it is possible to address strategic behavior changes by extending the capabilities of tools or integrating with other tools and discrete choice models. Examples of problems suited for MRM include major highway improvements expected to attract traffic from other alternative routes, managed lane and express lane projects, major new developments that generate high demand, bus rapid transit and bus lanes, road diet and Complete Streets projects, major construction and work zone projects, TSMO projects, and CAV applications that are expected to impact strategic decisions.

Performance Measure Identification

When planning for a simulation project, analysts should identify performance measures relevant to the project goals and objectives. When considering MRM as part of the estimation, analysts can examine the definitions and methods of the measure estimation in different tools, the portion of the network in need of estimation, the temporal and spatial resolution of measurements, the reporting requirement by traveler/vehicle type, and the modeling level anticipated for each portion of the network.

A critical aspect of MRM is to ensure consistency between the performance measures at different levels. However, understanding fundamental differences in metrics definitions at different levels is helpful before addressing these issues. Measures such as travel time, delays, stops, queues, and density have the same name in different tools but are defined and calculated differently. *Traffic Analysis Toolbox Volume VI: Definition, Interpretation, and Calculation of Traffic Analysis Tools Measures of Effectiveness* addressed differences in the definition, interpretation, and computation of measures in different modeling levels and tools (Dowling 2007). One example given by Dowling (2007) is that some simulation tools compute vehicle miles traveled only for vehicles that enter the link during the analysis period. Others include the vehicles present on the link at the start of the period.

Another example is that some tools include second-by-second calculation of the measures, while others only calculate measures for vehicles able to exit the link during the analysis period. Still another example is the computation of vehicle hours traveled (VHT). Some simulation tools include the delay incurred by vehicles denied entry to the system. Most others do not. Most tools calculate delay using free-flow speed as the basis. Dowling (2007) concluded that measures from simulation model tools are usually not directly translatable into *HCM* measures and LOS and recommended using measures calculated consistently based on vehicle trajectories to compare results between tools and methods.

The level of aggregation of the measures is also important. For example, demand forecasting models produce measures only for the whole analysis period and at the link level rather than the turning movement levels. The aggregation levels of the measures produced by mesoscopic simulation models vary and need to be examined by the analyst.

As with the selection of MRM, the performance measures selected may impact the levels of effort for data collection and analysis, calibrating simulation models to reflect each measure, alternatives analysis, and output utilization in the decisionmaking process. Analysts may decide to reconsider using some measures if the measures are difficult to generate from MRM levels or difficult to validate based on field measurements.

Based on the objectives, some projects may call for what the simulation community refers to as "nontraditional measures." Nontraditional measures include reliability, emissions, fuel consumption, and safety measures. Analysts can consider the need for such measures in the MRM planning stage. For example, one performance measure may be travel time reliability between O-D pairs. One option to achieve this is to have additional runs of the mesoscopic simulation model under different operational scenarios (e.g., congestion levels, incidents, weather, and work zones) and additional processing of the outputs.

Data Requirements and Availability

Data requirements, availability, quality, consistency, and filling data gaps are vital considerations when planning and scoping the project and selecting the modeling approach (Wunderlich, Alexiadis, and Wang 2017). Analysts should develop a detailed data plan at this stage. Depending on the modeling scope and configuration, MRM may call for additional traffic, network, control, and management data for a much larger network. The availability and cost of the additional data required for MRM can be a major component depending on the scope of the

MRM. For this reason, it is important to consider data requirements and availability in project planning and scoping. The data plan details the requirements, availability, quality assurance, and consistency. If the additional data required for MRM is not available or feasible to collect, analysts should reconsider using MRM.

In some cases, the data required for MRM is sufficient for conducting the modeling. In the downtown West Palm Beach, FL, case study discussed later in this report, the analyst studied the same network at the macroscopic, mesoscopic, and microscopic levels of MRM. The analyst used macroscopic and mesoscopic models to refine the estimated O-D matrices and assign the O-D demands to the network. Then the analyst exported networkwide demands to the microscopic simulation model to estimate performance. In this case, the only extra data cost could be the acquisition of O-D measurements to help refine the O-D matrices, if specified in the data plan. However, in many other projects, the macroscopic, mesoscopic, and microscopic modeling geographic and temporal scopes are different, thus increasing the data requirements compared to just using microscopic simulation or partial MRM (i.e., using demand forecasting models and microscopic models only).

The consideration and use of data at this stage can also provide a basis for using MRM and for the spatial and temporal project scope. For example, using simulation-based DTA and behavioral algorithms, O-D data (including path data and modes between O-D pairs) combined with travel-time information can justify extending the network to include additional routes and modes. This process is consistent with the data-driven analytic project scoping process recommended in *Scoping and Conducting Data-Driven 21st Century Transportation System Analyses* (Wunderlich, Alexiadis, and Wang 2017).

Analysts should also assess the data availability of different measurements across a wide range of facility types (FT) and area types (AT). In the Phoenix, AZ, metropolitan area case study discussed later in this report, the research team used speed and count data to construct a comprehensive supply-side calibration process. As a result, analysts can use complementary data sources to perform a joint calibration of traffic flow fundamental diagrams and volume-delay relationships across different analysis periods.

Geographic and Temporal Scope

An essential aspect of MRM is identifying the geographic and temporal limits for each resolution, including the analysis study area, time periods, time horizon, modes, and facilities modeled in each resolution (e.g., demand forecasting, macroscopic, mesoscopic, and microscopic models). This identification reflects the current system performance, analyzed alternatives, and the expected extent of the impacts. It is important to examine if it is possible to model the current conditions and improvement alternatives using each model resolution employed, the degree of precision and details of the model outputs, and the LOE required. The availability of data in space and time to develop and calibrate the model at the required level of resolution and accuracy is also an important consideration.

Of particular importance to MRM is identifying the impacted geographic area and time periods, particularly as traffic diverts to alternative routes or modes. It is also important to identify operational scenarios that analysts should consider when assessing alternatives or changes to the system in terms of congestion levels. The operational scenarios can also reflect event occurrences such as incidents, weather, and construction events.

An important consideration when setting the scope and selecting the modeling approach is determining the resources available to the analyst in terms of staffing and budget for the model development, calibration, use, and review. MRM may require additional funding and capabilities that may be unavailable. The resource limitations may also require the agency to adjust its scope to model as much of the impacted network as possible, considering the resource constraints. In this case, the analyst should set the model's temporal and spatial scopes at different resolutions and prioritize those areas and time periods expected to be the most impacted by the proposed improvement strategies.

Analysis Approach Selection

The analysis plan should include identifying the analysis approach, including activities that the analyst will perform. The activities may consist of identifying a testing hypothesis, operational scenarios, alternative strategies to evaluate, data requirements and availability, selected performance measures, and the MRM geographic and temporal scopes. The authors recommend that analysts conduct a risk assessment of the MRM effort to identify potential risks and how the project team would mitigate these risks. The risks could be associated with the large size of the network, availability of supporting data, lack of resources, limited experience with the utilized approach and tools, and time constraints on the project. The risks can also include the difficulty in obtaining accurate O-D demands, validating strategic traveler behavior (as in mode or route shifting), and estimating future-year demands.

The analysis approach will describe the transportation network and control representations, demand representation, and multimodal system supplies (e.g., freeway capacity, traffic control, and management policies and transit service plans) in each resolution level. The modeling approach will also identify interfaces between the MRM tools and any supporting tools. How the project will accomplish the forward loop from the low-resolution models to the high-resolution models should be specified in the analysis plan. The backward loop should be in the opposite direction, as discussed later in this chapter. Effectively implementing these loops is key to the success of the MRM effort. At this stage, the analyst should also identify methods to use for demand estimation under different scenarios and alternatives, calibration and validation of different resolution levels, and postprocessing of the modeling outputs.

The project modeling approach should also specify whether multiscenario analysis is needed and what the analysis scenarios are. If analysts select a multiscenario analysis, they can consider applying the procedure detailed in *Traffic Analysis Toolbox Volume III*, which recommends a cluster analysis to identify operational scenarios (Wunderlich, Vasudevan, and Wang 2019). These scenarios involve different levels of recurring congestion and nonrecurring factors such as traffic incidents, weather, work zones, and special events. In addition to impacting the needed budget, time, and data, multiscenario analysis effects other aspects of MRM project planning. For example, incident scenario modeling involves varying the capacities on incident links dynamically within the modeled period to reflect the dynamic changes in lane closures. If analysts want to study incident management and traveler information impacts, they may incorporate en route reassignment of traffic.

Tool Selection

In the planning stage, analysts select the combinations of tools needed for the project. Analysts can justify their selection by showing that the chosen tools, when used in concert, meet the AMS requirements of the project. An initial identification of appropriate tool categories and resolutions will have been made during the analysis approach described in the previous section. The next step is to confirm this selection and choose specific tools, focusing on identifying key capabilities needed for the analysis versus those provided by different tools. In *Scoping and Conducting Data-Driven 21st Century Transportation System Analyses*, Wunderlich, Alexiadis, and Wang (2017) recommend conducting a risk analysis when selecting the modeling approach and taking a high-level approach for evaluating and selecting analysis tools. *Traffic Analysis Toolbox Volume II* provides a spreadsheet-based tool for considering various factors to decide on the appropriate tools (Jeannotte et al. 2004). The report recommends the tool category but does not recommend a specific tool.

Transportation agencies face a challenge when selecting appropriate tools for their projects, given the range of functionalities and capabilities of available tools. The selected tools could include off-the-shelf commercial tools or open-source tools. In addition to meeting the project's technical requirements, analysts can consider other factors in the selection process, such as the input/output/interfaces, user training and support, and ongoing software enhancements.

Hadi et al. (2012, 2017) recommended developing tool assessment criteria to support multiresolution analysis. The purpose of developing the criteria was not to select a specific tool for States or regions but to provide a mechanism for assessing different tools and methods relative to the criteria. This module included criteria for assessing simulation-based DTA tools. The criteria can enable the comparison of various modeling tools to ensure they meet the needs of a specific project. The criteria for tool assessment cover general hardware and software, shortest path and path choice modeling, traffic flow modeling, network geometry modeling, network demand modeling, transit modeling, and calibration/validation and convergence assurance support. The module also developed additional criteria for specific applications such as managed lane, work zone, and advanced traffic management strategy modeling.

Hadi et al. (2012, 2017) recognized that not all identified criteria are applicable in all cases and that agencies can select additional criteria or a subset of criteria for the particular application. To assist the agencies in this selection, the authors specified whether each requirement should be a general requirement for all applications or specific types of applications such as long-range plan modeling, short-range plan modeling, TSMO and ITS, or corridor/impact studies. The project also demonstrated how the developed assessment criteria can help examine mesoscopic simulation-based DTA tool capabilities using three open-source and commercial tools as case studies.

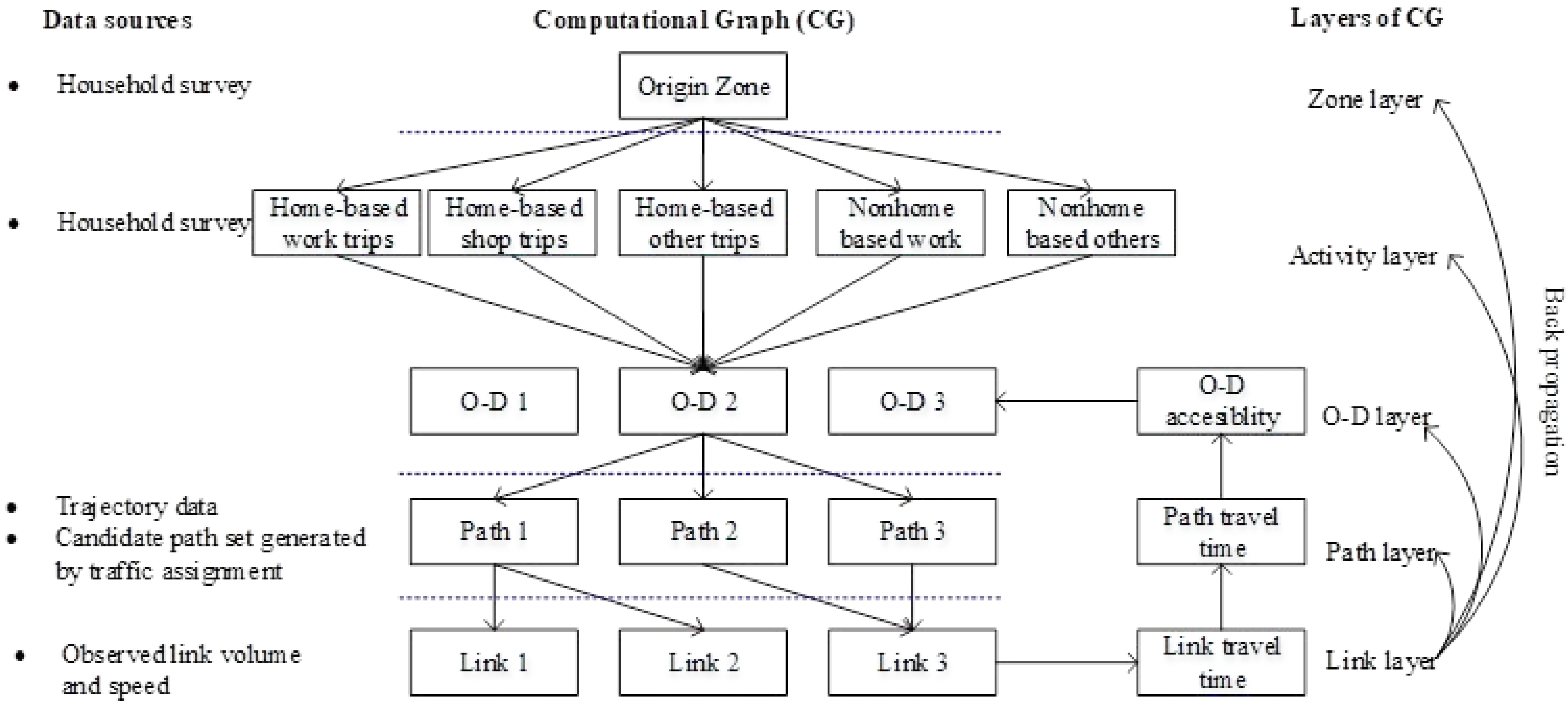
The tool selection process should consider the project needs and future applications for the developed model. For example, when modeling managed lanes in mesoscopic simulation, models may vary in their ability to support features such as dynamic tool pricing, stochasticity in the value of time, the value of reliability, lane-by-lane traffic flow modeling, signal control and ramp metering details, and CAV modeling. Suppose analysts select tools without considering the tools' ability to satisfy the requirements. In that case, analysts may need to change software after the modeling effort starts or accept less effective modeling within the project. In addition to selecting tools for different modeling resolution levels, analysts can select other tools for project activities, such as data processing, data conversion and integration, emissions estimation, dynamic transit assignment, behavioral mode and time-shift models, and postprocessing model outputs to support performance analysis and decision support.

Interoperability, Architecture, and Modularity of Tools

Recognizing that standards-based interoperability is more than just data exchange between modeled objects is important. Simulation interoperability can allow different MRM tools to work together in a common (virtual) environment. High-level architecture and distributed interactive simulation are examples of IEEE's specifications for using standardized networking protocol and protocol data units (IEEE 2021).

Analysts should systematically examine the concepts of MRM architecture and modularity to further determine specific mechanisms for executing the MRM analysis. The modularity of common MRM tools and algorithms can allow components to interact flexibly while also allowing easier monitoring by the analyst. Live virtual, constructive integrating architecture is an example from the nontransportation domains. Figure 3 shows a graph-based data model as an example of a standard mechanism for describing data elements within a transportation demand estimation domain. Specifically, different types of environmental sensor data are mapped to different formats across layers of internal AMS models, while various spatial dimensions of internal models (e.g., origin, O-D, path, and link) also systematically link with each other.

The computational graph is an essential building block in deep learning. The graph can decompose a function using elementary operations (+, –, ×, and ÷) and elementary functions (e.g., e^x, $\log x$, and $\sin x$). Using computational graphs in MRM domains can efficiently execute feed-forward and backward propagation through analytical derivation using automatic differentiation. Computational graphs may enable greater consistency between ABM and DTA models through flexible modeling and improved computational efficiency.



Source: FHWA.

Figure 3. Flowchart. Computational graph model for integrated ABM and traffic assignment model.

Resource Allocation

A key aspect of planning and scoping analysis projects is to estimate the budget and number of staff hours required to accomplish the project activities. Because an MRM approach may likely increase the project budget and effort, estimating additional requirements helps to allocate the necessary resources. If this is not feasible, analysts may need to consider other approaches. The extra effort required for MRM in lieu of current practices will vary depending on the modeled network. As stated earlier in the "Data Requirements and Availability" section, in the downtown West Palm Beach case study, the analyst studied the same network at the macroscopic, mesoscopic, and microscopic levels of MRM. The analyst used the macroscopic and mesoscopic models to refine the estimated O-D matrices and assign O-D demands to the network. Then the analyst exported networkwide demands to the microscopic simulation model to estimate performance. In this case, the extra effort was minimal. The team estimated an additional 5-6 w for calibrating the mesoscopic model, ensuring consistency between the mesoscopic and macroscopic model, and ensuring convergence of the DTA.

However, in other cases, the analysts model a much larger mesoscopic simulation network than what is modeled at the microscopic level. The mesoscopic simulation network could cover a large portion of the region, requiring extensive effort to create, calibrate, and validate. For these cases, the authors' meetings with MRM stakeholders revealed significant efforts to set up a full MRM, compared to just going from a demand forecasting model to facility-level microscopic simulation (Zhou, Hadi, and Hale 2021). The required effort is a function of the size of the network, coding requirements for signal timing, availability of signal timing data in a consistent format for the region, and the level of detail and correctness of the demand model coding. Coding a midsized network in mesoscopic DTA integrated with microscopic simulation requires several months of project teamwork, based on inputs provided by agencies that have had experience with these models. The integration of ABM with traffic simulation or DTA models involves 1- to 2-yr projects for large-sized networks. Such integration appears more feasible for small to midsized cities.

Scoping and Conducting Data-Driven 21st Century Transportation System Analyses presents information on staffing, resources, and effort required for analysis (Wunderlich et al. 2017). This information reflects the recommendations from an earlier FHWA report, *Guidance on the Level of Effort Required to Conduct Traffic Analysis Using Microsimulation* (Alexiadis et al. 2014). Although these reports do not specifically address the required effort for MRM, they provide information analysts may find useful when estimating required budgets and time for their projects. Wunderlich, Alexiadis, and Wang (2017) pointed out that many variables affect estimated levels of effort for the analysis, such as project documentation; data quantity, quality, and availability; cohesion in stakeholder vision; and staff experience with modeling tools in previous efforts. However, Wunderlich, Alexiadis, and Wang (2017) provided a rough order of magnitude estimate of the proportion of analysis resources by staff type and level required of the different analysis steps. Wunderlich, Alexiadis, and Wang recommended that analysts use labor-hour estimates as a point of reference, not as absolute numbers to apply to projects.

Wunderlich, Alexiadis, and Wang (2017) pointed out that larger models require a disproportionately greater LOE compared to smaller projects. Projects can require different levels of effort because of differences in project scope; data availability and requirements;

number and complexity of alternatives being analyzed; performance measures used; software used; project manager, analyst, and reviewer experience; number and effectiveness of project reviews conducted; and amount of stakeholder involvement. Wunderlich, Alexiadis, and Wang (2017) developed a software tool to produce ballpark estimates of staff hours to complete the tasks needed to support a transportation analysis. However, this tool does not address the additional cost required for MRM.

LOE Estimation

This section addresses different factors that influence the LOE of an MRM analysis project. During the MRM research project that produced this report, stakeholders were highly interested in understanding and predicting this LOE (Zhou, Hadi, and Hale 2021). Agencies routinely authorize conventional traffic simulation projects, partially because agencies better understand the LOE associated with such projects. Therefore, the authors offer the following simple principles for estimating the MRM LOE as a function of the conventional traffic simulation LOE, a more known commodity.

Model Development

Chapter 1 alluded to the fact that, for traffic analyses involving relatively small spatial and temporal scopes, agencies often use high-resolution (e.g., microscopic) models. Microscopic car-following, lane-changing, and gap acceptance behaviors may be a key to answering operational traffic questions at the facility or corridor level. Although microsimulation requires the most input data, the limited number of links (segments), nodes (junctions), and time periods often help to keep the LOE at a reasonable level.

Mesoscopic simulation of a medium network may involve a similar LOE compared to microsimulation of a small network because the medium traffic network may have more links and nodes than the small network (nominally requiring more LOE). However, the amount of input data needed for each link and node should be lower for the mesoscopic model. The same holds true for a macroscopic analysis that covers the largest possible spatial area but tends to require the least amount of input data for each link and node. This concept also implies that if an agency wants to pursue larger-than-usual spatial and temporal scopes for their respective modeling resolutions, the LOE could further increase. Similarly, smaller-than-usual spatial and temporal scopes for their respective resolutions could help decrease the LOE. For example, in the West Palm Beach case study in chapter 3, the research team reduced its LOE by having relatively small spatial and temporal scopes for its macroscopic and mesoscopic analyses.

However, analysts should recognize that temporal and spatial scope resolutions could differ based on the project objectives and requirements. In many cases, MRM requires modeling larger size mesoscopic simulation networks, and even larger macroscopic model networks, to model strategic traveler behaviors such as mode and route selection. In addition to the effort required to model the smaller network in the microscopic model, the medium-size network for the mesoscopic model, and the larger network for the macroscopic model, MRM will require additional effort for model integration and consistency through a feedback loop.

Automated generation of traffic networks is a key technology for making MRM more practical and cost effective because it drastically reduces the LOE associated with manual data entry. Each case study in chapter 3 performed a certain amount of automated traffic network generation, albeit in different ways. In some MRM projects, the analyst may have generated each traffic network (at each level and resolution) in an automated or semiautomated manner. In other MRM projects, the analyst may develop one network, primarily through manual data entry, and then generate the other networks (at other levels and resolutions) in an automated or semiautomated manner.

Another LOE-reducing item is when the analyst emulates a well-documented MRM project. According to chapter 7 of the *MRM SOPAGA Report*, one State department of transportation (DOT) used one of its university's MRM projects as a template and blueprint for dozens of follow-on projects (Zhou, Hadi, and Hale 2021). It stands to reason that the availability of a detailed and well-documented MRM project could substantially reduce the LOE for a new project if the new project was similar enough to the documented project. The blueprint project could reduce the LOE associated with model development and/or calibration.

Verification, Calibration, and Validation (VC&V)

VC&V efforts can vary greatly depending on agency requirements, analyst experience, and the nature of the traffic analysis project. In an MRM analysis project, the analyst or agency may perform VC&V for each analysis level or resolution. Some of the things that affect MRM LOE primarily affect the effort level associated with VC&V. One of these things could be using a blueprint project, as described previously. Specifically, when the analyst emulates a well-documented MRM project, the LOE associated with VC&V could be reduced, assuming that much of the project documentation pertains to VC&V.

Another item relates to the spatiotemporal analysis limits. In the West Palm Beach case study described in chapter 3, the research team used a traffic network at one resolution to automatically generate the other two networks at the other resolutions. As such, all three networks contained the same (or at least highly similar) spatiotemporal limits (i.e., geographic coverage area, link-node diagram, number of time periods, and duration of time periods). The team reported that this spatiotemporal similarity helped to simplify the VC&V process.

Although the blueprint projects and similar analysis limits could reduce the VC&V LOE, pursuing feedback and convergence between the different levels of MRM could increase the VC&V LOE. At the time of this writing, the available tools for traffic network simulation and analysis offer only a limited amount of functionality for automating and facilitating feedback and convergence. Despite these limitations, the authors encourage MRM users, vendors, and developers to pursue feedback and convergence as much as possible to maximize the analysis quality.

Learning Curves

Analysts attempting their first MRM projects may take significant time to learn how to properly use the tools, develop the model, and perform the analysis. Indeed, figure 2 illustrates many ways in which MRM could potentially complicate and expand the seven-step microsimulation analysis methodology. The amount of time needed to conquer such learning curves seems hard to predict and may vary widely by individual and/or agency. In addition to the MRM learning curves, there may be additional LOE involved in procuring the tools, configuring the tools, and hiring the staff.

STEP 2: DATA COLLECTION AND PROCESSING

Analysts can develop a data collection plan within the overall data plan to fill gaps in data needs and availability. Analysts should check all collected data for consistency and quality. If the project scope requires multiscenario analysis, analysts should also determine the data needed to identify operational conditions at this stage. *Traffic Analysis Toolbox Volume III* provides data collection and processing details (Wunderlich, Vasudevan, and Wang 2019). The following discussion highlights aspects of data collection relevant to conducting MRM.

The appropriate input data and resolutions vary between the various analysis levels and resolutions. Different tools of the same resolution may also vary in the data inputs. However, most simulation models require road geometry, traffic control (signal timing and signs), demand, travel times, and other performance measures needed for calibration. Regarding geometry, macroscopic analytical and some mesoscopic models require segment geometry, with few (if any) details for intersection lane assignments or turn bays. Some macroscopic models, most mesoscopic models, and all microscopic models require such information.

Depending on the tool and level of analysis, analysts can represent time-variant demands (usually at 15-min intervals) as entry volumes, turning movement volumes, O-D tables, individual vehicle trips, and selected paths and modes. However, most static and DTA tools utilize O-D matrices as inputs. Where possible, analysts should provide turn movement counts for O-D demand estimation (explained in the "Model Development" section) rather than providing the segment counts, as some analysts do. This provision of turn movement counts in the O-D estimation is beneficial for operational-level analysis. For detailed operational analyses (such as in the West Palm Beach case study in chapter 3), the project team collected data at all freeway mainlines and ramps, all signalized intersections, and all significant unsignalized intersections. If congestion is present at or upstream of a count location, analysts should ensure the counts reflect demands and not capacities. Thus, identifying bottleneck locations is important, as discussed later in this report.

In the Phoenix metropolitan case study, the research team systematically assessed the number of sensors and measurements available for different VDF types. The team also enhanced the congestion and bottleneck identification (CBI) tool to utilize both speed and flow count data (Hale et al. 2016, 2021). Using the CBI tool this way allowed the team to identify the congestion period, queued demand, and queue discharge rates. By developing a systematic MRM-oriented data plan, agencies can allocate additional resources to collect and combine heterogeneous data sources for improving the accuracy of the subsequent model calibration and validation stages.

STEP 3: MODEL DEVELOPMENT

Traffic Analysis Toolbox Volume III outlines the steps for developing microsimulation models (Wunderlich, Vasudevan, and Wang 2019). These steps include producing a link-node diagram and inputting the physical and operational characteristics of the links or the roadway, traffic control details (no control, yield signs, stop signs, signal control, ramp metering, and roundabouts), traffic operations and management data (event warning, variable speed limit, managed lanes), traffic demand data, driver behavior data, event data, and simulation control data. These steps are also applicable to MRM. However, this section addresses specific gaps in that guidance to support and inform MRM development.

Model Integration

The most basic method of integrating different MRM resolutions is to input the same data into different models. In the past, manual integration was common. However, analysts soon recognized the benefits of automated model integration tools to support MRM. Software developers and vendors have provided commercial and open-source tools for model integration. The categories for these tools are as follows:

- Commercial model importing tools: These tools automatically import the networks and demands from demand forecasting models. The tools can also convert the macroscopic and mesoscopic models to microscopic models. The analyst usually imports a subarea model from the regional demand forecasting model. A singular software suite can sometimes contain and integrate both the regional modeling tool and the subarea modeling tool. The analyst then refines the network at the more detailed macroscopic modeling level or the mesoscopic simulation level. The analyst can enter more detailed geometry, zonal representation, traffic control data, traffic operations and management data, and event data. Once completed, the analyst can export the network to the microscopic model and enter additional microscopic simulation-level details, such as advanced control features, driver behavior data, event data, and simulation control data.

- Commercial tools with a unified user interface: These tools have an integrated user interface in which the same coded network provides the required level of detail for all utilized resolutions. Analysts can run the models in different resolutions for various parts of the network. These tools may also allow users to import data from regional demand forecasting models similar to what the commercial model importing tools bullet describes.

- Open-source unified model integration tools: These unified model integration tools use open data specifications. The remainder of this section discusses this type of tool.

This section discusses a unified data importing and conversion workflow and a prototype of organizing step-by-step data integration tools to allow effective modeling and analyses across various domains and scales. The following principles guide the workflow design:

- Workflow should connect different transportation model resolutions step-by-step (e.g., macro-, meso-, and micronetwork building) from four-step aggregated demand methods to agent-based simulation.

- Open data specifications, which represent a multiresolution physical traffic system and support secure data sharing, lay the foundation for the AMS method and tool development. For example, the General Travel Network Specification could help through flexible and efficient support, education, guidance, encouragement, and incubation (Zephyr Foundation 2021).

- Workflow in the base model development stage should organize different modules in a sequential process to reduce coupling complexity across macro-, meso-, and micronetworks.

- Effective AMS integration requires available commercial tools, enterprise open-source tools, and coordinated MRM data sharing among metropolitan planning organizations (MPO), State DOTs, private software vendors, community citizens, and planners.

- Feedback loops between MRM computational engines is important, especially for future-year scenarios involving signal timing generation and demand-side candidate path adjustment across different resolutions.

- Workflow in the model calibration stage should support both demand-side and supply-side models, individually or simultaneously; the former includes O-D flow and path flow estimation. The latter covers parameter identification of the underlying traffic flow models and VDFs.

- Workflow should include feedback loops, iteratively updating the lower-level supply-side travel time estimates in the upper-level demand-side choice decisions to ensure supply-demand consistency across different model layers.

- Workflow should establish an AMS data hub to connect tools from various software vendors and emerging data sources through typical human- and machine-readable formats with routable network structures.

To address the last principle, the authors recommend using the General Modeling Network Specification (GMNS) as the building block for MRM data exchange. GMNS integrates multimodal static and dynamic transportation planning and operations models. Analysts can further enhance the base GMNS specification to map dynamic link performance measures (e.g., 15-min link speed and volume) to the central node-link structure. In addition, analysts can connect external point of interest (POI) and land-use data to the node, link, and zone layers in a GMNS-oriented transportation model structure.

OpenStreetMap™ (OSM) is a free, open-source collaborative mapping website. Its user-contributed data can be a useful source for creating MRM base models. However, the original map in OSM is not completely routable, and many key attributes in travel models do not exist in OSM, such as capacity and detailed signal timing information. The following streamlined MRM workflow demonstrates how to use different data integration tools to construct a GMNS-compatible base model from widely available OSM data sources.

Step 1. Convert the Map to a Routable Network

Analysts should convert the Extensible Markup Language-based OSM data files to the standard node and link network files in GMNS. OSM map data cover a range of transportation modes, such as automobile, bicycle, walking, rail, or air, which facilitate a multimodal MRM integration effort. However, crowdsourced OSM data have many loosely defined attributes (e.g., the land-use attributes in many POIs are not explicitly defined in OSM), so it is not easy to apply any specific trip-generation rates. Multiple OSM "nodes" correspond to one real-world signalized intersection. As a result, analysts should take additional steps to consolidate related OSM nodes into a macroscopic signal node required by GMNS.

Step 2. Generate Mesoscopic and Microscopic Networks from Macroscopic Base Networks

MRM networks provide the foundation for maintaining consistency between different model resolutions. Macroscopic models are suitable for sketch-planning tools and regional and statewide traffic demand models. Using a macro-to-meso network creation tool to support mesoscopic DTA models and freeway bottleneck identification models better represents turning movements and geometry features on critical bottlenecks. A meso-to-micronetwork creation tool can also address lane-by-lane traffic and support the description of complex geometric configurations. As microsimulation models involve a wide range of elements to capture individual behaviors and advanced features of traffic control devices, it is practically difficult to develop a one-size-fits-all microscopic network representation. To be consistent with the overarching GMNS requirement and maintain the mapping with macroscopic and mesoscopic layers, the prototype developed in the Maryland case study (see chapter 3) suggests a space-discretized, cell-by-cell microscopic network coding scheme.

Step 3: Connect Zone-to-Zone Travel Demand with High-Fidelity Land-Use Data

A key challenge involves rapidly constructing traffic analysis zones (TAZs) and generating initial O-D transportation demand for a subarea of interest. To construct accurate trip tables for ABMs and microscopic simulation, analysts could use available high-fidelity POI data (such as detailed resident locations and land-use properties) to generate trips through empirical trip rates per trip purpose and per mode. Analysts can further aggregate these POI-based trips to the standard TAZs and grid zones typically used in land-use planning. The grid cell system is particularly useful to aggregate trip production and attraction in a hierarchical manner across different spatial resolutions. One can also map the standard TAZ-based attributes to finer-resolution grid zones to reduce approximation errors.

Step 4: Signal Timing Generation for Mesoscopic and Microscopic Layers

A signal data integration tool can automate the generation of movement-based, phase-based signal control strategies for future-year scenarios. Analysts can apply the GMNS signal timing representation to both mesoscopic and microscopic resolutions, which covers the National Electrical Manufacturers Association (NEMA) phase-movement convention, timing phase description, and multiple timing plans (NEMA 2021). A lightweight but automated signal timing generation engine is helpful for planning applications and could even start with a less sophisticated quick estimation method (QEM) from the *HCM* (TRB 2016).

Step 5: Mesoscopic Dynamic Assignment as the Bridge Between Macroscopic and Microscopic Models

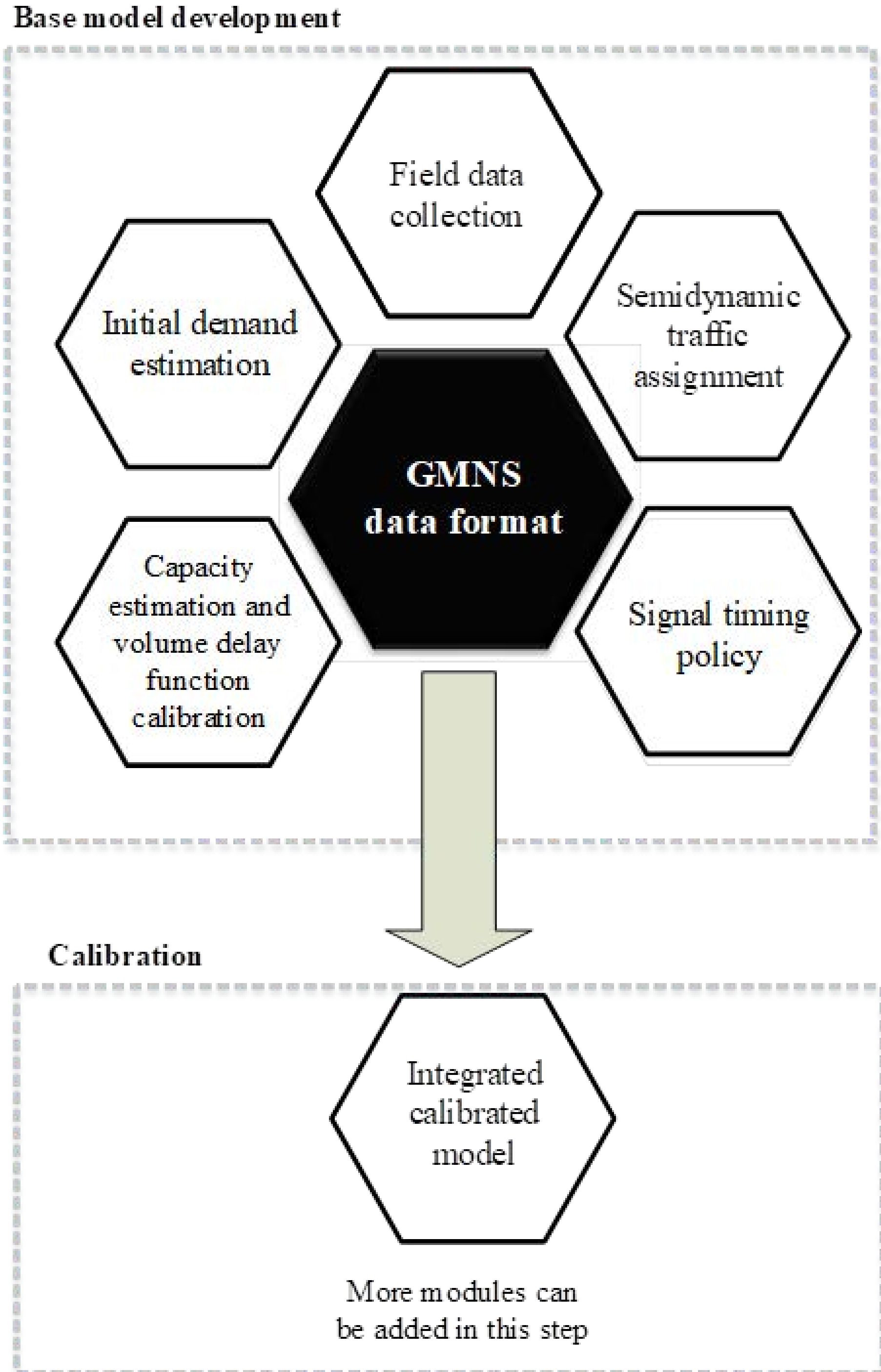
A mesoscopic DTA tool helps link macroscopic model results to balanced demand inputs in the microscopic simulator. Analysts should carefully calibrate mesoscopic-level path flows to improve the input data quality on both the demand and supply sides of MRM.

Step 6: Data-Driven Capacity Estimation and Parameter Identification

An automated module can help calibrate capacity and other coefficients in the traffic stream model. A few of these automated modules include ultimate capacity, critical density for distinguishing congested versus uncongested states, free-flow speed, and speed at capacity. Analysts should also calibrate parameters in the VDF using available volume and speed measurements. As an important preprocessing step, the data integration tool in this category should consistently map link measurements to the underlying planning network in GMNS. Analysts should also use a data-driven process to carefully define excess demand in the VDF, especially under oversaturated traffic conditions. This tool is the key to connecting the traffic volume and delay at the macroscopic level and the underlying mesoscopic queuing dynamics.

Step 7: Model Calibration Using Multiple Data Sources Across Different Resolutions

A demand estimation tool is helpful to construct a hierarchical representation of the standard four-step process (especially for trip generation, distribution, and traffic assignment in the driving mode) when aiming to develop a consistent framework to estimate travel demand using multiple data sources. Analysts should systematically map different data sources—ranging from household travel surveys, link speed, counts, and trajectories—to different layers of the proposed network structure. A feed-forward computational graph construct from the deep-learning field can help sequentially implement the standard four-step process. In addition, the back-propagation of "loss errors" between internal model results and external observations can help update estimates and improve consistency. When applied to a specific traffic analysis problem, the entire process of the MRM workflow can consist of two main stages: base model development and model calibration. It is important to map the MRM workflow to the commonly used modeling process in *Traffic Analysis Toolbox Volume III* (Wunderlich, Vasudevan, and Wang 2019). Figure 4 shows the relationship between steps 0–6 and step 7. Steps 1–6 are the base model development, and step 7 is the calibrated model that can expand on the base model.



Source: FHWA.

Figure 4. Flowchart. Model development enhancements using open data standards.

Zone and Connector Disaggregation

A regional demand model usually consists of TAZs that are typically too large for mesoscopic or microscopic simulation. A more refined zone system is needed to ensure accurate representation of O-D trips and appropriate access to the network when developing a mesoscopic model. Without such updates, the simulation models may show unrealistic gridlock due to vehicles accessing the network in large numbers at the wrong locations.

A number of approaches can help disaggregate trips from larger regional TAZs to the smaller zones (Sloboden et al. 2012). The simplest approach is to distribute trips to the smaller zones based on the ratio of the subarea zone to the larger regional zone. This approach does not take into account the locations of developments within the zone. *Traffic Analysis Toolbox Volume XIV* recommends distributing the trips based on the actual land uses within smaller subzones by applying trip rates to the land use from sources such as the Institute of Transportation Engineers' (ITE) *Trip Generation Manual* or by applying trip rates developed for the regional model (Sloboden et al. 2012; ITE 2018). The analysis team should also examine the locations of zone connectors to ensure they provide reasonable access to the network, similar to what is expected in real life. During the development of the West Palm Beach downtown model used as a case study in this project, the model development team examined the actual access points of different developments, parking facilities, and local street connections on each street block and modified the model accordingly.

Some demand forecasting models have disaggregated TAZs into microanalysis zones (MAZs) when developing ABMs to replace the four-step models or as an option in demand forecasting. These MAZs can serve as a starting point in the TAZ segregation.

Demand Estimation

This section discusses generating the demand input required for MRM. Most MRM efforts and tools use time-dependent O-D demand matrices as demand inputs. However, some open-source tools also allow inputting individual vehicle trips, possibly generated using the activity lists from ABM tools.

Analysts have recognized that O-D matrices produced by demand forecasting models can be too macroscopic for MRM. In some cases, the O-D matrices produced from the demand models reflect the daily demands, but total peak-period demands are produced in most cases. Usually, these matrices do not produce accurate traffic counts when used in the assignment. The analyst typically estimates existing time-variant O-D table(s) (e.g., at 15- or 30-min resolutions) from the O-D data combined with other data sources, such as traffic counts.

STA and DTA tool vendors have developed O-D matrix estimation (ODME) modules. These modules estimate the O-Ds based on initial seed matrices obtained from demand forecasting models or other sources, such as measured O-Ds or O-Ds provided by a third-party vendor. Depending on the specific tool, the ODME utilities accept other types of data, such as link counts; turning movement counts; production/attraction data; measured partial O-D matrices (possibly); and even travel times, densities, and queues. Traffic counts are the commonly used field measurements in the optimization process of these tools. The authors recommend using measured partial O-Ds and turning movements as inputs to the ODME process.

The objective function used in the O-D demand optimization process is usually based on minimizing the deviation between simulated and observed counts and the distance between an initial set of demands (seed O-D matrices) and the estimated demands. However, analysts can extend the objective function to consider the deviation between simulated and observed speeds, densities, and queue lengths. Incorporating other measures, such as travel times, densities, and queue lengths, in the optimization process can help compensate for the fact that identical volume measurements can occur in both congested and uncongested conditions.

One of the issues that analysts can carefully consider is that measured link flows do not represent the demand in congested areas with capacity constraints. Analysts should carefully examine the mapping from O-D demand changes to link flow and density changes based on existing bottleneck congestion duration (Lu, Zhou, and Zhang 2013). Similarly, analysts should carefully examine the estimated link counts resulting from the ODME procedure at bottleneck locations. The use of travel time skim matrices as inputs to the ODME, if these data are available and if the utilized tool allows inputting these data, can help account for congestion in the optimization. Some utilities allow the user to put constraints on the optimization, such as fixing specific O-D flows, specifying or fixing production and attraction counts, or even limiting the percentage of vehicles using a specific O-D path. Analysts can also put weights on specific link counts, O-D pair demands, and the relative importance of O-D matrices versus counts in the optimization. The analyst can examine the impacts of these parameters on the resulting quality using measurements, observations, local knowledge, and engineering judgment in the process.

Most of the utilized O-D estimation methods are assignment-based methods, requiring the running of the assignment as part of the loops to optimize the O-D demand estimation. Assignment-based models use traffic assignment to minimize the deviation between model outputs and observed or estimated measures such as initial O-D matrices and measured traffic volumes. In general, O-D estimation is underspecified, which means that the number of equations based on traffic count measurements is far lower than the number of unknowns (O-D table cells). Thus, different combinations of O-D pairs can produce the same set of link volumes if assigned to the network, and analysts should be careful when running these procedures to estimate demand. Analysts should carefully examine the resulting matrices and counts compared to count measurements, partial O-D demand measurements, and demand matrix estimation.

Analysts should also examine the results produced using different options in the tools. Some utilities use simulation-based dynamic assignment, while others use macroscopic-based assignment models. In addition, some tools use utilities with different algorithms in the estimation. These tools give the user options to provide additional data types. The analyst should use various options and examine the quality of the results.

The deviation of the estimated O-D matrix needs to be limited from high-quality initial or historical matrices. Certain features should be kept depending on initial or historical O-D matrix's source and quality. For instance, some or all of the attraction production rates or some O-D pairs might remain constant during the estimation process. Doblas and Benitez (2005) pointed out that modelers should not replicate traffic counts at the expense of preserving the initial O-D structure and pattern. Thus, they proposed using an ODME that preserves the number of production and attraction trips for each zone. However, the modeling partners should ensure that the demand forecasting model and/or measured O-D matrix data used to estimate the seed matrix are the highest possible quality, so the produced counts from the O-D matrix are at the required level of accuracy.

Another consideration is that some projects may require the specification and modeling of different types of demands. Projects may include different vehicle types (e.g., passenger cars, truck types, and truck sizes), demand types (e.g., commuters, noncommuters, and tourists), and vehicle capabilities (e.g., automation, connectivity, cooperative driving automation classes, electronic toll transponders, and access to traveler information). The analyst should consider this when selecting the modeling tool and specifying the demand estimation procedure.

There has been increasing interest in using data from automatic vehicle identification technologies, such as license plate readers, or third-party vendors based on automatic vehicle location systems, such as global positioning system (GPS) and cell phone-based technologies, to estimate O-D matrices. By including partial trips retrieved, such data sources may improve the ODME performance (Hadi et al. 2017). The incorporation of turning movement counts can also produce better matches to the real-world counts compared to using link counts (Hadi et al. 2017). Producing good turning movement counts from DTA models is particularly difficult. However, inputting the turning movement counts and coding the real-world signal control can help produce better turning movement counts.

Traffic Control

Traffic control includes yield signs, stop signs, signal control, ramp metering, and roundabouts. Signal control can be fixed time, actuated, responsive, or adaptive. Microscopic simulation models are generally capable of modeling these control types and allow model extensions to incorporate advanced control algorithms. However, the ability of the macroscopic and mesoscopic tools to model these control types varies. For example, some mesoscopic simulation tools may not have unsignalized intersection control. Most mesoscopic simulation models allow fixed-time signal control but not actuated or adaptive signal control. The analyst should understand the capabilities of the MRM components used and plan how to model the impacts of traffic control on capacity and performance.

Signal control data are usually required, at least for the mesoscopic and microscopic resolutions of MRM. Signal control synthesis is a feature available in some existing DTA tools. Experience shows that inputting real-world signal control data in the mesoscopic simulation model-based DTA produces much better results than requesting the synthesis of signal timing as part of DTA modeling (Hadi et al. 2017).

When converting networks from demand forecasting models to higher resolution models, analysts must add the signal timing details. For existing conditions, analysts can obtain the information from the signal control agencies. Supporting tools could be helpful in automatically converting the signal timing into formats accepted by the detailed modeling tools and archiving these plans for future use. For example, the San Francisco County Transportation Authority developed a Python™-based signal importing function as part of the DTA Anyway effort (Hadi et al. 2017).

Traffic Operations and Management

MRM is particularly effective in modeling the impact of TSMO on the strategic behavior of travelers. This modeling includes the provision of information and guidance during incidents, work zones, lane drops, and exits; dynamic regulatory data, such as variable speed limits, managed lanes, pricing, truck restrictions, and weight restrictions; surveillance detector types and locations; ramp metering; incident management; and CAV applications that support TSMO. MRM components vary widely in their ability to model TSMO, depending on the specific tool used in the analysis. For example, some mesoscopic simulation tools allow en route assignment to account for drivers receiving event information during their trips and allow the dynamic changing of capacity and traveler responses during the events. Other tools do not offer this capability. The analyst should identify the requirements for TSMO modeling and select the tool that meets these requirements.

Advanced Vehicle Technologies Modeling

MRM can comprehensively assess emerging technologies and strategies, including automated, connected, electric, and shared vehicles and TSMO. Mahmassani et al. (2018) developed a comprehensive CAV AMS framework. Depending on the project's objectives and scope, analysts can model all or a subset of the following four dimensions:

- Supply changes: Changes to the physical and digital infrastructure will enable connectivity and new mobility options such as MaaS, shared fleet utilization, last-mile automation, and automated trucks. These changes will impact drivers' strategic, tactical, and operational behaviors. Thus, the analyst should model these changes in different resolution levels.

- Demand changes: Advanced technologies will have major impacts on demand changes. For example, the value of time due to multitasking is likely to decrease with the newer technologies because of less stressful driving and multitasking capabilities. Shared mobility will also significantly impact demand generation, associated activities, and the decision to own a vehicle. Analysts can assess such impacts using demand forecasting models, simulation-based DTA, and even land-use models.

- Operational performance: CAVs will significantly impact capacity, stability, and performance of traffic flow. Microscopic simulation may be the best resolution for assessing CAV impacts on operational performance. Microsimulation can realistically capture the interactions among vehicles, infrastructure, and other travel modes like pedestrians and bicycles. Microsimulation explicitly considers the heterogeneous mix of traffic, including manual drivers, different levels of automated vehicles with and without connectivity, and vehicles with different collaboration classes. These vehicles will have different reaction times, driving errors, acceleration and deceleration, car-following headways, gap acceptance, lane changing, speed setting, merging behaviors, and weaving behaviors.

- Networkwide demand-supply integration: MRM's advanced vehicle modeling will include multiple tools, tool extensions, algorithms, and preprocessing and postprocessing tools. Integrating the tools to capture interactions at the network level is needed, for example, to use an optimization-based model framework to integrate trip requests, vehicle supply, and infrastructure with consideration of endogenous congestions (Liu, Mirchandani, and Zhou 2020).

Analysts can use demand forecasting models to estimate demands and microsimulation models to estimate impacts on capacity and performance in an integrated manner to ensure consistency between different tools. This integration can include a feedback loop between the lower- and upper-resolution models, allowing fine-tuning of lower-resolution model performance to capture the estimated impacts at the microsimulation level. If the analyst specifies a percentage of vehicles equipped with technology at the microsimulation level, the outputs will allow the analyst to derive an updated VDF function and link capacity at the macroscopic model level and to update mesoscopic model parameters to consider the impact of connectivity and automation.

Multiscenario Analysis

The transportation system AMS focuses on a “typical” or “normal” day. However, traffic changes significantly throughout the year due to stochastic changes in demand and capacity and incidents, adverse weather, and construction events. Modeling the system under different scenarios is recommended when the variations in the conditions during the year are significant. Modeling different scenarios is even more important when modeling TSMO and other advanced technology and strategy applications that effectively relieve congestion during nontypical days. In many cases, it is necessary to model different traffic patterns when conducting MRM. *Traffic Analysis Toolbox Volume III* recommends using cluster analysis to group days into clusters with similar patterns and using the representative day from each cluster in the analysis (Wunderlich, Vasudevan, and Wang 2019).

Selecting multiscenario analysis as part of MRM will require estimating O-D demands for each identified pattern (representative day of the cluster). In addition, it will require the input of different signal control and management parameters if these parameters are different for different patterns. The analyst should determine if the utilized mesoscopic model can model the required features, such as time-variant capacities, which are important for modeling the impacts of incidents and weather events.

STEP 4: ERROR CHECKING

The MRM methodology seeks to enhance and fill the gaps of the seven-step microsimulation analysis methodology from *Traffic Analysis Toolbox Volume III*, as shown in figure 2 (Wunderlich, Vasudevan, and Wang 2019). The primary enhancements occur within step 1 (analysis planning), step 2 (data collection), step 3 (model development), and step 5 (calibration). For MRM, the authors do not have significant additional information to offer for step 4 (error checking) beyond what is discussed in *Traffic Analysis Toolbox Volume III* (Wunderlich, Vasudevan, and Wang 2019).

STEP 5: CALIBRATION, VALIDATION, AND CONVERGENCE

Calibrating and validating simulation models are key to the success of the AMS effort. *Traffic Analysis Toolbox Volume III* and information produced by State agencies provide detailed procedures for calibration and validation of simulation models (Wunderlich, Vasudevan, and Wang 2019). State agencies have also developed standards regarding the performance of their demand forecasting models. These procedures apply to the components of MRM. However, there are additional considerations to ensure models that comprise MRM are consistent with each other in terms of capacity consideration, bottleneck modeling, and performance estimation given the capacity and demand. Another important aspect of MRM is ensuring the quality of estimated demand solutions produced by the MRM traffic assignment, including the convergence of the assignment. This section discusses aspects of the calibration related to MRM.

General Calibration Process Overview

The calibration process presented in *Traffic Analysis Toolbox Volume III* involves the following steps (Wunderlich, Vasudevan, and Wang 2019).

Identification of Representative Days

This step involves the identification of one representative day for each modeled travel condition (operational scenario). Analysts should not use a random day or a synthetic day based on averaging the demands that represent traffic conditions, since an average synthetic does not exist in the real world. Calibrating a model for a synthetic day is technically impossible since the average traffic demands do not correspond to the average travel times.

Identification of Calibration Targets

This step involves setting calibration targets for the difference between the measured and modeled volumes and travel times. Traditionally, State documents have provided fixed (static) thresholds that do not change with changing traffic conditions in the network. *Traffic Analysis Toolbox Volume III* and the forthcoming *Transportation System Simulation Manual*[1] recommend a new method that dynamically estimates the targets based on variations in the measures based on archived data (Wunderlich, Vasudevan, and Wang 2019). The analyst produces a dynamic time envelope for each representative day based on the variation in observed field data for all days in the modeled scenario. This envelope creates a data-driven calibration target. Analysts should calibrate all components of MRM, including the mesoscopic and microscopic models, according to standards adopted by the agency.

Calibration of Model Parameters According to Targets

This step involves iteratively adjusting the modeling tools' parameters in the planning and scoping stage to achieve the acceptability criteria according to adopted standards. After calibrating all models according to the targets, the analyst can ensure consistency between different models and convergence of the assignment. The authors expect that even when analysts calibrate all the components, such as the mesoscopic and microscopic models according to the adopted standards, only the additional fine-tuning of parameters will ensure consistency between the models. For example, the analyst can ensure that assignment results produced by the mesoscopic simulation component produce acceptable results when modeled in microscopic simulation. Analysts should categorize some of the adjusted parameters as global and modify these first. Subsequently, analysts can fine-tune the local parameters.

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[1]List, G., R. Dowling, R. Bertini, D. Hale, S. Warchol, and Z. Qian. Forthcoming. *Transportation Systems Simulation Manual.* Washington, DC: Federal Highway Administration.

The remainder of this section presents details of the calibration process, emphasizing the components related to MRM. Analysts can categorize the parameters adjusted during the calibration process into those that impact the assessed capacity/throughput in the model; additional parameters that impact performance, such as travel times and queue lengths; and parameters that impact demands, such as O-D demand patterns and traffic assignment. This section discusses bottleneck identification and calibration, traffic flow model calibration, travel demand calibration, and consistency between different modeling levels.

Bottleneck Identification and Calibration

A critical first step in model calibration is to fine-tune model parameters to accurately model the bottleneck attributes. *Traffic Analysis Toolbox Volume III* recommends a procedure for estimating bottleneck throughputs (Wunderlich, Vasudevan, and Wang 2019). The CBI tool can facilitate the detection of bottlenecks on freeways, intersections, and arterials (Hale et al. 2016, 2021). Analysts can filter, aggregate, and visualize, and probe the input data on heat maps according to their geographic information and flow features. From the heat maps, analysts can identify three important time points: the time of queue appearance, the time with the longest queue, and the time of queue dissipation. The congestion period from the time of queue appearance to queue dissipation is an important measure to evaluate roadway link performance.

Based on the results of the CBI tool, analysts can automate capacity and supply-side calibration. Both freeways and intersections have recurring bottlenecks where the discharge rate is constrained, and queuing occurs upstream of bottlenecks during rush hours. Analysts can focus on the queue discharge rate at bottlenecks to calibrate the traffic flow model parameters by establishing a (cumulative) supply-demand relationship during a peak period.

Traffic Flow Model Calibration

Analysts can adjust traffic flow model parameters at different resolution levels to produce bottleneck capacity and throughput, according to the adopted capacity calibration targets. Analysts should further adjust these parameters to achieve the required targets for performance metrics, such as travel times and queues, given specific demands and capacities.

Calibrating the traffic flow parameters associated with different levels of modeling is important to meet the throughput and traffic flow acceptability targets. The calibration and validation of mesoscopic simulation models are important considerations due to the industry’s limited experience with the available tools. Mesoscopic simulation tools vary in how they model traffic flow. Some of these tools model traffic through macroscopic traffic flow relationships. Others use combinations of simplified microscopic (vehicle-level) traffic flow models such as car following, lane changing, and gap acceptance. Other models use a combination of macroscopic and simplified microscopic models.

Many existing mesoscopic simulation tools, and all macroscopic analysis tools, use some macroscopic relationships. These relationships may include functions that relate the speed to the v/c ratio or fundamental diagram relationships between volume, speed, and density. Depending on the specific relationship used in the tool, the analyst needs to estimate free-flow speed, critical density, capacity, and/or speed at capacity. In these models, capacity and throughput values are inputs. Other mesoscopic models require the specification of microscopic parameters, such as headways and gap acceptance parameters. Analysts can calibrate the parameters according to the adopted standards based on real-world data. However, in an MRM environment, analysts can also fine-tune parameters of the lower resolution models based on well-calibrated microscopic simulation models to ensure consistency between the different levels of analysis. Analysts can apply this calibration for specific segments and/or movements or by segment type.

Travel Demand Calibration

The goal of the travel demand estimation step is to adjust model parameters to produce volume data consistent with observed data. This effort involves two major components: estimating the time-variant demands between each O-D and assigning this demand to the network. The first component was discussed earlier in the "Model Development" section. This section provides additional information regarding the traffic assignment component. An effective preliminary check of the assignment results is to conduct a screenline count check. In addition, all link volumes should meet the adopted acceptability targets of the project. Furthermore, the generated volumes should not create unrealistic congestion as assessed by microscopic simulation.

Traffic assignment is a key component of MRM, considering the main reason for using MRM is to better identify the path changes used by motorists based on the analyzed alternatives. Analysts can categorize traffic assignments into static and dynamic assignments. STA assumes that link flows and link travel times remain constant over the modeling horizon. In DTA models, the link flows and link travel times are time variant.

STA and DTA share basic concepts. The main components in an assignment are shortest path identification between each O-D, assignment of trip demands to the identified paths, and network loading, which refers to representing the movement of vehicles in the network as they travel from their origins to their destinations (Ortúzar and Willumsen, 2001; Sheffi 1985). The difference is that these components in the DTA are time variant, meaning that the resulting estimates vary during the modeled period.

In DTA models, analysts can classify network loading procedures as analytical or simulation procedures. Although analytical traffic model-based DTA is an option in some tools, most users think of simulation-based DTA when referencing DTA, with mesoscopic simulation-based DTA as the most widely referenced. Due to the complexity of traffic operations, particularly with the presence of congestion and traffic control, simulation-based procedures are the most widely used DTA at present.

Analysts must also understand the value of the analytical traffic flow models and DTA models. For example, analysts typically implement dynamic O-D demand estimation problems through nonlinear optimization models. However, analytical traffic queueing models are also key as a seamlessly integrated modeling element to describe traffic flow relationships using mathematically tractable equations (e.g., point queue model, spatial queue, and simplified kinematic wave model). Furthermore, MRM users should recognize the potential of integrating analytical and traffic simulation models, especially for real-time traffic state estimation and prediction in MRM applications. In this case, analysts should embed a set of theoretically sound analytical models to capture the following three categories of dynamic traffic system equations:

flow conservation; traffic flow models involving speed, flow, and density; and partial differential equations.

An important concept in DTA and STA is implementing an iterative process to reach user equilibrium. Equilibrium emulates drivers' long-term selection of their routes, assuming that they are familiar with the recurrent congestion in the network or receive perfect information, such as the congestion level and toll fees they will encounter. Some system users may not have this information, such as tourists, noncommuters, and commuters with no access to traveler information systems during nonrecurrent events, such as incidents, weather, and short-term work zones. In response to these situations, some tools allow the user to specify a noniterative assignment (sometimes referred to as a one-shot assignment). Such procedures involve assigning the entire volume in one iteration. The analyst should consider this option in addition to user equilibrium when selecting the analysis tool and procedure. For example, the user may specify a certain percentage of travelers to be tourists with no access to traveler information and thus be given a noniterative assignment.

Another important DTA categorization is a pretrip versus en-route assignment. STA only allows pretrip assignment to modeled travelers who select their routes before departure. In addition to pretrip assignment, some DTA tools allow the analyst to model travelers' adjustment of their routes during their trips based on information received about unexpected conditions, such as incidents. En-route assignment methods are only required for specific applications of traveler information systems.

The assignment procedures make assumptions regarding traveler behaviors. The most widely used behavioral factors impacting the traveler's route choice are travel time, monetary costs (such as tolls), and distance. Other factors have also been used or proposed, such as the number of turns, number of signals, and bias toward freeway driving. Including reliability as part of the assignment objective functions has gotten some interest. The analyst should examine objective function settings used in the assignment and the weights assigned to factors used in the objective function. The weights may change between user groups based on socioeconomic factors, access to information, and onboard equipment. For example, high-income travelers are more willing to pay for alternatives with lower travel times, even when charged higher costs. In addition, the weights for each user group can be stochastic. For example, some individuals may have jobs that emphasize on-time arrivals compared to others in the same user group. The same individual may have a different willingness to pay depending on the individual's schedule on that day. Although most users specify the same weights for objective function variables in the assignment, users may consider the aforementioned conditions when selecting the tool and analysis procedure.

Convergence assessment is important to ensure the quality of traffic assignment results. The convergence of user equilibrium assignment is necessary to ensure the integrity of the solution. Such integrity is required to ensure the model properly assesses alternative designs and operational strategies. The assignment achieves equilibrium when travelers cannot improve their travel times by selecting alternate paths[2] (Chiu et al. 2011). Analysts should examine the tool's convergence criteria and whether an acceptable convergence is achieved when running the

[2]Resource Systems Group. 2010. "Convergence Peer Exchange Read-Ahead Information." Memorandum from DaySim-TRANSIMS Project Team.

assignment as part of MRM. A widely used measure for convergence is relative gap, which measures the difference between the current iteration solution and the ideal solution. Researchers and tool developers have suggested and implemented different formulations of link-based and path-based gap[3]. In static assignment, it is much easier to achieve a small relative gap than it is in simulation-based DTA, particularly for congested conditions (Chiu et al. 2011).

Feedback and Convergence

As mentioned earlier, a key aspect of MRM is to ensure consistency of traffic performance between the different levels of resolution used in the analysis. This section discusses methods to ensure capacity estimation, performance measure estimation, and demand estimation consistency. An important aspect of ensuring consistency is the close collaboration with demand forecasting modelers. This close collaboration helps ensure the coded network geometry is correct and at an acceptable level of resolution, demands are accurate, and the traffic flow model is calibrated. Traditionally, the demand forecasting community and simulation community have worked as separate entities with minimal interaction. Agencies should collaborate to ensure consistency between different AMS tools in the region, including demand forecasting models.

Analysts have usually conducted MRM by providing information from the upper (lower resolution) level to the lower (higher resolution) level. However, the authors' recommended consistency assurance procedure involves a feedback loop from the lower level resolution to the upper level resolution. For example, this feedback loop can involve providing information based on microscopic simulation tool outputs for use in fine-tuning mesoscopic and macroscopic model parameters. It can also include using information from the mesoscopic model to inform the upper level macroscopic model. This process is key to the success of MRM because the ODME and assignment conducted at the macroscopic and mesoscopic levels produce demands used as inputs to the microscopic level. If the macroscopic and mesoscopic models underestimate delay on a given path, the heavy assigned traffic may produce unrealistic gridlock in the microscopic network.

To facilitate continual discussion and development within transportation MRM integration, one can further examine the consistent modeling and model linkage issues in typical traffic impact or subarea study. For example, one could simply extract vehicle path data from a (macroscopic) DTA tool and feed the data into a microsimulation model. The analyst could then estimate various performance measures and generate second-by-second vehicle speed and acceleration output for detailed emissions-related analysis. Nonetheless, multiple impediments are associated with such a loose linkage.

There is a potential inconsistency between the macroscopic traffic flow models used in STA, the mesoscopic simulation models used in DTA, and the microscopic car-following and lane-changing models used in traffic simulation tools. The low-resolution traffic flow models used in DTA can reasonably approximate the complex, real-world traffic flow dynamics. However, by mixing models with different resolutions, without attempting to replicate the microsimulation performance in the lower resolution levels as much as possible, microsimulation travel times can

[3]Resource Systems Group. 2010. "Convergence Peer Exchange Read-Ahead Information." Memorandum from DaySim-TRANSIMS Project Team.

differ significantly from the link performance statistics previously obtained from the DTA module. This difference leads to internal discrepancies between modeling resolution levels, hinders the tight connections, and complicates the iterations between simulation and assignment components.

Capacity and Throughput Consistency

The first measure to adjust for consistency between different resolutions is capacity or throughput at the bottleneck. Capacity is an input to the macroscopic models. However, capacity is an output in most mesoscopic models and all microscopic models, as it is assessed based on microscopic traffic flow parameters. The analyst should fine-tune the macroscopic, mesoscopic, and microscopic model parameters to obtain segment-level and turn movement-level capacities consistent with each other. The analyst can use the calibrated capacities at the lower level (higher resolution) models to refine the initially calibrated capacities in the upper level models used in the first iteration of MRM.

Table 2 in the Case Studies section compares the capacities used in the demand forecasting model calibrated for the region with those estimated for critical links based on microsimulation in the West Palm Beach downtown area. As shown in table 2, the capacity assessed by microscopic simulation is much lower for the investigated downtown facilities than for the whole region.

The capacity assessed for individual turn movements in the mesoscopic and microscopic models should also be consistent. Table 3 compares the capacities as assessed by the mesoscopic simulation model used in the West Palm Bach network and the resulting capacity after fine-tuning the model parameters to ensure consistency between the mesoscopic and microscopic models.

Traffic Model Parameter Calibration

The next step is to adjust macroscopic and microscopic traffic flow parameters in the different levels of analysis to ensure travel time/delay performance consistency between the different levels, given the realized demands and capacities. This adjustment involves a feedback loop for modifying parameters used in the initial runs of the lower resolution models, based on results from the lower level (higher resolution) models. This step involves deriving VDF parameters in the macroscopic model based on the mesoscopic or microscopic simulation results. Derivation of the VDF can be for the whole network or, preferably, on a segment-by-segment basis, if the LOE is feasible. The analyst can also change mesoscopic model parameters to produce the same delays, under various demand-to-capacity ratios, as in the microscopic models.

In chapter 3, figure 8 compares the VDF used in macroscopic models for the West Palm Beach downtown area. The research team derived the first VDF from microscopic simulation. The team obtained the second VDF from the default model in the utilized tool. The team obtained the third VDF from the regional demand forecasting model across the entire network. However, it is possible for analysts to calibrate the BPR curve for individual links in the network at higher spatial resolutions to extract sufficient data from the simulation model for a more accurate representation of the BPR curve.

To ensure consistency, analysts can examine the relationships between average delay and v/c ratio of the utilized models. The authors recommend plotting this relationship for critical segments in the network and fine-tuning the model parameters to ensure consistency. It is notable that even with the capacity and traffic flow model calibration, some inconsistencies between the performance measures estimated by the models are likely to occur. The VDF may not produce realistic results for oversaturated conditions, particularly if the analyst calibrated at the subnetwork level rather than the segment level. Mesoscopic simulation may not correctly estimate the impacts of all traffic operation variants. For example, mesoscopic models may not be able to model the effect of spillover from the left-turn bay to the through-movement lanes and the impact of lane-changing maneuvers on traffic flow. These limitations will motivate an iterative process to modify parameters in the macroscopic and mesoscopic models to reflect various impacts observed in the microscopic model.

Another way to improve consistency is through data integration tools. These tools should improve consistency across different traffic flow variables from aggregate trip production to spatial and temporal distribution to travelers' route choice parameters.

Convergence Between ABMs and DTA

Measures of convergence between ABM and DTA motivate a systematic consideration of their underlying mathematical definitions and resulting solution methods. The DTA literature typically describes gap functions to quantify the supply-side convergence (Chiu et al. 2011). It is challenging to use optimization formulations to describe disaggregate ABMs, not to mention additional complexities due to random solution sampling and solution feasibility (associated with preferred arrival times of individual travelers). Thus, researchers typically adapt fixed-point formulations from the static case (integrated four-step process) to the integration of ABM and DTA. Specifically, in the iterative solution methods, researchers define the convergence criteria in terms of cost or flow changes in system states across two consecutive iterations.

Vovsha et al. (2018) provided a useful convergence example for MRMs with ABM-DTA interaction. The research team implemented all ABM-DTA interactions at the individual level to avoid aggregation bias.

Analysts should recognize the value of data-driven calibration and refinement of integrated ABM–DTA models. A common understanding is that a complex integrated model might be too difficult to calibrate fully. However, analysts should also maximize the use of emerging mobile data sources and innovative data acquisition methods to address the following challenges:

- How far can analysts calibrate the integrated models and replicate the transportation system?
- Can integrated models run better than individual methods, and can they receive dynamic sensor, probe, or survey data to evaluate proactive or dynamic traffic management capacities?

- Can analysts integrate the models, achieve a multiresolution tool that can evaluate a network at various levels, and assess the impact of physical and operational conditions on travel demand and behavior?

STEP 6: ALTERNATIVES ANALYSIS

Agencies frequently conduct simulation modeling to compare alternative scenarios. Thus, analysts often create variations of a developed model to assess each alternative for each travel condition (operational scenario).

Accounting for Model Stochasticity

Recognizing the stochasticity of microscopic simulation models, current Federal and State practices use multiple runs by varying random number seeds for alternatives analysis. For example, *Traffic Analysis Toolbox Volume III* recommends analysts run the model four times under different random number seeds (Wunderlich, Vasudevan, and Wang 2019). Next, they should analyze the variation in results to determine an appropriate number of simulation runs to satisfactorily assess statistical validity when comparing the impacts of competing alternatives. Finally, the analysts can conduct statistical hypothesis tests to identify any statistically significant differences between the two analyzed alternatives. Wunderlich, Vasudevan, and Wang (2019) provide equations to estimate an appropriate number of microscopic model runs and describe hypothesis testing for the difference in performance between examined alternatives.

Mesoscopic models can be deterministic or stochastic, but existing macroscopic models are usually deterministic. In general, analysts do not conduct multiple runs of mesoscopic simulation models even if they have stochastic components due to prohibitive computer running times. The authors recommend that analysts should at least understand if there is any stochasticity associated with mesoscopic models and its potential impacts.

Future-Year Demands

Conducting alternatives analysis using MRM for a future year involves forecasting future demands. Such forecasting can build on the information provided in *Analytical Travel Forecasting Approaches for Project-Level Planning and Design*, which describes methods, data sources, and procedures for producing travel forecasts for analyses at the highway project level (CDM Smith et al. 2014).

It is important to precisely characterize demand-supply consistency and feedback loops in future-year scenarios involving significant infrastructure and demand changes. The computational graph construct can also extend to describe a tight integration of an ABM with DTA. Figure 3 shows how to insert a new layer in the computational graph to express the disaggregated level of multidimensional trip-level or tour-level travel decisions. Furthermore, the time-dependent demand can further help calculate dynamic link travel time, path travel time, and O-D skim, which will further feed back to the upper levels of behavioral decisions.

Analysts should carefully examine results from the methodology used to estimate future demand. The whole process can be iterative. Analysts can examine the results and refine the estimation if the results are not reasonable or differ significantly from the expected change in network demands. The *Analytical Travel Forecasting Approaches for Project-Level Planning and Design* procedure uses results from a demand forecasting model developed for a future year, usually 20-25 yr in the future (CDM Smith et al. 2014). However, the demand forecasting model may overestimate or underestimate demands for the future year. Thus, the analyst should work closely with demand forecasting modelers to refine the results. For example, in the West Palm Beach downtown case study, analysts determined that the demand forecasting model underestimated demands for the year 2045 because it did not include several buildings approved for construction in the downtown area. These buildings generate significant demands not accounted for in the model. The model developers worked closely with Palm Beach County to include the demands from these buildings in the model and used those results in conjunction with *Analytical Travel Forecasting Approaches for Project-Level Planning and Design* procedure (CDM Smith et al. 2014).

Signal Timing Estimation and Optimization

When modeling future years or improvement alternative scenarios that change the demands of the network, new signal timing plans are needed. Efficient tools will be required to optimize the signal control for future conditions. For example, a spreadsheet-based tool aims to offer a lightweight computational engine to generate optimal signal control timing data and analyze the effectiveness of signal control strategies (Zlatkovic and Zhou 2015). The tool relies on the *HCM2010* methodology for signalized intersection analysis and the QEM but also uses other methodologies for computing signalized intersection parameters, as described in the *Signal Timing Manual* (*STM*) (TRB 2010; Koonce and Rodegerdts 2008). The packages mainly consist of the following modules:

- Phase designation: The phase designation determines the major street (north-south or east-west), defines phases for each movement, and determines the left-turn treatment based on the criteria defined in the *HCM* and *STM* (protected only, permitted only, or protected + permitted). This step also defines the ring-barrier structure.

- Lane volumes: This step calculates critical lane volumes for each intersection approach. It follows the methodology defined in chapter 31 of the *HCM* (TRB 2010).

- Phase calculation: This step performs calculations of all signal control parameters. It uses inputs defined by the user and outputs from the previous steps. It uses the critical movement methodology for cycle-length calculations. Furthermore, it determines green time (splits) allocations, movement capacities, v/c ratios, and LOS. This step goes beyond the typical QEM since it gives realistic signal timing parameters common in all North American ring-barrier controllers. The macro function can also optimize cycle lengths. The optimization minimizes the total intersection delay.

- Phasing: This step calculates phasing data for the correct export of an error-free analysis.

Sensitivity Analysis

Wunderlich, Vasudevan, and Wang (2019) recommend performing sensitivity analysis to test the reliability of microsimulation results. In the sensitivity analysis, the analyst identifies uncertain input assumptions and varies them to identify their impact. The analyst makes additional runs with changes in demand levels and other parameters, which helps determine the model's robustness in producing results that can inform decisionmaking. The variation in demand within a range is particularly interesting in this regard.

STEP 7: FINAL REPORT

The MRM methodology seeks to enhance and fill the gaps of the seven-step microsimulation analysis methodology from *Traffic Analysis Toolbox Volume III*, as illustrated in figure 2 (Wunderlich, Vasudevan, and Wang 2019). The primary enhancements occur within step 1 (analysis planning), step 2 (data collection), step 3 (model development), and step 5 (calibration). For MRM, the authors do not have significant additional information to offer for Step 4: Error Checking, beyond what is discussed within *Traffic Analysis Toolbox Volume III* (Wunderlich, Vasudevan, and Wang 2019). However, if the MRM analysts pursue feedback and convergence, they could consider reporting additional details and statistics associated with the feedback and convergence effort.

RECOMMENDATIONS TO IMPROVE ORGANIZATIONAL CAPABILITY

This section discusses how agencies can improve their capabilities to ensure and increase MRM effectiveness. At the time of this writing, FHWA is developing a traffic analysis capability maturity framework (CMF) to help agencies assess their strengths and weaknesses for incorporating and mainstreaming traffic analysis activities into their business processes. The CMF will also help agencies develop an action plan to improve their capabilities in traffic analysis. The framework follows the capability maturity model (CMM) approach and frameworks previously developed for TSMO program areas (FHWA 2012). Although the developed framework will generally support traffic analysis, many of the capabilities and actions are also relevant to MRM. The authors encourage agencies to apply the traffic analysis CMF with a focus on MRM if stakeholders identify MRM as a need for the region or the State. Such utilization will enable agencies to identify opportunities for improvement and develop a programmatic focus for MRM to create analytical consistency and uniformity.

This section discusses potential improvements that agencies can consider based on the gaps identified during previous tasks of the MRM project(Zhou, Hadi, and Hale 2021). The discussion focuses on the six capability maturity dimensions of the traffic analysis CMF (i.e., business process, data and performance estimation, tool utilization, organization and workforce, collaboration, and culture) as identified in the gap analysis. The authors encourage agencies to review documents produced from the FHWA traffic analysis CMF project for a more thorough discussion. The authors also encourage agencies to review the *SOPAGA Report* (Zhou, Hadi, and Hale 2021).

Business Processes

Business processes include developing and institutionalizing problem identification, project objective and performance measure setting, scoping, analysis approach selection, resource identification, data and related analytic scoping requirement consideration, and model archiving and maintenance. State agencies may want to consider formalizing and institutionalizing MRM use. Developing MRM-specific standard operating procedures (SOPs) and procurement procedures could support the adoption of MRM by the modeling community. Currently, most stakeholder agencies have demand forecasting model procedures, and some have procedures for microscopic simulation modeling. However, no such procedures are generally available for mesoscopic simulation, DTA, three-level multiresolution, or hybrid simulation modeling.

Transportation agencies, including MPOs and State agencies, should consider adopting detailed processes for maintaining and updating already-developed MRM networks. Larger scale, higher cost MRM should motivate agencies to develop models once and use them multiple times to increase MRM cost effectiveness.

Performance Estimation

It is helpful to examine the definitions of the performance metrics and their calculations in different levels of the MRM tools and how different they are from the definitions and calculations of the *HCM* (TRB 2010). Agencies may want to extend their MRM tool capabilities by integrating them with other tools and utilities to better estimate additional measures in space and time, including those for estimating mobility, reliability, emission, safety, and equity.

Data Collection and Management

Microscopic simulation uses detailed input data for traffic demands, geometry, and control. However, MRM adds pertinent data. First, MRM can imply a larger network size in a mesoscopic simulation model-based DTA tool or hybrid tool to better simulate diversions in alternative tools. The increase in modeling scope likely requires a significant increase in data collection, including collecting signal control data for an increased number of signals, travel time and count data across the network, and O-D demand and path selection data. Agencies should establish processes at the State and regional levels for data collection, processing, quality assurance, archiving, and sharing. Agencies should learn from other agency processes and activities that collect and use data from multiple sources to increase cost effectiveness.

Standard Operating Guidance

The authors recommend that agencies develop SOPs that cover all aspects of the modeling process, including demand estimation, model development, DTA, calibration and validation, and forward and backward feedback between different resolution levels, and model output use in decisionmaking. The agencies should ensure effective SOP implementation.

Tool Utilization

Transportation modeling and simulation tools are key elements in supporting decisionmaking for the design and operation of transportation systems. The behaviors of transportation systems involve interactions of these models among the supply and demand sides with the assistance of fast-growing computer technology. Different tools exist for different purposes and applications. Each tool has its strengths and weaknesses for a particular application and level of modeling detail. Each agency should understand the detailed tool requirements for different applications to select the right tools for a project. Project analysis teams can then use these requirements in their tool selections.

Workforce Development

Using MRM effectively requires qualified staff to develop, calibrate, and peer-review the developed models. Most of the user and vendor feedback reported that lack of experience, background, and training are major barriers to using MRM. The agencies should establish a strong traffic analysis workforce development program that includes recruiting, retaining, and training to support the MRM effort.

Collaboration

MRM usually covers large subnetworks that may cross jurisdictions. In addition, activities like data collection and different modeling levels can involve various agencies or departments within an agency. MRM will entail more collaboration and interaction between modelers of different levels, including those within the same agency and those at partner agencies. In some cases, there is a "stovepiping" problem (i.e., minimal interaction) between the modelers of different resolutions and organizations and in data collection and other project activities. Increased understanding and collaboration among the agencies that impact, or are impacted by, MRM in a region or State is needed.

Culture

Culture refers to the degree to which different staff levels at a transportation agency value the benefits of implementing MRM. All staff needs to understand the strengths of MRM in supporting agency operations and the potential cost savings of applying MRM. Champions within agencies who can effectively message MRM's value and lessons learned can build a supportive culture among agency staff and partner agencies.

CHAPTER 3. CASE STUDIES

INTRODUCTION

During the early stages of the FHWA MRM project, stakeholders reported that the lack of case studies presented a barrier for transportation agencies to adopt MRM. The authors developed the *MRM Case Studies Report*[1] to blueprint the successful pilot studies conducted during and within the MRM project. This chapter describes key aspects of the MRM case studies. Because these are case studies, agencies should not consider them a standard or an accepted practice. The following is a list of the fundamental case study characteristics:

- West Palm Beach:
  - Macroscopic travel demand forecasting model.
  - Macroscopic analytical STA model of a refined subarea network with ODME.
  - Mesoscopic DTA model.
  - Microscopic simulation model.
- Phoenix:
  - Macroscopic analytical STA model.
  - Macroscopic analytical ABM.
  - Mesoscopic DTA model.
- Maryland:
  - Macroscopic travel demand forecasting model.
  - Macroscopic analytical model.
  - Mesoscopic simulation model (with 0.2-s resolution).

The *MRM SOPAGA Report* provides a comprehensive assessment of barriers to MRM adoption, based on extensive literature reviews and agency outreach (Zhou, Hadi, and Hale 2021). This gap analysis informed both the case studies and the MRM methodology. Given the variety of gaps associated with MRM, the project team used the six dimensions of the CMM framework in the gap analysis (FHWA 2012). The six dimensions of the CMM are the business processes, performance measurement, system and technologies, organization and workforce, collaboration, and culture.

The MRM methodology in chapter 2 focuses on the performance measurement and the system and technologies dimensions. The other four dimensions relate to high-level institutional activities, which are more difficult to address in the case studies. Table 1 presents identified gaps in the two most pertinent dimensions and summarizes the extent to which the case studies address these gaps. Following is a detailed explanation of each column of table 1:

- Dimension—this column documents each of the six CMM dimensions.

- Gap—this column documents the identified gaps in MRM practice (Zhou, Hadi, and Hale 2021).

[1]Hadi, M., X. Zhou, and D. Hale. Forthcoming. *Multiresolution Modeling for Traffic Analysis: Case Studies Report.* Washington, DC: Federal Highway Administration.

- West Palm Beach downtown—this column documents the section in the case studies report that discusses how the West Palm Beach downtown case study fills the gaps listed in the gap column[2].

- Phoenix metropolitan area—this column documents the section in the case studies report that discusses how the Phoenix metropolitan area case study fills the gaps listed in the gap column[3].

- Maryland I–95—this column documents the section in the case studies report that discusses how the Maryland I–95 case study fills the gaps listed in the gap column[4].

- MRM methodology steps—this column documents the MRM methodology steps presented in chapter 2 that address the gaps listed in the gap column.

- Guidebook subsections—this column documents subsections in chapter 2 that address the gaps listed in the gap column.

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[2]Ibid.
[3]Ibid.
[4]Ibid.

Table 1. Overview of case study information.

Dimension	Gap	Case Study: West Palm Beach Downtown	Case Study: Phoenix Metropolitan Area	Case Study: Maryland I–95	MRM Methodology Steps in Chapter 2
Performance measurement	2.1 Variations in the definitions of measures.	Refer to the "Performance Measure Definitions" section.	Refer to the "Performance Measure Definitions" section.	N/A	Step 1: Planning/Scoping.
	2.2 Variations in the methods used in estimation of various performance metrics.	Refer to the "Performance Measure Consistency" section.	Refer to the "Performance Measure Consistency" section.	N/A	Step 2: Data Collection/Analysis.
	2.3 Data needs.	Refer to the "O-D Demand Estimation" section.	N/A	N/A	Step 2: Data Collection/Analysis.
	2.4 Types and resolutions of measures used in model calibration and validation.	Refer to the "Performance Measure Consistency" section.	Refer to the "Performance Measure Consistency" section.	Refer to the "Performance Measure Consistency" section.	Step 2: Data Collection /Analysis.
Systems and technology	3.1 Methods and tools that support integration and data conversion between different modeling levels.	Refer to the "Model Conversion Effectiveness" section.	Refer to the "Model Conversion Effectiveness" section.	Refer to the "Model Conversion Effectiveness" section	Step 3: Model Development. Step 6: Alternatives Analysis.
	3.2 Enhancement of MRM tools.	Refer to the "O-D Demand Estimation" section.	N/A	Refer to the "Enhancement of Tools" section	Step 3: Model Development. Step 6: Alternatives Analysis.
	3.3 Multimodal modeling.	N/A	N/A	Refer to the "Multimodal Modeling" section.	Step 1: Planning/Scoping. Step 3: Model Development.

Dimension	Gap	Case Study: West Palm Beach Downtown	Case Study: Phoenix Metropolitan Area	Case Study: Maryland I–95	MRM Methodology Steps in Chapter 2
	3.4 Behavioral responses to advanced technologies and strategies.	Refer to the "Impacts of Advanced Applications" section.	N/A	N/A	Step 1: Planning/Scoping. Step 3: Model Development. Step 5: Model Calibration. Step 6: Alternatives Analysis.
	3.5 Simulation/model coupling for real-time management applications.	N/A	N/A	N/A	Step 1: Planning/Scoping.
	3.6 Feedback loop in internally consistent cross-resolution traffic representation.	Refer to the "Performance Measure Consistency" section and the "Benefit of MRM" section.	Refer to the "Feedback Loop" section.	Refer to the "Performance Measure Consistency" section and the "Benefit of MRM" section.	Step 1: Planning/Scoping. Step 3: Model Development. Step 5: Model Calibration. Step 6: Alternatives Analysis.

N/A = not applicable. No information available from the referenced case study for the referenced gap.

O-D DEMAND ESTIMATION (GAP 2.3 AND GAP 3.2)

This section addresses issues related to gap 2.3 (data needs) and gap 3.2 (MRM needs and capabilities). O-D demand estimation is key to the success of MRM, since static and dynamic assignment models require O-D matrices as inputs. Some assignment models also accept individual vehicle level origins and destinations in lieu of O-D matrices. The simplest method to obtain the demands for traffic assignment is to import the O-D demands directly from a subarea network extracted for the project from the regional demand model. However, modelers have found that O-D demand matrices obtained from demand forecasting models may result in large errors compared to real-world counts when used in assignment procedures (Zhou, Hadi, and Hale 2021). This situation implies the need for further refinement of regional demand forecasting models to allow these models to produce acceptable results for simulation modeling.

Given this issue, most existing commercial and open-source demand forecasting and assignment tools have ODME procedures to update the O-D demands generated by the demand forecasting models. These tools allow better correspondence with real-world traffic counts and sometimes other measures, such as travel times. These procedures generally use optimization algorithms to estimate the O-D matrices by minimizing errors between the model outputs and inputs considering input variables, resulting in improved O-D demand matrices compared to those produced by the demand forecasting models. The existing ODME varies in the type of input variables used in the estimation. These input variables can include the segment counts, turning movement counts, initial O-D matrices used to seed the optimization, attractions per zone, and production demands per zone. Some tools also allow additional measures and inputs to the O-D estimation process, including travel time measurements, queue lengths, and densities. However, practitioners have not widely used these additional measures, despite their proven ability to improve the results (Hadi et al. 2013).

Modelers currently perform ODME procedures with or without a seed O-D demand matrix. In some cases, modelers completely ignore the provision of the seed matrix and only use count data to obtain the network's time-varying O-D demand. However, the quality of ODME results depends on the availability of high-quality initial O-D demand matrices (Lin 2006). Analysts have used volume measurements combined with seed matrices based on demand model results as inputs to the ODME estimation algorithms in most applications. Practitioners also use partial O-D demand matrices obtained based on roadside reader data, vehicle tracking using GPS data, and third-party vendor data as seed matrices to the O-D demand estimation (Zhou, Hadi, and Hale 2021). The ODME algorithms produce O-D demands that minimize deviations from the counts and seed matrices. In the optimization objective function used to estimate the O-D matrices, analysts can assign weights on different variables to reflect the level of confidence in the data. For example, in the tool used in this case study, the analyst can assign a weight ratio that reflects the relative weight of the seed matrix to traffic volume measurements in the optimization. For example, the analyst may assign a lower weight ratio if there is higher confidence in traffic volume measurements than the seed O-D demand matrix.

Comparison of Algorithms

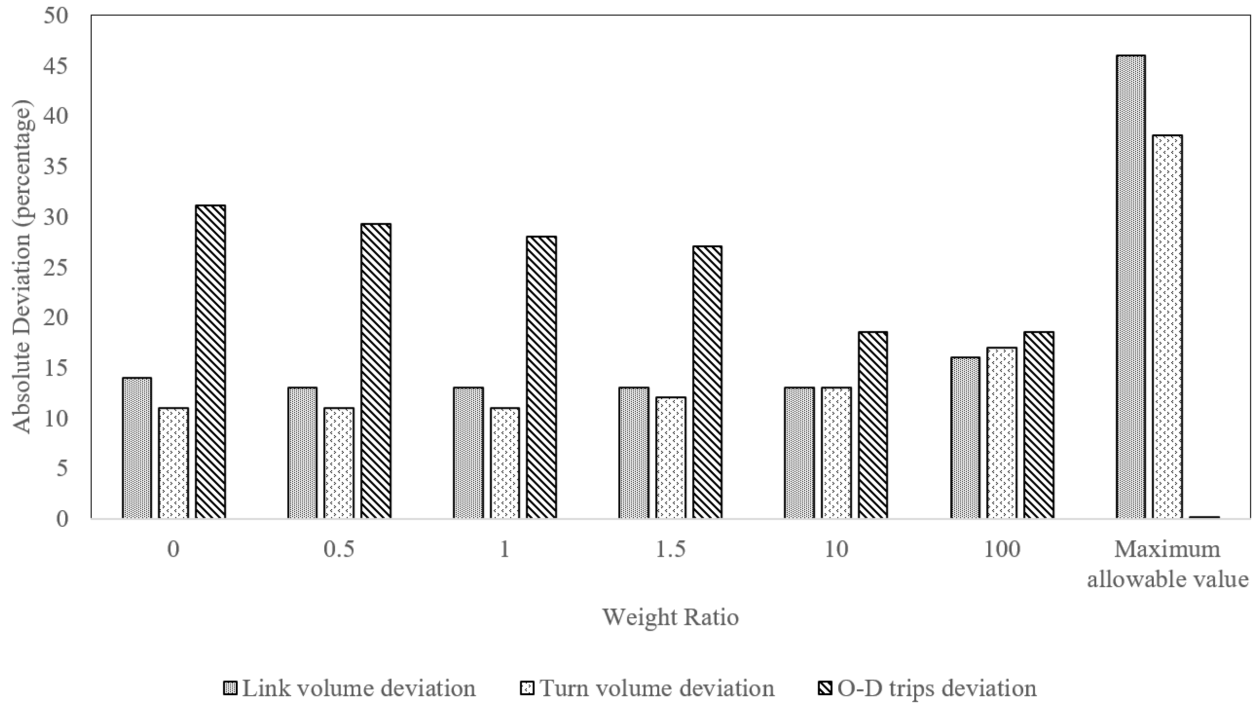
In the West Palm Beach case study, the research team first considered two ODME procedures built in a macroscopic modeling tool. These procedures are the least-squares method and the

TFlowFuzzy method (PTV Group 2019a). The team conducted sensitivity analyses during this case study, which showed that the least-squares method produced better results (in terms of the deviation of link/turn counts and O-D trip values) than the TFlowFuzzy procedure. Other advantages of the least-squares method are that it always delivers a solution and its run time is significantly lower than other methods available in the tool. Analysts can also use the least-squares method in large networks containing many count locations. Thus, the team used the least-squares method for the remainder of the analysis. The least-squares method minimizes the squared distance between the assignment value and the count value. Analysts can also minimize the deviation from the initial O-D matrix that is used as an input to the ODME process by minimizing the squared distance between old and new trip values at the same time as the count values.

Effect of the Seed Matrix

In the least-squares method, analysts can define weighting factors for count locations to reflect their importance. Analysts can also specify another weighting factor, the weight ratio of matrix deviations versus count deviations. A weight smaller than 1.0 means the procedure will give count deviations higher importance than matrix deviations. Weight ratios higher than 1.0 indicate the procedure will put a higher weight on the seed matrix compared to count value deviations, resulting in smaller deviations in the O-D trip values. This section discusses the impacts of using the O-D matrix produced by the demand forecasting model as an input to the utilized ODME algorithm (seed matrix), as seen within the West Palm Beach case study. This section compares the updated O-D demands produced by the ODME algorithm used with different weight ratios assigned to the seed matrix relative to the turning movement counts in the ODME algorithm. This section also examines several relative weights of the seed matrix ranging from zero (no consideration of the seed matrix) to a very high number (no consideration of the traffic counts in the optimization).

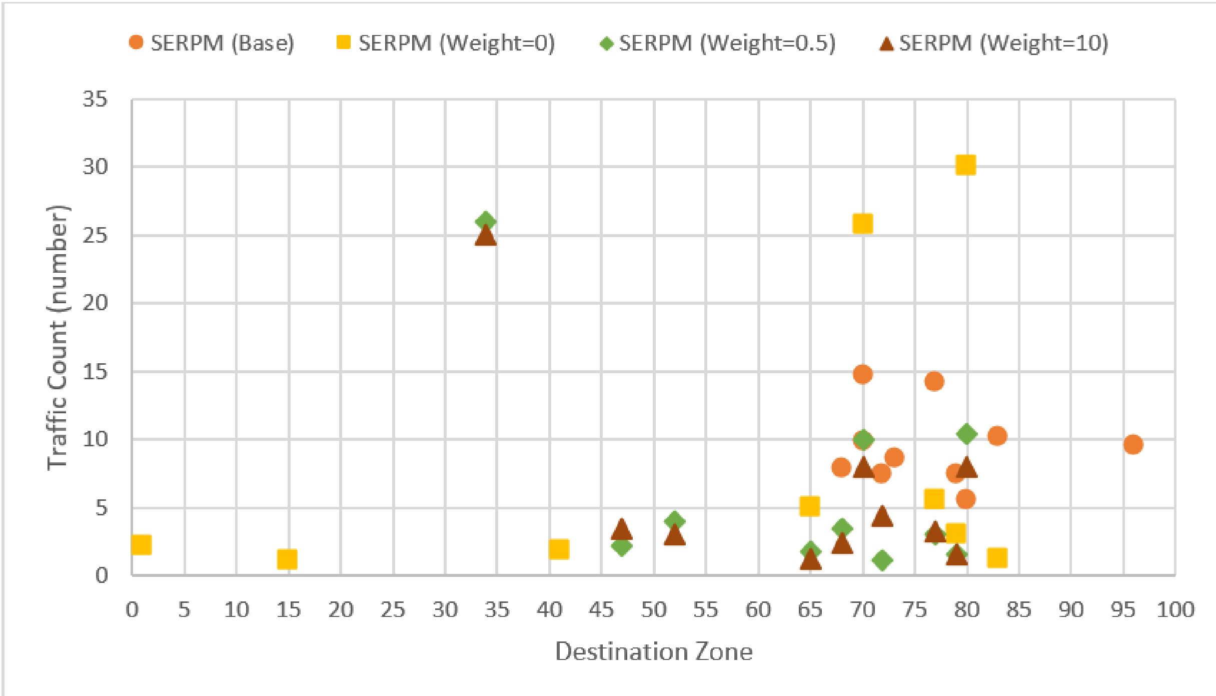
Figure 5 shows an overall comparison of different weight ratios on the seed matrix compared to the counts when using the least-squares method. Figure 5 shows that as the weight ratio defined in the least-squares ODME procedure increased, the O-D trips deviation became smaller. The link-volume deviation and turn-volume deviation changed only slightly with the change in the weight ratio, even when increasing the weight ratio on the matrix up to 10. However, link- and turn-volume deviations increased significantly when using a weight of 100. These deviations became very high when entering the maximum value for the weight ratio into the utilized tool, which is equivalent to using the matrix produced by the demand forecasting model with no consideration of the link or turn counts. Figure 5 shows that using ODME with a weight ratio of 10 on the demand matrix reduced the mean absolute deviation of turn movement volume and link volumes from 38 to 13 percent and 46 to 13 percent, respectively. The O-D matrix resulting from the ODME had a 20 percent deviation from the initial O-D matrix. Notably, the magnitude of deviation from the original seed matrix depends on the quality of the matrix.



Source: FHWA.
Note: Weight ratio refers to the ratio of weights for demand deviation relative to count weights.

Figure 5. Bar Chart. Link and turn deviations with different weight ratios.

The research team further analyzed O-D volume changes under different ODME setups by examining the trip destinations generated from several critical zones. For each generation zone, the study estimated the number of trips to the 10 destination zones with the highest number of trips. Figure 6 shows the results for one of these zones, while other zones exhibit a similar pattern. The results show how different ODME parameters can produce different results but indicate that the ODME with a weight on the seed matrix (the matrix from the demand forecasting model) can result in lower deviation from the seed matrix. Still, the results show large differences between the regional model O-D demands and the O-D demands resulting from the ODME with different parameters. This result indicates the need for better calibration of the regional models, possibly based on real-world partial O-D matrices. Performing the ODME with no seed matrix results in fewer destinations and higher deviations from other setups of the ODME procedure.



Source: FHWA.
SERPM = Southeast Florida Regional Planning Model.

Figure 6. Scatterplot. Examination of volumes to the top 10 destinations for zone 40.

PERFORMANCE MEASURE DEFINITIONS (GAP 2.1 AND GAP 2.2)

MRM helps ensure consistency between the performance measures at different levels. However, before addressing these issues, understanding fundamental differences in metrics definitions at different levels is helpful. Measures such as travel time, delays, stops, queues, and density have the same name in different tools but are defined and calculated differently. The discussion in this section addresses gap 2.1 (variations in the definitions of measures) and gap 2.2 (variations in the methods used to estimate various performance metrics).

Traffic Analysis Toolbox Volume VI addressed differences in the definition, interpretation, and computation of measures in various modeling levels and tools (Dowling 2007). One example given in the report is that some simulation tools compute vehicle miles traveled only for vehicles that enter the link during the analysis period, while others include the vehicles present on the link at the start of the period. Another example is that some tools include second-by-second calculation of the measures, while others only calculate measures for vehicles able to exit the link during the analysis period.

Yet another example is the computation of VHT (Dowling 2007). Some simulation tools include the delay incurred by vehicles denied entry to the system. Most others do not. Most tools calculate delay using free-flow speed as a basis. The report concluded that the measures from simulation model tools are usually not directly translatable into *HCM* measures and LOS (Dowling 2007). The report recommended using measures calculated consistently based on vehicle trajectories for comparing results between tools and methods. Mesoscopic and microscopic models make such computation possible. The following discussion describes how the macroscopic, mesoscopic, and microscopic models consider movement capacity and calculate the travel time or delay.

Utilized Macroscopic Traffic Model

Most demand forecasting models apply VDFs, which are the relationship between speed and the v/c ratio, such as the BPR equation, Akçelik equation, modified Davidson equation, and conical equation (BPR 1964; Akçelik 1991; Tisato 1991; Spiess 1984). The macroscopic modeling tool uses the BPR equation for static assignment for this case study. Figure 7shows the expression of the BPR curve, which has been widely used in travel demand models to calculate link travel time.

$$\boldsymbol{t_i} = \boldsymbol{t}_0 \left[1 + \boldsymbol{\alpha} \left(\frac{\boldsymbol{v}}{\boldsymbol{c}} \right)^{\boldsymbol{\beta}} \right]$$

Figure 7. Equation. BPR VDF (BPR 1964).

Where:

- α = coefficient.
- β = BPR exponential coefficient.
- c = link capacity.
- t_i = congested travel time for link i.
- t_0 = free-flow travel time for link i.
- v = traffic volume on link i.

Analysts usually calibrate these parameter values by FT based on local conditions using real-world traffic data. Analysts have also used microscopic simulation modeling to estimate these parameter values.

VDFs like the BPR require capacity and free-flow speed as inputs. They calculate delay as the difference between the free-flow travel time and the calculated travel time using the equation in figure 7. Although the BPR curves are very popular in static route choice assignment as part of demand forecasting, modelers often criticize it for underperforming in congested traffic conditions where demand exceeds capacity. The BPR relationship suggests that if volume (or flow) increases relative to the capacity, the speed decreases (or the travel time increases). The BPR curve defines delay as a function of link length instead of the number of vehicles in the queue (TRB 1999). Thus, the shorter the coded link is with the high v/c ratio, the lower the delay. No spillback of congestion projected to upstream links is considered. In addition, the model allows having v/c ratios higher than 1.0 (Hadi et al. 2019). This discussion indicates major deficiencies in the BPR curve and similar VDF relationships.

The traditional values for α and β are 0.15 and 4, respectively (Martin 1998). However, the value of α could vary from 0.1 to 1.0, and the value of β could vary from 4 to 11, according to Dowling (1997). Different studies have calibrated the BPR equation for various conditions and found different values for the parameters (Dowling 1997; Martin 1998; Moses et al. 2013; Horowitz et al. 2014).

Utilized Mesoscopic Simulation

Simulation-based assignment (SBA) is a DTA procedure that uses network loading based on mesoscopic simulation. The algorithms used in the SBA reflect the work of Mahut (2001). In the West Palm Beach case study, the mesoscopic SBA simulates individual vehicles with a simplified car-following model and lane-changing assumptions. The car-following model keeps a temporal distance to the rear end of the leading vehicle based on the reaction time, plus the time required by the vehicle to stop. The lane-selection procedure accounts for the lanes and turns that allow the vehicle to follow its route. Intersection modeling accounts for signal control and gap acceptance. SBA assumes a fixed-time traffic signal control. SBA accounts for conflicts between turning flows similar to the *HCM*.

The default values for time gaps are from the *HCM*, but the analyst can overwrite these if desired. The critical gap defines the time headway between two vehicles of the higher ranked traffic stream, allowing one vehicle from a lower ranked movement to turn in the desired direction (PTV Group 2019a). The critical gap determines how the capacity of the lower ranked movement changes, depending on the higher ranked traffic stream with the right-of-way. The followup gap in the SBA is the time headway between the departures of two consecutive vehicles from the same lower ranked approach. Consequently, the followup gap determines the saturation flow rate of the minor flow. Followup gaps only impact vehicle behavior if they lead to a longer minimum time headway than defined by the car-following model (PTV Group 2019a).

In the SBA, capacity is an output of the model rather than an input, as in the BPR. The capacity is a function of the reaction time and the effective vehicle length per link using the corresponding link attributes “SBA reaction time factor” and “SBA effective vehicle length factor.” SBA calculates delay time from the loaded travel times on the network object (links/turns) minus the unloaded travel times. Loaded travel time implies the travel time with traffic assigned to the network, while the unloaded travel time is with no traffic assigned to the network. Other important parameters that affect capacity for opposed movements (at unsignalized intersections or permissive movements at signalized intersections) are related to gap acceptance, which are the critical gap and the followup gap.

Utilized Microscopic Simulation

In the West Palm Beach case study, the traffic flow model in the microscopic simulation tool contains a detailed car-following model, lane-changing model, and gap-acceptance model. The tool uses the psychophysical perception model developed by Wiedemann (PTV Group 2019a). In addition to the car-following model parameters that affect capacity (which is also an output of the model rather than an input) and performance, many other parameters have significant impacts. Analysts usually fine-tune these parameters during the calibration process.

The microscopic simulation tool calculates delay as the difference between individual vehicle travel time and desired travel time (PTV Group 2019b). This calculation is different from other models, such as the SBA, that calculate the delay as the difference between the loaded and unloaded travel time, as described in the “Utilized Mesoscopic Simulation” section. In addition, the microscopic simulation tool accounts for reduced turn speeds in the ideal travel time. The travel times and delays are computed from the actual travel times of all vehicles passing the destination point (PTV Group 2019b).

PERFORMANCE MEASURE CONSISTENCY (GAP 2.4 AND GAP 3.6)

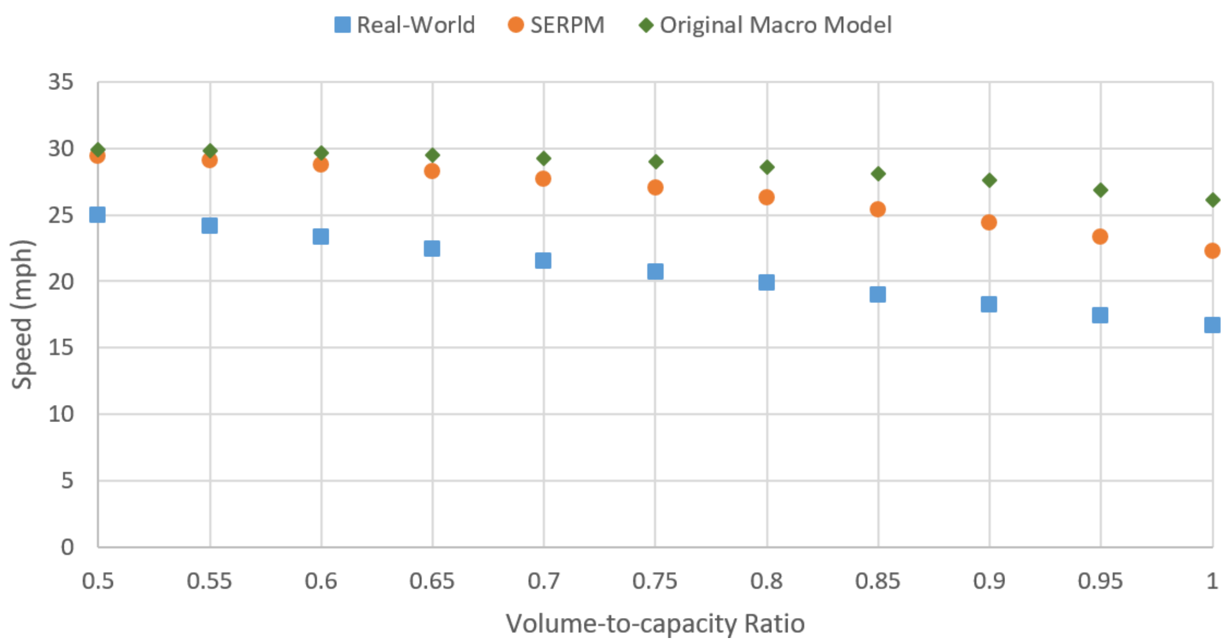
This section discusses the feedback loop that can improve the consistency between the performance measures at different levels. The section addresses gaps 2.4 and 3.6 by examining the impact of more consistent measures among levels on assignment results and the impact of a feedback loop that improves consistency on MRM performance.

Different model resolutions calculate the performance measures differently. In the West Palm Beach case study, the utilized macroscopic model requires capacity as an input and calculates delay as the difference between travel time calculated by the BPR equation and free-flow travel time. The utilized mesoscopic model calculates capacity based on reaction time, effective vehicle length, and gap acceptance parameters and calculates delay as the difference between loaded and unloaded travel times. In the utilized microscopic model, capacity results from the simulation of individual vehicles with the specified microscopic traffic flow model parameters. The utilized microscopic simulation tool calculates delay as the difference between each vehicle’s travel time and its desired travel time.

Thus, the three resolution levels assess capacity and delays using different definitions and methods. However, fine-tuning the specific parameters of the traffic flow models in each resolution can result in comparable estimates of capacity and delay in the three resolutions. This adjustment is key to the success of MRM because the ODME and assignment conducted at the macroscopic and mesoscopic levels produce demands used as inputs to the microscopic level. If the macroscopic and mesoscopic models underestimate delay on a given path, the heavy assigned traffic may produce unrealistic gridlock in the microscopic network. This study used a precalibrated microscopic simulation model (Palm Beach County 2020). Thus, the researchers investigated fine-tuning model parameters in the macroscopic and mesoscopic models to produce capacities and travel times consistent with those produced by the microscopic model.

VDF Calibration

The West Palm Beach case study examined the impact of using the microscopic simulation model at the lower level of MRM to calibrate the BPR curve used in the static assignment at the upper macroscopic level. The research team compared the calibrated curves with the curves used in the Southeast Florida Regional Planning Model (SERPM) and those used in the base macroscopic model from Palm Beach County (FSUTMSOnline 2021). Figure 8 shows a comparison of the SERPM curve ($\alpha = 0.35$ and $\beta = 4.05$), the base curve used in the original macroscopic network ($\alpha = 0.15$ and $\beta = 5$), and the developed evening period model considering all critical network links ($\alpha = 0.8$ and $\beta = 2.0$). It is possible to calibrate the BPR curve for individual links in the network at higher spatial resolution (shorter links) if the analyst can extract sufficient data from the simulation model for a more accurate representation of the BPR curve. Using shorter links would likely decrease the speed at higher v/c ratios than using longer links, as was done in the networkwide BPR calibration.



Source: FHWA.

Figure 8. Chart. Comparison of the BPR curve derived from simulation models with those used in the demand forecasting model and base macroscopic model.

In addition to the BPR calibration, the research team also used the microsimulation model capacity as an input to the BPR curve. As stated earlier, capacity is an input to the macroscopic model in the demand forecasting tools, but it is output from the microscopic simulation model. Table 2 compares the capacities used in the demand forecasting model and the base macroscopic model to those obtained from the microscopic simulation model. The team used the calibrated BPR curve and capacities in an updated version of the macroscopic modeling tool for use in the static assignment. The team examined the impacts on results, as described in the "Impact of Feedback Loop on Assignment Results" section later in this report.

Table 2. Comparison of capacities derived from simulation with those used in the demand forecasting models and the base macroscopic model.

Critical Links	Capacity Per Lane Per Hour		
	Measured from Micro Model	Default in Macro Model	Default in Demand Model
Okeechobee Boulevard	850	1,715	1,035
South Tamarind Avenue	650	1,470	1,035
Banyan Boulevard	400	1,470	1,035
South Australian Boulevard	850	2,205	1,902

SBA Model Calibration

The next step was to examine the capacity and travel time/delays outputs from the utilized mesoscopic model (the SBA model). As described earlier, unlike the utilized macroscopic model, capacity is an output rather than an input from the SBA. The research team performed this examination for both signalized and unsignalized intersections. First, the team compared capacities estimated by the SBA mesoscopic model, the microsimulation model, and the *HCM* signalized intersection procedure within the Highway Capacity Software™ (HCS™) (McTrans 2021). The results in table 3 indicate that capacities between the three models were comparable. However, both the mesoscopic and microscopic model could be further calibrated to better match the HCS-estimated capacities or real-world measured capacities.

Table 3. Estimated capacities of Okeechobee Boulevard at South Tamarind Avenue intersection using different methods.

Approach	Movement	Mesoscopic Model Capacity (vphpl) (Default Reaction Time)	Mesoscopic Model Capacity (vphpl) (Fine-Tuned Reaction Time)	Microscopic Model Capacity (vphpl)	HCS Capacity (vphpl)
Eastbound	Left	503	495	411	369
	Through	835	774	655	638
	Right	1,117	818	794	637
Westbound	Left	390	375	326	278
	Through	765	592	664	558
	Right	830	753	720	558
Northbound	Left	386	367	339	304
	Through	487	421	390	326
	Right	1,118	881	686	552
Southbound	Left	325	320	289	253
	Through	470	388	342	291
	Right	958	843	559	528

vphpl = vehicle per hour per lane.

As stated earlier, analysts can calibrate protected movement capacities by varying the reaction time and vehicle length in the mesoscopic model. However, the research team found a large deviation between capacities of the SBA turn movements compared to those estimated by the other two models. The team attributed this to the right-turn-on-red gap acceptance algorithm in the SBA. The team increased the critical gap and followup gap times from the default values. The resulting capacity was closer but still higher than the other capacities, indicating the need to further examine gap acceptance models in the SBA. The team performed the comparisons assuming no spillback from downstream intersections or other activities, such as railroad and drawbridge preemptions. The calibration of specific movement capacities can account for these impacts too. The next step was to examine the consistency of the relationship between average delay and v/c ratio. The team compared the microscopic, mesoscopic, noncalibrated macroscopic

BPR, and calibrated macroscopic BPR models at a critical intersection in the network. Although the BPR model calibration improved the results slightly, the analysis showed that the BPR curve underestimates the delays, particularly for v/c ratios higher than 0.9.

The delay versus v/c ratio variations were similar in the microscopic and mesoscopic simulation models. However, on the northbound approach, there was a large difference in delays for v/c ratios higher than 0.8. Further examination indicated this was due to spillover from the left-turn bay to the through-movement lanes. The research team performed further explorations assuming that the left-turn lane is a full lane rather than a turn bay. The difference decreased significantly but still existed. Further examination indicated this difference between mesoscopic and microscopic models was due to a large number of vehicles changing lanes in the microscopic model. Many vehicles changed lanes from the right lane to the left lane to make a left turn, and the left-turn movement was heavy. The result indicates that lane-changing behavior in microscopic models can produce capacity drops that are difficult to account for in mesoscopic models. One option is to adjust the capacity or the BPR curve parameter for the segment to consider such impacts.

Regarding the unsignalized intersections, with no calibration there were large differences in the capacities according to the microscopic and mesoscopic models of the minor streets of two-way, stop-controlled intersections. However, after calibrating the gap acceptance parameters, the differences in capacities between the two models were significantly smaller.

Impact of Feedback Loop on Assignment Results

This section compares the results of the assignment with and without this feedback loop when exported to the microscopic model. The assignment's objective was to minimize travel times on selected routes between each O-D pair in the network. Thus, a better assignment procedure should result in lower overall travel times when analysts import assignment results into a microscopic simulation model. The static assignment results showed that the sum of travel time on critical links was lower after fine-tuning the BPR curve (1,334 versus 1,667 s per vehicle, or a 20-percent improvement). Subsequently, the critical link travel times assessed by microscopic simulation dropped, some of them significantly, after fine-tuning traffic flow model parameters in the assignment stage.

Integrated Supply-Side Calibration

Through an integrated supply-side parameter calibration package with consistent definitions of traffic flow models and macroscopic VDFs, analysts can use open-source or commercial software to streamline data processing. In this manner, analysts can focus on key parameter estimation steps and reasonably expect good-quality calibration based on peer agencies' results, rather than relying on engineering judgment in error checking for supply-side parameters. This aspect is vital. In current practice, analysts expend most of their energy on error checking for network topology and lane configuration, as opposed to traffic stream model parameters (e.g., ultimate capacity, critical density, free-flow speed, and speed at capacity). The authors recommend different MPOs maintain consistent definitions of those parameters and ensure the transferability of supply-side models across regions and states. Figure 9 through figure 11 depict the speed-flow, speed-density, and flow-density relationships based on dataset 1 in the Phoenix case study, respectively, for freeways in the CBD (Wu et al. 2021). Covering 85 sensors and 3 million records, dataset 1 includes 2 mo of speed and volume data on the freeway’s managed lanes and general-purpose lanes at 15-min intervals, from January 1 to February 29, 2020.

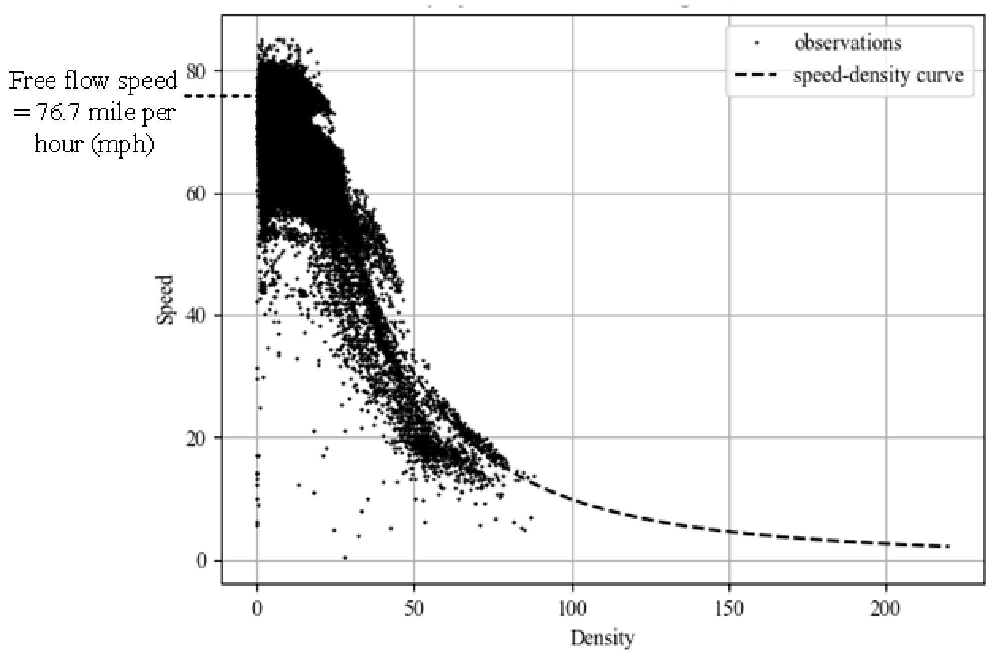


Figure 9. Graph. Calibrated speed-density relationship using freeway data in the CBD (Wu et al. 2021).

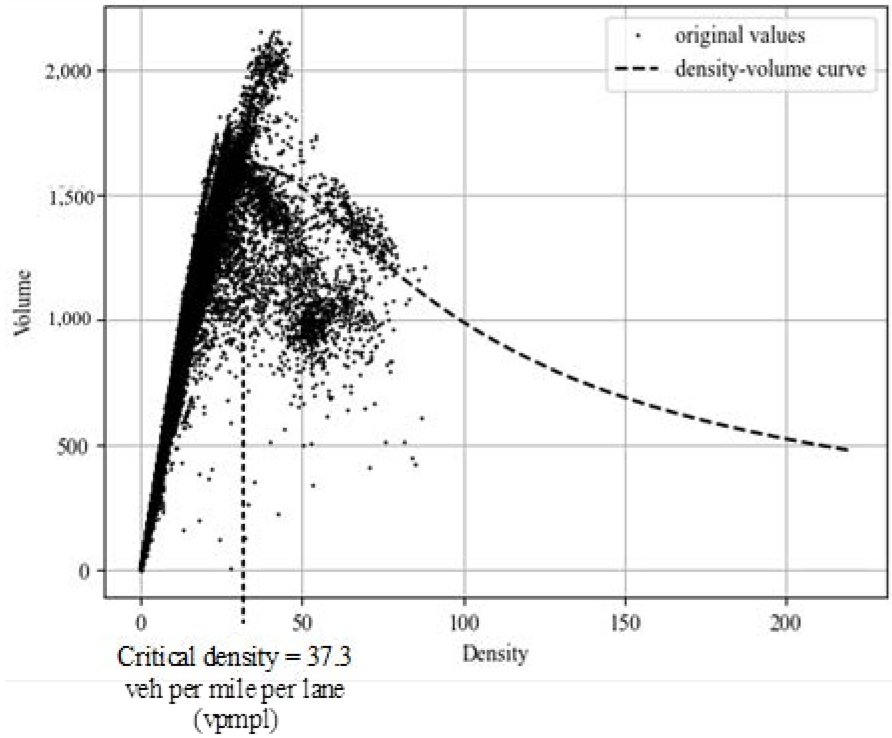


Figure 10. Graph. Calibrated volume-density relationship using freeway data in the CBD (Wu et al. 2021).

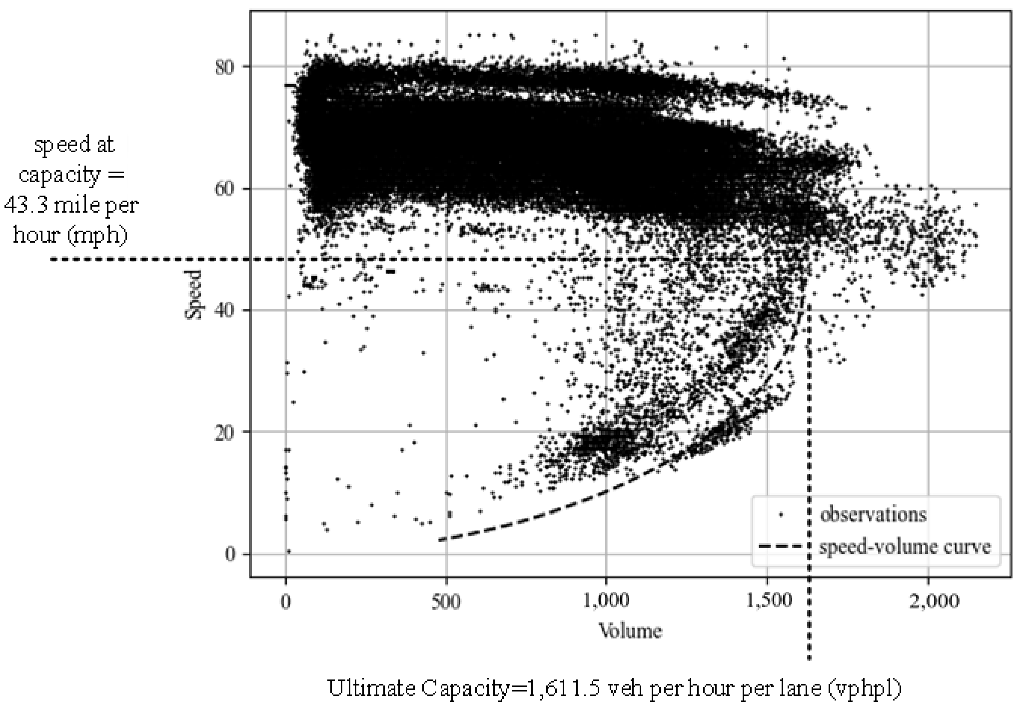
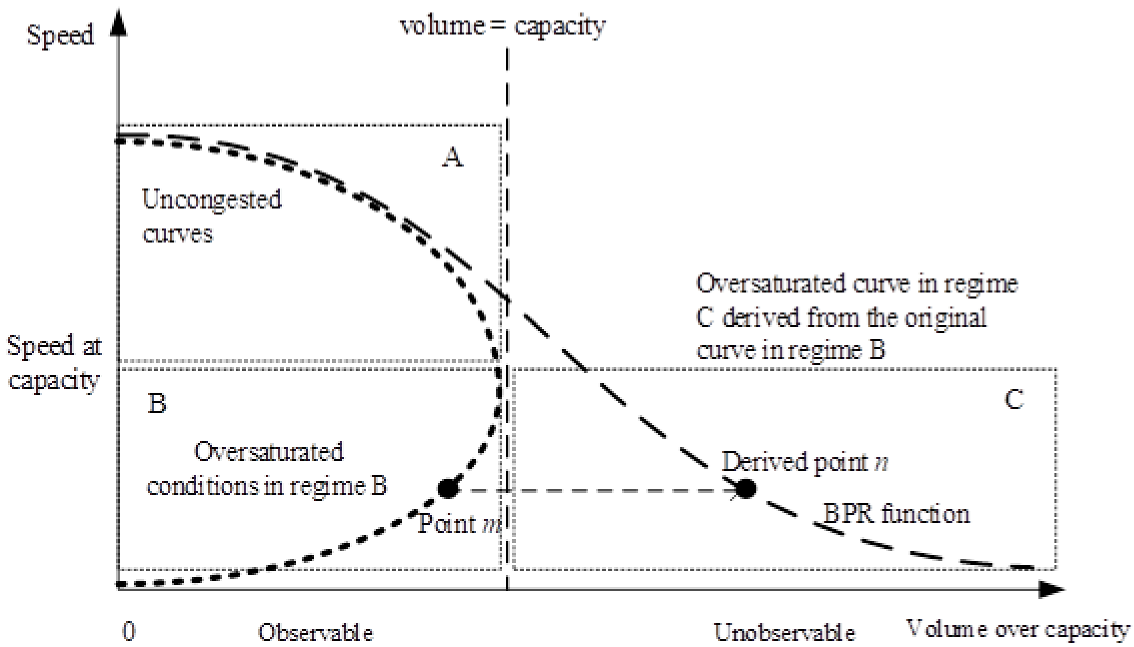


Figure 11. Graph. Calibrated speed-volume relationship using freeway data in the CBD (Wu et al. 2021).

The standard BPR function is a normalized VDF expressed in the v/c ratio. Analysts should calibrate α and β in the BPR function with the peak hour factor (PHF) for FT and AT using traffic sensor data. To bridge the gap between different resolutions of the demand-supply relationship, and specifically to consider the oversaturated case, the Phoenix case study used a queue-based method (QBM) for the BPR calibration (Belezamo 2020; Wu et al. 2021). The QBM is a demand-oriented calibration approach that closely connects traffic flow measures and queue dynamics (e.g., bottleneck, evolutions, and capacity drop). For a clear demonstration, figure 12 partitions the VDF coordinate plane into three regimes with speed at capacity:

- Regime A: observed flow rate undersaturated with v/c ≤ 1 and uninterrupted free speed.
- Regime B: observed reduced flow rate saturated with v/c = 1 and reduced speeds.
- Regime C: unobserved but derived "demand" volume oversaturated with v/c ≥ 1 with reduced speeds.



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m = observed point; *n* = derived point.

Figure 12. Graph. Regimes in the speed versus v/c ratio coordinate plane (Wu et al. 2021).

The term "derived demand" is used in regime C because analysts should ensure that traffic counts reflect demands instead of the road capacity constraints. As Huntsinger and Rouphail (2011) discussed, the demand in regime C is not simply the traffic volume measured by the detector for a given time interval (e.g., a peak hour defined as 4–5 p.m.). At a certain interval with queue measured, the demand D at the bottleneck includes two elements, namely the queue length and the demand at the bottleneck capacity. Accordingly, a concept of demand-over-capacity (D/C) ratio should be introduced when queuing occurs.

Figure 12 uses the traffic flow model and BPR function to illustrate the three regimes. According to the flow model, observed flow falls into regime B. Comparatively, the oversaturated part of the BPR function falls in regime C. As a result, the calibration process maps the speed-flow measurements (point *m*) from observable regime B to derived point *n* in regime C. The Phoenix case study uses the QBM, which defines the volume corresponding to point *n* as queued demand, including the bottleneck discharge rate and queued vehicles during a time interval. The v/c ratio in the BPR function is the D/C. A v/c greater than or equal to one implies that demand exceeds supply. The research team defined the queue demand factor (QDF) in figure 13 to convert assigned volumes to peak-hour demands in relation to ultimate hourly capacity.

$$QDF = \frac{\text{Total volume of an assignment period}}{\text{Queued demand of a peak hour}}$$

Figure 13. Equation. QDF formula.

In figure 14, the morning peak assignment period covers 6–9 a.m. The minimum speed u_{min} happens between 8 and 8:15 a.m. The peak hour is between 7:45 and 8:45 a.m., including data collected in four 15-min periods. Volume within the peak hour is denoted as D_h. To enable mapping from regime B to regime C, the research team first found the lowest speed u_{min} during the assignment period, then extended the congestion period range until the speed was higher than the speed at capacity (u_c), as shown in figure 15. Next, the team considered a congestion period from t_0 to t_3 containing the peak hour. The total volume *D* within the congestion period is equivalent to the queued demand for the peak hour's capacity under oversaturated conditions. This situation implies that when t_3–t_0 exceeds 1 h, *D* is greater than or equal to D_h, and *D* becomes the queued demand for the peak hour.

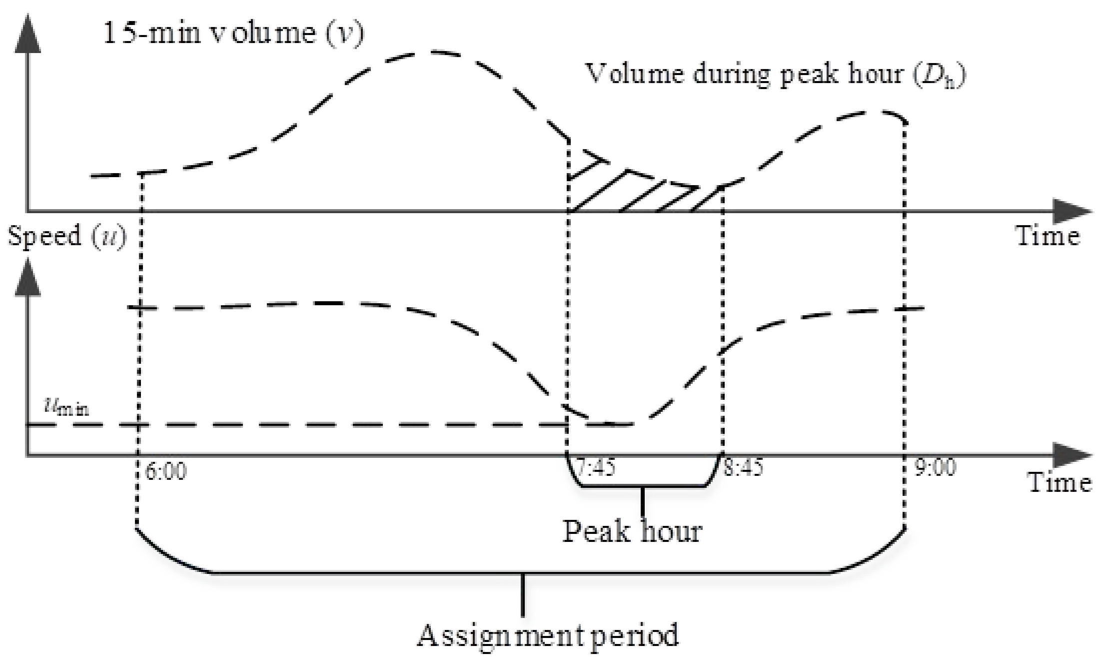
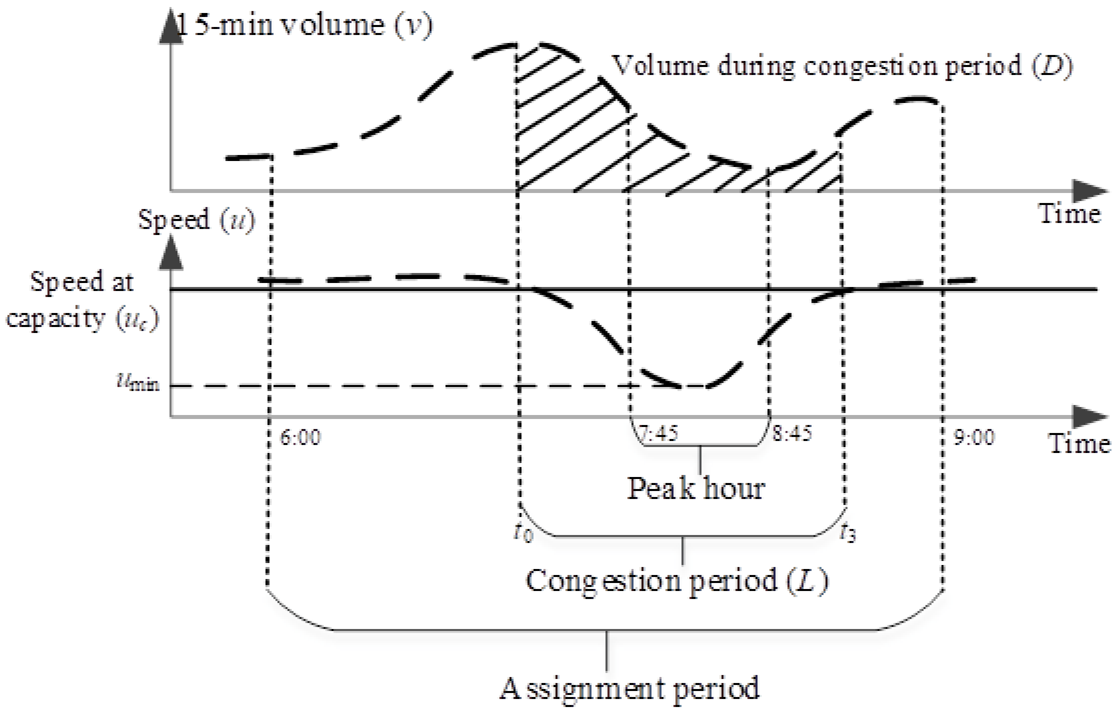


Figure 14. Graph. Derived queued demand when congestion duration is less than 1 h (Wu et al. 2021).



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t_0 = start of congestion period; t_3 = end of congestion period.

Figure 15. Graph. Derived queued demand when congestion duration exceeds 1 h (Wu et al. 2021).

In this task, the research team compared the QBM with two existing methods: the volume-based method (VBM) and the density-based method (DBM). The VBM is adapted from the Florida Standard Urban Transportation Modeling Structure (Moses et al. 2013). The DBM uses a direct approximation of density measurements to cover regimes A and C to connect fundamental diagrams with the VDF function (Drabicki, Kucharski, and Szarata 2017). The team used the mean absolute percentage error to evaluate the effectiveness of the calibration for all links in each FT/AT combination. The team calibrated the VDF under the following conditions and assumptions, producing the results shown in figure 16:

- CBD area.
- Evening peak period.
- $\alpha = 0.21$.
- $\beta = 4$.
- AT = 1.
- FT = 1.

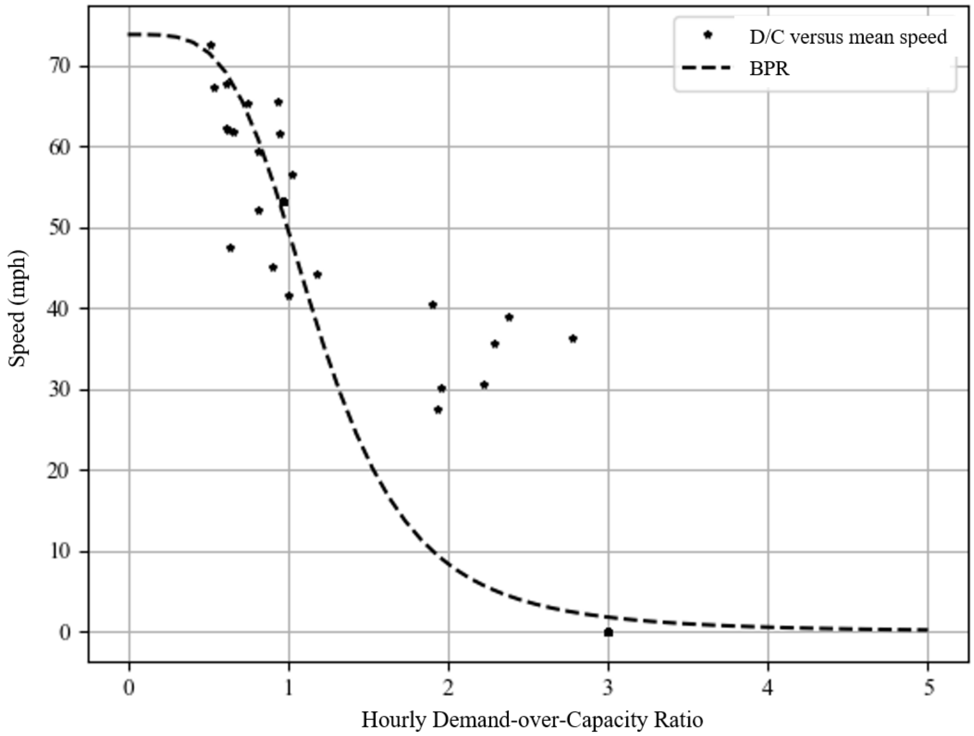


Figure 16. Graph. VDF calibration results for the Phoenix network.

The research community acknowledges different perspectives within traffic flow theories and the VDF function. The speed-volume relation plotted using field data has a parabolic U shape, while the fitting of the VDF requires the monotonously decreasing function. Thus, figure 16 does not use the common v/c ratio on the *x*-axis to avoid confusion with the speed-volume relationship. Instead, researchers have adopted the D/C ratio to properly address oversaturated conditions in which D/C ≥ 1 (Huntsinger and Rouphail 2011).

The developed joint traffic stream model and VDF calibration framework allow modelers to estimate the congestion period during which both speed and flow drop due to oversaturation. This MRM approach can better characterize the volume term in the traditional v/c ratio as the queued demand after a bottleneck. Researchers could further enhance the CBI tool (Hale et al. 2016, 2021) to enable a congestion-period demand-oriented calibration framework, which closely connects traffic flow measures and queue dynamics (e.g., bottleneck, evolutions, and capacity drop).

BENEFIT OF THE FEEDBACK LOOP (GAP 3.6)

The effective integration of different AMS tools should carefully address gap 3.6 (feedback loop in internally consistent cross-resolution traffic representation). For example, integrating microsimulation tool outputs into macroscopic demand models could provide improved accessibility indicators from the agent-based traffic simulation model to the upper level demand model. Accordingly, the macroscopic demand model could adjust the demand to be loaded in the lower level representation.

Without systematic O-D demand and supply-side calibration, as shown in the West Palm Beach case study and the Phoenix case study[9], simply loading initial demand into a microsimulation network could lead to unrealistic oversaturated conditions. In addition, analysts and planners should also address gap 6.1 (the transportation agency valuation of the MRM implementation benefits), as exchanging accurate roadway attributes across open data and existing planning models could be mutually beneficial.

Microsimulation Results Feedback

In the West Palm Beach case study, the researchers calibrated the capacity outputs from the mesoscopic model (the SBA model) to be consistent with those obtained from microsimulation. Unlike in the utilized macroscopic model, capacity is an output of the SBA rather than an input, as in the microsimulation and the mesoscopic model. The research team performed this calibration for both signalized and unsignalized intersections. The team also examined the consistency of the relationship between average delay and v/c ratio in the SBA compared to the microsimulation. The analyst could further use such examination to fine-tune the model parameters to consistently estimate delays in the two models.

This study showed that it is possible to fine-tune model parameters in the SBA to produce capacities close to those produced by the microsimulation. The study also showed the variations of delay with the v/c ratio are similar in the microscopic and mesoscopic simulation (SBA) models. However, certain traffic flow characteristics that affect capacity are not explicit inputs to microsimulation, producing inconsistency between the models. This inconsistency occurs at locations with weaving, lane changing, permissive movements, and spillovers from left-turn bays. Under such conditions, achieving 100 percent consistency between the models is difficult. However, analysts should try to maintain consistency as much as possible. Without such consistency, assigning traffic to paths identified as optimal in the SBA may produce unrealistic gridlock in the microsimulation.

DTA Results Feedback

The Maricopa Association of Governments (MAG) is currently working on implementing an integrated ABM and regional traffic assignment. This section summarizes the current modeling effort at MAG. The MAG research team plans to use this integrated model to link travel behavior choices, such as departure time, route choice, and mode choice. In the Phoenix case study, the research team examined feedback loops between ABM, DTA, and microsimulation tools in the subarea. The team used the feedback loop mechanism to integrate ABM and DTA for demand modeling. The ABM output includes the trip-chain files to describe the personal/household travel behaviors. Analysts can then use the trip-chain files as input demand files for DTA models. In a real-world situation, ABM and DTA integration may create inconsistencies (e.g., ABM demands estimated from households may exceed the capacities of DTA models) since they use different models to estimate travel demand and capacity.

Two approaches can improve MRM consistency. First, modelers can carefully calibrate link capacities within DTA models. Second, modelers can build feedback loops between ABM and

[9]Ibid.

DTA to adjust O-D demands within the DTA model. Figure 17 illustrates the ABM-DTA integration provided by MAG.

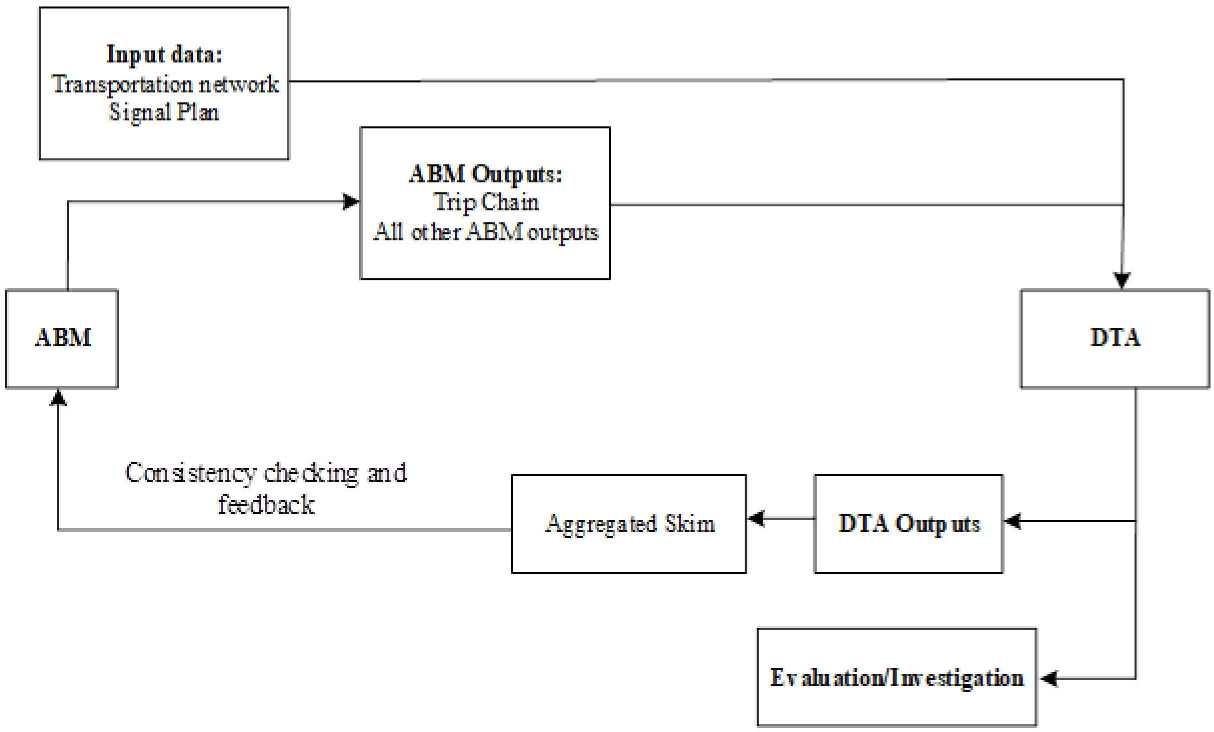


Figure 17. Flowchart. ABM and DTA integration.

MODEL CONVERSION EFFECTIVENESS (GAP 3.1)

This section addresses gap 3.1 (methods and tools supporting the integration and data conversion between different modeling levels). In the West Palm Beach case study, the automated conversion of networks between three modeling tools (demand forecasting, macroscopic and mesoscopic, and microscopic) was easy to use, and the converted networks had no significant issues.

Integrated Multiresolution Calibration

In the Phoenix case study, to support integration and data conversion between different modeling levels in MRM, especially mesoscopic tools using traffic stream models and macroscopic regional models using VDFs, the research team aimed to deliver a consistently calibrated set of traffic flow models and VDFs. As documented in the study supported by MAG, the challenge in calibrating VDFs comes from a lack of mathematically rigorous definitions for the v/c ratio, and more importantly, its underlying long-term planning resolution is different from the operational perspective of traffic flow theories (Wu et al. 2021). The analysis described in this section attempts to demonstrate a theoretically consistent and practically effective framework for a data-driven joint traffic flow model and VDF calibration process.

If necessary, the team planned to implement a refined BPR function (or other function). The team used speed and flow data in the developed validation database to calibrate the key parameters of α and β in the BPR function. The team compared calibration outputs with results from the previous round of BPR model calibration and conducted a comparative analysis to demonstrate the benefits of any updated functional form to improve the predictive accuracy in STA. A flowchart from the case studies report illustrates the joint traffic stream model and VDF calibration process, which includes the following six major steps[10]:

1. Traffic stream model calibration: For each VDF type, calibrate coefficients of the traffic stream model, including free-flow speed, ultimate capacity, and speed at capacity.
2. Queued demand: For each link, calculate the queued demand during the congestion period.
3. VDF calibration: For different peak periods and VDF types, calibrate VDF coefficients (i.e., α and β) in the BPR function.
4. QDF: Calibrate the QDF and period capacity.
5. Traffic assignment: Given the peak period O-D matrix, perform STA using a standard transportation planning package; compare outputs with the base-year observations.
6. Calibration extension: Extend the static link volumes to time-dependent queue lengths.

Open-Source Data Integration

To demonstrate the MRM process, the Maryland case study used open-source tools to build a multiresolution I–95 network, with additional detail provided in the case studies report[11]. The research team first downloaded original map data for the subarea network from OSM, then converted it to macroscopic GMNS network files. The team generated corresponding mesoscopic and microscopic networks by using the open-source tools. Notably, OSM often represents one large intersection with multiple nodes to allow flexibility of user input; however, this structure makes the simulation of traffic signal timing very difficult. Accordingly, the team developed a function to consolidate intersection nodes, generating a new node to replace existing nodes for each intersection within a certain buffer.

The open-source tools support five different transportation modes to facilitate multimodal modeling, including automobile, bicycle, walking, rail, and air. The tools can also import POI nodes and create connectors. This case study adopted and extended the GMNS-based representation for ABM and macro-, meso-, and microlayers of representation to achieve a hybrid-resolution network construction. The study adopted the GMNS standard for multiresolution transportation network representation, even though the developers mainly designed GMNS for macroscopic networks. As a result, this MRM-oriented study extends the GMNS-based representation for both mesoscopic and microscopic networks. In the long run, the researchers intend the proposed open-data and open-source framework to create a free open-package and open-data ecosystem, which could reduce the cost and complexity of managing computers and simulation models. The base representation of GMNS would allow different

[10]Ibid.
[11]Ibid.

communities to build versions of a high-fidelity virtual model from different open and user-contributed data sources.

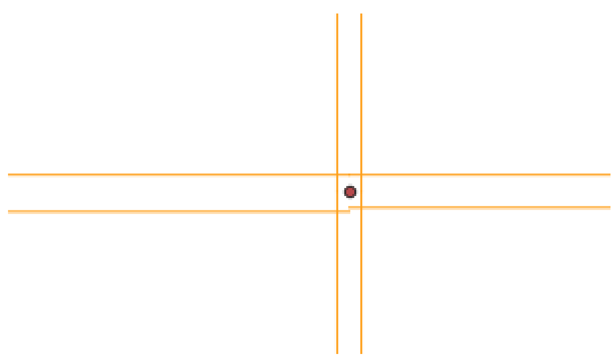
Mesoscopic Network Representation

Compared to the original macroscopic network, the mesoscopic network has more detailed information in the intersections. In the mesoscopic network, the research team expanded each intersection represented by a node in the macroscopic network. The team built a connector link for each intersection movement to facilitate intersection modeling, especially for signalized intersections.

Macroscopic and mesoscopic networks have different link-level coding schemes. Macroscopic networks often represent a road segment between two adjacent intersections as a link; however, lane changes sometimes occur within a link, especially when close to intersections. Changes in the number of lanes result in capacity changes, but the link attributes cannot properly reflect these changes. This situation may bring inconvenience or even potential errors when performing network modeling. In the GMNS standard, the comma-separated values (CSV) file, segment.csv, stores lane changes. The research team split and converted each link with lane changes from a macroscopic network to multiple mesoscopic links so that each mesoscopic link has a homogeneous capacity.

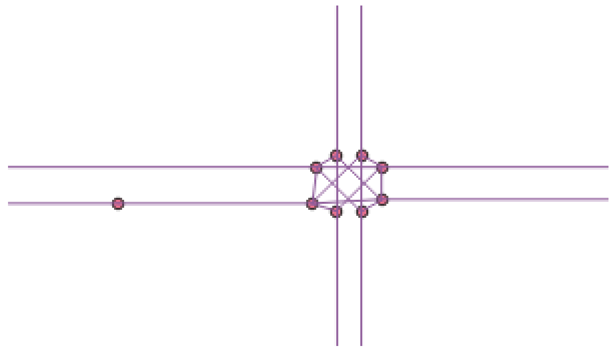
Microscopic Network Representation

In the Maryland case study, microscopic networks used a lane-by-lane, cell-based representation. Instead of a conceptual line segment, lanes represented each link. The research team further discretized lanes into small cells to accurately describe vehicle motion status when moving on the road, as shown in figure 18-C. The team also created changing cells to enable vehicles to switch trajectories between lanes. Users can customize the length of cells to accommodate different modeling needs.



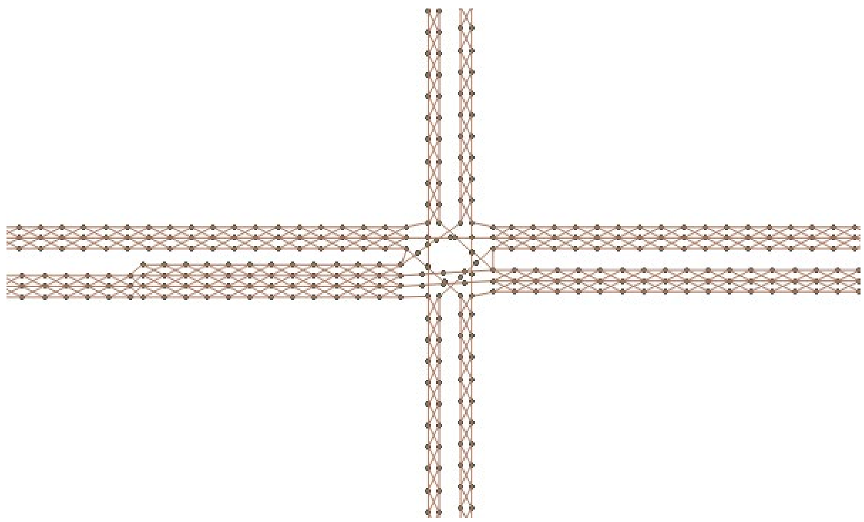
Source: FHWA.

A. Macroscopic network representation.



Source: FHWA.

B. Mesoscopic network representation.



Source: FHWA.

C. Microscopic network representation.

Figure 18. Illustrations. Multiresolution network representations in the Maryland case study.

SUMMARY

In this chapter, the authors discussed the outcomes and lessons learned from the MRM case studies conducted during the project. In the early stages of the project, stakeholders reported the lack of MRM case studies as a barrier to MRM adoption for transportation agencies. Based on stakeholder feedback, a comprehensive gap analysis informed these case studies. These case studies focused on the technical aspects of MRM, as opposed to the high-level institutional activities that may help support MRM. More detailed information on these case studies is available in the *MRM Case Studies Report*[12]. The following sections summarize the outcomes and lessons learned from the MRM case studies.

[12]Ibid.

O-D Demand Estimation

The research team obtained good results from the least-squares ODME procedure in the macroscopic modeling tool. This method always delivers a solution, and its run time is significantly lower than other methods. Analysts can also use the least-squares method in large networks containing many count locations.

Using an O-D matrix directly from the demand forecasting model in the assignment does not produce realistic turning movement volumes. Using an ODME based on the counts without using a seed matrix (as many users do) also does not produce good results. Simulation modelers should work with demand forecasting modelers to improve the demand forecasting model results and increase its applicability as a seed matrix in the ODME. It is preferable to use turning movement counts for operational level analyses rather than link counts in the ODME process.

Performance Measure Definitions

Traffic Analysis Toolbox Volume VI addressed differences in the definition, interpretation, and computation of measures in different modeling levels and tools (Dowling 2007). The report concluded that the measures from simulation model tools are usually not directly translatable into *HCM* measures and LOS. The report recommended using measures calculated consistently based on vehicle trajectories for comparison of results between tools and methods. Such computation is possible with mesoscopic and microscopic models. Capacity is an input to the BPR function for traffic assignment at the macroscopic level. At the mesoscopic and microscopic levels, capacity is an output of the model.

Performance Measure Consistency

Microsimulation model results helped calibrate the capacities and BPR function parameters for static assignment at the macroscopic level. This calibration of the BPR function parameters and capacities improved the assignment results, as assessed by the microsimulation. Further improvement is possible if analysts calibrate BPR curve parameters for each segment in the network. Although the BPR model calibration improved the results, the BPR curve underestimates the delays, particularly for v/c ratios higher than 0.9. Analysts can calibrate capacity, v/c ratio, and delay outputs from the mesoscopic SBA model to be consistent with those obtained from microsimulation. However, certain traffic flow characteristics that affect capacity are not explicit inputs to microsimulation, producing inconsistency between the models. This inconsistency occurs at locations with weaving, lane changing, permissive movements, and spillovers from left-turn bays. Under such conditions, achieving 100 percent consistency between the models is difficult. However, analysts should try to maintain consistency as much as possible. Without such consistency, assigning traffic to paths identified as optimal in the SBA may produce unrealistic gridlock in the microsimulation.

Another important aspect is to ensure consistency between ABM and DTA. Speed and flow data can help calibrate key parameters in the BPR function. Using traffic sensor data, analysts should calibrate α and β in the BPR function with the PHF for FTs and ATs. To bridge the gap between different resolutions of the demand-supply relationship, MRM users can calibrate the BPR for the three regimes, as previously described in the "Performance Measure Consistency" section.

Benefit of the Feedback Loop

Integrating the microsimulation tool outputs into macroscopic demand models could provide improved accessibility indicators from the agent-based traffic simulation model to the upper level demand model. Accordingly, the macroscopic demand model could further adjust the demand to be loaded in the lower level representation. Without systematic O-D demand calibration and supply-side calibration, simply loading initial demand into a microsimulation network could lead to unrealistic oversaturated conditions.

The West Palm Beach case study showed that it is possible to fine-tune model parameters in the SBA to produce capacities close to those produced by the microsimulation. However, certain traffic flow characteristics that affect capacity are not explicit inputs to microsimulation, producing inconsistency between the models. This inconsistency occurs at locations with weaving, lane changing, permissive movements, and spillovers from left-turn bays. Under such conditions, achieving 100 percent consistency between the models is difficult. However, analysts should try to do this as much as possible. Without such consistency, assigning traffic to paths identified as optimal in the SBA may produce unrealistic gridlock in the microsimulation.

The research team proposed a feedback loop mechanism to integrate ABM and DTA for demand modeling in the Phoenix case study. Figure 17 illustrates the recommended ABM–DTA integration.

Model Conversion Effectiveness

In the West Palm Beach case study, the automated conversion of networks between the demand forecasting, macroscopic, mesoscopic, and microscopic levels was easy to use and greatly reduced the LOE. In the Phoenix case study, an integrated calibration procedure helped facilitate data conversion between the different MRM levels.

The Maryland case study demonstrated that open-source tools are now available to build MRM networks. The tools can convert map data available through OSM to macroscopic GMNS network files and generate corresponding mesoscopic and microscopic networks. The GMNS format facilitates enhanced calibration of traffic bottleneck locations, durations, and capacities using probe data. GMNS also facilitates the generation of traffic signal timing data for all scenarios and allows a more consistent definition of bottleneck locations and intersection turning movements for all modeling resolutions. GMNS is not yet compatible with all simulation tools and does not support all types of simulation input data.

CHAPTER 4. CONCLUSIONS

FHWA and the Traffic Analysis and Simulation Pooled Fund Study sponsored a research project on MRM. The project intended to develop consistent definitions and a unified modeling framework for MRM to help transportation professionals better understand the opportunities and challenges associated with MRM. The project team developed this guidebook to assist agencies with developing a fully integrated MRM analysis. The guidebook summarizes MRM terminology and definitions, provides a methodology for MRM analysis, and illustrates in three case studies the benefits of applying MRM. The proposed MRM methodology extends the seven-step methodology provided in FHWA's *Traffic Analysis Toolbox Volume III* for simulation analysis (Wunderlich, Vasudevan, and Wang 2019). This guidebook will help transportation professionals assess the LOE needed and the benefits of developing multiresolution models for their analyses and guide model development.

The project team created the *MRM Guidebook* to provide a detailed overview of MRM, a methodology for conducting an MRM analysis, and a set of MRM real-world case studies to illustrate the MRM methodology. Prior to creating the *MRM Guidebook*, the authors also developed a separate pair of publications: the *MRM SOPAGA Report* and the *MRM Case Studies Report*[1] (Zhou, Hadi, and Hale 2021).

In chapter 1 of this publication, the authors discussed the most fundamental MRM terms, definitions, and tools. More detailed information on these items is available in the *MRM SOPAGA Report* (Zhou, Hadi, and Hale 2021). In chapter 3 of this publication, the authors discussed the high-level outcomes and lessons learned from the MRM case studies conducted during the project. More detailed information on these case studies is available in the *MRM Case Studies Report*[2]. The suggested MRM methodology in chapter 2 is exclusive to the *MRM Guidebook*, although the *MRM SOPAGA Report* and *MRM Case Studies Report* may allude to certain components of the methodology.

Feedback from project stakeholders was instrumental in developing these three MRM publications (i.e., the *MRM SOPAGA Report*, *MRM Case Studies Report*, and *MRM Guidebook*). The project team held a series of informal virtual meetings with transportation agency representatives and modeling experts. Stakeholders reported a lack of MRM case studies as a barrier to MRM adoption for transportation agencies. However, different stakeholders have different analysis capabilities and needs. Based on stakeholder feedback, a comprehensive gap analysis informed both the case studies and the MRM methodology. Given the variety of gaps associated with MRM, the project team used the six dimensions of the CMM framework in the gap analysis: business processes, performance measurement, system and technologies, organization and workforce, collaboration, and culture (FHWA 2012). While four of these six dimensions relate to high-level institutional activities, the MRM methodology and case study chapters in this guidebook focus on the two more technical dimensions (i.e., performance measurement, system, and technologies).

[1]Hadi, M., X. Zhou, and D. Hale. Forthcoming. *Multiresolution Modeling for Traffic Analysis: Case Studies Report*. Washington, DC: Federal Highway Administration.

[2]Ibid.

The authors have some recommendations for using this guidebook. The high-level information available within each chapter should be informative for readers who are simply interested in learning more about MRM benefits, challenges, and mechanics. Alternatively, other readers may be motivated to apply certain aspects of the MRM methodology and case studies (e.g., scoping, level-of-effort estimation, model development, model calibration, alternatives analysis, feedback, and convergence) in the near future. In this case, the authors recommend locating and reviewing the information specific to their analysis needs. For example, regional analyses (having relatively large spatial and temporal scopes) involve a specific subset of analysis methods, tools, and options.

Portions of all three MRM publications address regional analysis considerations, such as demand estimation, ABMs, and STA. By contrast, other sections address operational analysis considerations, such as O-D matrix estimation, SBA options, and calibrating problematic network locations (e.g., locations with weaving, lane changing, permissive movements, sign-controlled movements, and queue spillover from turn bays). In addition, some readers may be interested in specific tools, such as commercial or open-source tools. In each case, the *MRM Guidebook* provides case studies specific to these tools, plus information on the level-of-effort estimation and model development associated with these tools.

In summary, the authors and the project team hope that the *MRM Guidebook* encourages more transportation agencies and analysts to apply MRM in projects where it may be beneficial. MRM could help a broader portion of the traffic AMS community achieve the benefits that the early adopters have witnessed.

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For figure 1, the original map is the copyrighted property of Google® Maps™ and can be accessed from https://www.google.com/maps. The map overlays showing regional, subregional, and corridor-level boundaries were developed as a part of this research project. The research team adapted figure 1 from Sloboden et al. 2012 (see References section).

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