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Chapter 12

SMART mobility via prediction, optimization and personalization

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Chapter outline

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1. Introduction

Technological advancements are altering the paradigm of transportation in various aspects. Information and communication technology is the key for this change providing new forms of travel platforms. Given the widespread availability of smartphones and ubiquitous connectivity, users are now planning their transportation activities through smartphone apps which enable them to reach various services easily. They also receive real-time information regarding their trips as advanced sensors are widely available. Therefore, they can reconsider their choices based on the latest updates. Furthermore, vehicle technology is advancing with electrification, automation, and connectivity. Technological advancements, taken together with a growing demand for mobility under environmental and energy constraints, have been key drivers of emerging mobility options that are on-demand, shared, integrated, real-time, energy efficient, and flexible. Ridesourcing, provided by transportation network companies (TNCs) such as Uber and Lyft, is one prominent example of a disruptive mobility alternative that matches passengers and drivers via location-enabled smartphone apps in real-time. Another emerging example is Mobility as a Service (MaaS) whereby consumers "buy mobility services (from participating providers) based on consumer needs instead of buying the means of mobility" using a single intermodal platform and payment (Kamargianni et al., 2016). In addition to increased passenger convenience and service efficiency, these new modes and services have the potential to reduce car ownership in the long term (e.g., Iacobucci et al., 2017; Schechtner and Hanson, 2017) and to complement mass transit as a first-/last-mile access mode (e.g., Jiao et al., 2017; Lyft, 2015). Automated vehicles will make these trends even more likely and will further enable new forms of mobility supply (Mahmassani, 2016).

Smart Mobility is broadly defined as the family of mobility solutions that use appropriate technologies and methodologies and that may leverage the availability of big data for the sustainability of transportation systems (e.g., Benevolo et al., 2016). Smart Mobility is acclaimed to bring about benefits including gains in safety, reduction in individual travel costs due to increased efficiency of operation, greater consumer choice, and more sustainable travel (Docherty et al., 2018).

We present in this chapter a Smart Mobility approach that consists of three key features: (1) *prediction*, (2) *optimization,* and (3) *personalization*. Firstly, *prediction* is the key for adapting the system to changing conditions on the network. Real-time data therefore needs to be incorporated to predict network conditions, e.g., congestion, in order to have proactive decision-making mechanisms. Secondly, *optimization* is the key to have decision-making mechanisms that achieve system-level objectives, e.g., minimizing network-wide travel times and maximizing revenue and/or consumer surplus. Appropriate optimization models need to be formulated (based on predicted network conditions) and solution methodologies need to be developed to ensure real-time efficiency. Finally, *personalization* is the key to safeguard users' benefits and attract various types of travelers through understanding their preferences. Methodologies need to be developed for estimating and updating individual-level preferences (e.g., willingness to pay) and optimizing the travel option to match those preferences while maintaining the system-level objectives. Furthermore, Smart Mobility solutions need to be assessed in terms of their user-level and system-level impacts. Multilevel simulation is a core of our approach for assessing the impacts of Smart Mobility before real-life implementation.

As an example of a Smart Mobility service that embeds the above features, Tripod (Lima Azevedo et al., 2018) is a smartphone-based system to influence individual real-time travel decisions by offering information and incentives to optimize system-wide energy performance. A system-wide incentive strategy is optimized using predictions for the multimodal transportation network in real-time, while its app menu is personalized for each user based on her/his travel preferences on an on-demand basis. Bringing together these methodologies in an appropriate and efficient way is the key distinction we bring for Smart Mobility. Yet, today's Smart Mobility solutions are characterized by just one or two of these features with similar principles and goals. For example, the MaaS concept may allow for personalization of mobility plans and accommodate for demand optimization given real-time supply conditions observed through participating mobility providers.

The remainder of the chapter is organized as follows. Section 2 presents the proposed Smart Mobility approach with the formulation of specific prediction, optimization and personalization methodologies, as well as the simulation-based evaluation. For each of them, we also introduce the platforms that have been developed to facilitate those methodologies and present example applications to show their added values. Section 3 provides examples of Smart Mobility together with their implications on the transportation network. Finally, Section 4 concludes the chapter and discusses future developments.

2. Smart mobility methodology

This section presents the three key methodologies and the simulation-based evaluation that constitute the proposed Smart Mobility approach.

2.1 Smart mobility: prediction

Effective smart mobility solutions need accurate and reliable traffic state estimates and predictions. This involves explicitly considering demand and supply-side characteristics and their interactions. The traffic state prediction approaches in the literature can be divided into two categories: data driven and model-driven. The data-driven approaches rely on the availability of big data

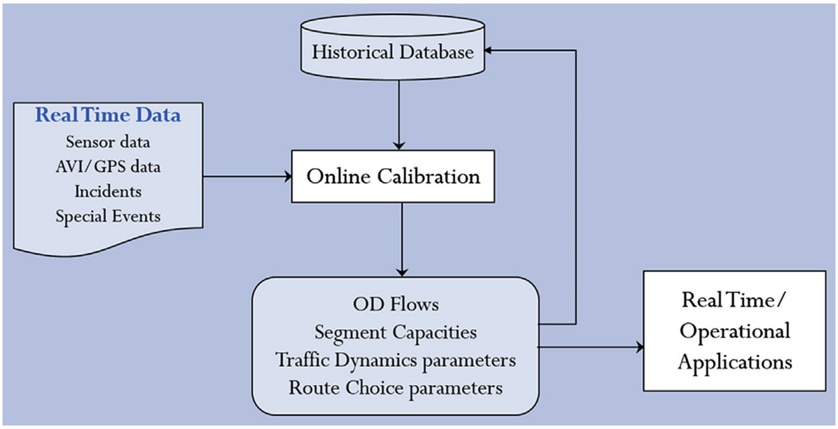

FIGURE 12.1 Online calibration framework.

(e.g., from sensors and other equipment) and filtering or machine learning algorithms. On the other hand, there are model-driven approaches that rely purely on traffic flow models. We propose a hybrid approach that combines the empirical nature of data-driven approaches with theoretically sound traffic flow models: we term the approach as *online calibration*. Thus, the hybrid approach has the advantage of using data to model recurring congestion and using models to predict the traffic evolution under nonrecurrent congestion, especially when the data on rare events is sparse. Online calibration entails calibrating a dynamic traffic assignment (DTA) system in real-time, which involves adjusting the demand and supply parameters of the DTA system, using the most recent observed traffic measurements (see Fig. 12.1). Note that for the methodology presented below, the DTA system can be either analytical or simulation based.

2.1.1 State space formulation

The online calibration problem can be formulated either as an optimization problem or as a state-space problem. We present the state-space formulation as it is more general, i.e., it can be adapted to different parameters and measurements. The reader is referred to Ashok and Ben-Akiva (2002) and Antoniou et al. (2007) for a more detailed discussion.

Consider an analysis period which is divided into equal intervals $h = 1, 2, \dots, T$ of size t. The transportation network is represented by $G(N, L, S)$, where N represents the set of nodes, L represents the set of links, and S represents the set of segments. The network has n_N nodes, n_L links, and n_S segments. The segments are sections of road with homogeneous geometry; a link comprises one or more segments. The set of OD pairs are represented by R

and are n_R in number. Further, n_s of the n_S segments are assumed to be equipped with surveillance sensors.

The state-space formulation consists of three main components: (i) a state vector that succinctly characterizes the system, (ii) a transition equation that captures the evolution of the system, through the state-vector, in time, and (iii) a measurement equation that captures the relationship between the state-vector and the measurements or observations of the system. Following the proposal in Ashok and Ben-Akiva (2002) and Antoniou et al. (2007), it is better to express the state-space formulation in terms of the *deviations* of the relevant variables from their historical values. By modeling in terms of the deviations in parameters, we can capture the critical structural information of the trip and network patterns present in the historical values.

In the current context, let $\boldsymbol{\pi}_\mathrm{h}$ represent a vector containing the parameters of the DTA system in the time interval h; it can contain the OD flow variables along with behavioral and supply parameters. Let $\boldsymbol{\pi}_\mathrm{h}^\mathrm{H}$ represent the historical values of the parameters in interval h. The historical values $\boldsymbol{\pi}_\mathrm{h}^\mathrm{H}$ are generally obtained through offline calibration (Balakrishna, 2006). The state-vector is then denoted by $\Delta\boldsymbol{\pi}_\mathrm{h} = \boldsymbol{\pi}_\mathrm{h} - \boldsymbol{\pi}_\mathrm{h}^\mathrm{H}$, whose evolution can be represented through the following generic transition equation:

$$\Delta\boldsymbol{\pi}_\mathrm{h} = f(\Delta\boldsymbol{\pi}_{\mathrm{h}-1}, \ldots, \Delta\boldsymbol{\pi}_{\mathrm{h}-\mathrm{q}}) + \boldsymbol{\eta}_\mathrm{h} \tag{12.1}$$

where q denotes the number of previous interval states that influence the current interval state; and $\boldsymbol{\eta}_h$ is a vector random of errors in the transition equation in interval h.

Further, let $\mathbf{m}_h$ denote the vector of measurements in interval h; these can be both point-based measurements (like flows and speeds) or spatial measurements (like GPS or AVI). As before, let $\mathbf{m}_\mathrm{h}^\mathrm{H}$ represent the historical values of the measurements in interval h. The historical values of measurements are generally obtained by running the DTA system with the historical parameters or they can also be actual measurements used for offline calibration. The measurement-vector in deviations is then denoted by $\Delta\mathbf{m}_\mathrm{h} = \mathbf{m}_\mathrm{h} - \mathbf{m}_\mathrm{h}^\mathrm{H}$, which is related to the state-vector through the following generic measurement equation:

$$\Delta\mathbf{m}_\mathrm{h} = g(\Delta\boldsymbol{\pi}_\mathrm{h}, \ldots, \Delta\boldsymbol{\pi}_{\mathrm{h}-\mathrm{p}}) + \boldsymbol{\zeta}_\mathrm{h} \tag{12.2}$$

where p denotes the number of previous interval's states that influence the current interval's measurements; and $\boldsymbol{\zeta}_\mathrm{h}$ is a vector of random errors in the measurement equation in interval h.

Eqs. (12.1) and (12.2) together form the state-space formulation of the generic online calibration problem. In practice, two assumptions are made on the generic formulation: (i) the transition equation is approximated through a linear autoregressive process and (ii) the measurement equation uses a DTA simulator to relate the parameters and measurements. After applying the above assumptions, the resulting transition and measurement equations are as follows:

$$\boldsymbol{\Delta\pi}_{\mathrm{h}} = \sum_{i=h-q}^{h-1} \mathcal{F}_{\mathrm{i}}^{\mathrm{h}} \boldsymbol{\Delta\pi}_{\mathrm{i}} + \boldsymbol{\eta}_{\mathrm{h}} \tag{12.3a}$$

$$\boldsymbol{\Delta m}_{\mathrm{h}} = \mathcal{S}(\boldsymbol{\pi}_{\mathrm{h}}, \ldots, \boldsymbol{\pi}_{\mathrm{h-p}}) - \mathcal{S}\left(\boldsymbol{\pi}_{\mathrm{h}}^{\mathrm{H}}, \ldots, \boldsymbol{\pi}_{\mathrm{h-p}}^{\mathrm{H}}\right) + \boldsymbol{\zeta}_{\mathrm{h}} \tag{12.3b}$$

In Eq. (12.3a), $\mathcal{F}_{\mathrm{i}}^{\mathrm{h}}$ represents a matrix relating the parameter estimates of interval i to the estimates of interval h, and q denotes the degree of the autoregressive process in the deviations. In Eq. (12.3b), $\mathcal{S}$ represents a DTA model, that can be either analytical or simulation-based, whose inputs are the parameters and outputs are the simulated measurements in the current interval, and p represents the maximum number of previous intervals whose parameters influence the measurements in the current interval.

Finally, to predict the parameters in the subsequent intervals $h+1$, $h+2$, …, the estimates calculated using equation in (3a) are used. For example, the prediction for the time interval $h+1$, if the current interval is h, is calculated as

$$\boldsymbol{\pi}_{\mathrm{h+1}} = \boldsymbol{\pi}_{\mathrm{h}}^{\mathrm{H}} + \sum_{i=h-q}^{h-1} \mathcal{F}_{\mathrm{i}}^{\mathrm{h}} \Delta\widehat{\boldsymbol{\pi}}_i + \boldsymbol{\eta}_{\mathrm{h}} \tag{12.4}$$

where $\Delta\widehat{\boldsymbol{\pi}}_i$ represent the a posteriori estimates of OD-flow deviations in interval i.

In the context of online systems, as presented in this chapter, the problem in Eq. (12.3) is solved to obtain an estimate of only the parameters in interval h, $\boldsymbol{\pi}_{\mathrm{h}}$. The parameter estimates of the earlier intervals $h-1, h-2, \ldots$ are not reestimated. In effect, the parameter estimates of the previous intervals are treated as constants in the current interval.

However, the observations in the current time interval might contain information about parameters from the previous time intervals. For example, sensor flow counts in the current intervals can be a result of OD flows from previous intervals. Therefore, ideally, the parameter estimates from the previous time intervals need to be corrected based on the measurements in the current interval. In the context of state space formulation, this correction of the parameters estimated in previous time intervals is formulated using state augmentation approach (Ashok, 1996). Although state augmentation results in better estimates of the parameters, it can be computationally intensive as it requires "rolling back" the simulator in real-time. In other words, the simulator needs to rerun with the new parameter estimates (from the previous time intervals) to update the simulated measurements. Ashok and Ben-Akiva (2002) found that the state augmentation can be reasonably approximated using the sequential estimation procedure we described in the chapter.

2.1.2 Solution procedure

The Kalman filter−based approaches are a natural and efficient way to recursively solve the system of equations in (3). The Kalman filter efficiently determines the estimate of the current interval using the estimate from the previous interval and the measurements in the current interval. The classical Kalman filter, which is a minimum mean square estimator, is applicable to linear state-space models. For the nonlinear state-space models, as in the problem in Eq. (12.3), the extended Kalman filter (EKF) was introduced. The EKF linearizes the nonlinear transition or measurement equations around the a priori estimates and adopts the procedure for linear state-space models to estimate the state-vector. The main conceptual drawback of the EKF is that it is not an optimal estimator; however, its practical application has been demonstrated in various studies (Antoniou, 2004). Note that for the application of the Kalman filter−based methods, we impose an assumption that the error terms $\boldsymbol{\eta}_{\mathrm{h}}$ and $\boldsymbol{\zeta}_{\mathrm{h}}$, from Eqs. (12.3a) and (12.3b), are zero mean Gaussian variables and that they are independent over time.

There are three main steps in the EKF algorithm: (i) time-update, (ii) linearization, and (iii) measurement update. In the time-update step, the prediction for parameter deviation vector $\Delta\boldsymbol{\pi}_{(\mathrm{h}|\mathrm{h}-1)}$ is made using the transition equation and the optimal estimates from the previous interval $h-1$, $\Delta\boldsymbol{\pi}_{(\mathrm{h}-1|\mathrm{h}-1)}$. These estimates, $\Delta\boldsymbol{\pi}_{(\mathrm{h}|\mathrm{h}-1)}$, are termed *a priori* estimates as they use data only until the previous time interval $h-1$. In the second step, the measurement equation is linearized around the a priori estimates of the current interval, $\Delta\boldsymbol{\pi}_{(\mathrm{h}|\mathrm{h}-1)}$. In the third step, the a priori estimates are updated using the linearized measurement equation to obtain the a posteriori estimates for parameter deviation vector $\Delta\boldsymbol{\pi}_{(\mathrm{h}|\mathrm{h})}$. Please refer to Antoniou (2004) and Prakash et al. (2018) for a more detailed discussion of the procedure.

The main bottleneck to apply the EKF algorithm to the online calibration problem is the linearization of the measurement equation, which involves calculating the Jacobian of the measurement equation. As the measurement equation represents the simulator, it has no closed-form expression. Therefore, the Jacobian is calculated through the numerical derivatives of $\mathcal{S}(\boldsymbol{\pi}_{\mathrm{h}},\ldots\boldsymbol{\pi}_{\mathrm{h}-\mathrm{p}})$. Determining the centered numerical derivative involves perturbing each of the parameters and running the simulator $2n_K$ times, which can be computationally intractable. To overcome the computational intractability under nonlinear measurement equation, two approaches have been proposed in the literature: (i) limiting extended Kalman filter (LimEKF) and (ii) dimensionality reduction. The LimEKF entails using a constant "gain" matrix, thus eliminating the need to estimate the Jacobian at every time-interval (Antoniou et al., 2007). The gain matrix is then estimated offline periodically and an updated matrix is used whenever available. The second approach, involves reducing the dimensions of the parameter vector so that the computation requirements of the Jacobian are mitigated. Prakash et al. (2018) formulate the problem using principal components of the parameters resulting in the reduction of state vector by 50 times.

2.1.3 Example application

As an example of the prediction methodology, we present a case study conducted on the Singapore Expressway Network. The road network is depicted in Fig. 12.5, which has 939 nodes, 1157 links, and 3906 segments. The network specification also contains information about segment lengths, segment curvatures, speed limits, lanes specifications, lane-connections, and dynamic tolling gantries which are replicated from the real-world.

The network has 4121 OD pairs, whose locations and historical values were determined by an earlier work through offline calibration. The network has 357 sensors, each of which is associated with a segment; these video camera—based sensors count the vehicular flow for a period of 5 min. For the current case study, the simulation time-period was taken from 06:00—12:00, which includes the morning peak period and also the peak to off-peak transition. The estimation interval was 5 min and the prediction interval, to estimate future traffic states and provide guidance, was 15 min. Thus, we have 72 estimation intervals with a total of $72 \times 4121 = 102,312$ variables.

For this study, sensor count data of 30 weekdays in August—September 2015 was used. The 30-day data was divided into a training set of the first 25 days and the calibration procedures were tested on the last 5 days. As a real-time DTA system, DynaMIT (see Section 2.2.1 for a description of DynaMIT) was employed. For more details, please see Prakash et al. (2017) and Prakash et al. (2018).

The performance measures adopted were the normalized root mean squared (RMSN) errors and mean absolute percentage errors (MAPEs) which are defined as

$$\mathbf{RMSN} = \frac{\sqrt{\boldsymbol{n}\sum_{i=1}^{\boldsymbol{n}}\left(\boldsymbol{y}_i - \widehat{\boldsymbol{y}}_i\right)^2}}{\sum_{i=1}^{\boldsymbol{n}}\boldsymbol{y}_i} \tag{12.5a}$$

$$\mathbf{MAPE} = \frac{100}{\boldsymbol{n}}\sum_{i=1}^{\boldsymbol{n}}\frac{\left|\boldsymbol{y}_i - \widehat{y}_i\right|}{\boldsymbol{y}_i} \tag{12.5b}$$

where y_i represents actual measurement and $\widehat{y}_i$ represents simulated measurement. Note that as MAPE is not normalized to consider the size of measurement, it can be high when the sensor-flows are small even though the deviation from the observations is acceptable.

The aggregate RMSNs and MAPEs of the procedures for estimation and prediction across the five test days are presented in Table 12.1. In the context of estimation, the OD-EKF on average exhibits an RMSN of 0.287 and MAPE of 28.21%. It improves over historical by 32% in RMSN and 30% in MAPE. The results from the predictions are represented in three steps, which represent the three 5-minute intervals in the complete 15-minute prediction interval. From Table 12.1, the EKF on average exhibits an RMSN of 0.290, 0.295, and 0.3 for the three steps and MAPE of 24.60%, 26.44%, and 27.71% for the three steps. By comparing the RMSNs and MAPEs after calibration with those of the historical values, we see that RMSNs after calibration are significantly better than those of the historical, but the MAPEs after calibration are only marginally better than those of the historical. It implies that calibration improves on the predictions of sensor-flow counts of the sensors with higher flows than those with the lower flows.

Fig. 12.2 depicts the scatter plots of estimated and predicted sensor counts across the five test days. The complete 5 days' sensor-flow count values are represented in a single plot as a heat map. A line was fit between the estimated/predicted and the actual values in each of the plots and its equation is presented. From the plot, we see that the fits are closer to 45-degree line with no significant systemic bias or variance; however, for longer prediction intervals there seems to be some evidence of bias.

Some of future research directions in predicting short-term traffic states include (i) incorporating disaggregate data, at individual level including trajectories, into online calibration, (ii) fusing DTA and machine learning techniques, specially to predict the advent and impacts of incidents, and (iii) exploring adaptive dimensionality reduction techniques that are specific to the situation.

2.2 Smart mobility: optimization

The design and operation of efficient and sustainable smart mobility solutions require the application of "online" optimization models that drive the system toward desirable system-level objectives. These models are of relevance in various contexts to make real-time operational decisions such as ride-sharing pricing policies and operational strategies including matching of vehicles to requests and rebalancing, incentive allocation schemes, tolls, signal timings, and so on.

The literature on optimization in the context of smart mobility is vast and includes both emerging on-demand services (ride-hailing, car sharing, bike sharing) and network control strategies (tolls, ramp metering, signals, etc.). The optimization of on-demand services has traditionally focused on vehicle routing and scheduling and falls under a broad class of dial-a-Ride problem or DARP (refer to Cordeau and Laporte (2007) for a review). More recently, studies have focused on incorporating the ride-sharing component of on-

TABLE 12.1 Aggregate values of RMSNs and MAPEs of sensor-flow counts (5 min) for historical and EKF.

		RMSN prediction			MAPE estimation	MAPE prediction		
Method	RMSN estimation	step1	step2	step3		step1	step2	step3
Hist	0.423	0.422	0.42	0.419	28.21	28.18	28.19	28.1
OD-EKF	0.287	0.290	0.295	0.305	19.77	24.60	26.44	27.71
% diff	32.15	31.28	29.76	27.21	29.92	12.70	6.21	1.39

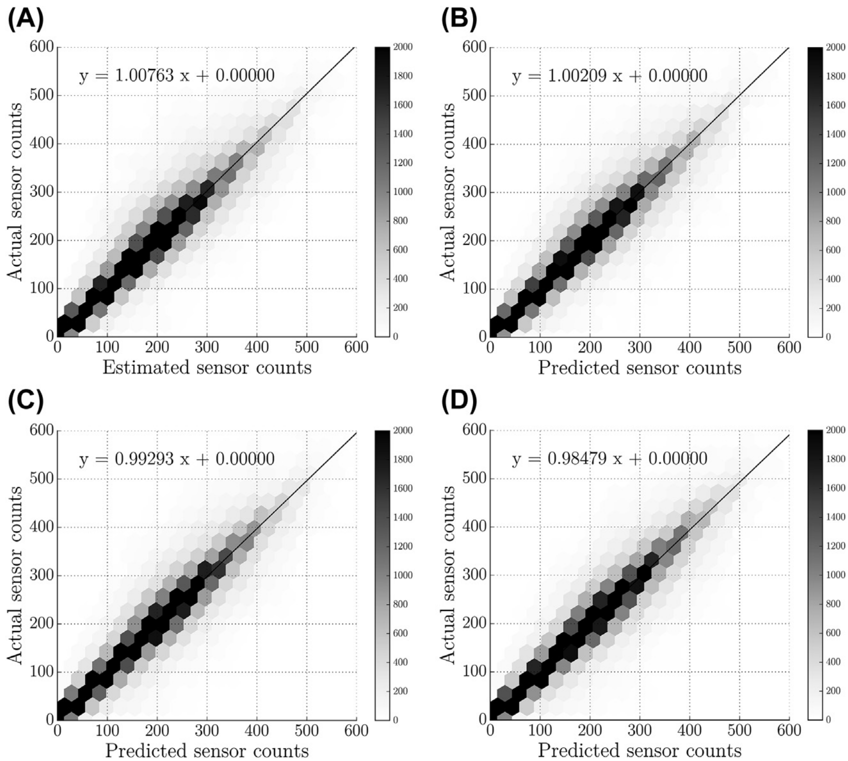

FIGURE 12.2 Comparison estimations and predictions of EKF procedures through the scatter plots of 5 min predicted versus actual sensor counts across all the five test days. The darker the cell, higher the number of points in it. (A) Estimations, (B) 1-step predictions, (C) 2-step predictions, (D) 3-step predictions.

demand services to estimate minimum fleet sizes required to service existing taxi demands in different urban contexts (Santi et al., 2014; Vazifeh et al., 2018; Alonso-Mora et al., 2017). The aforementioned studies typically employ graph theoretic and operations research techniques and do not explicitly model the complex demand and supply interactions within the transportation system. Extensive literature also exists on the optimization of network control strategies and the most commonly used approaches include feedback control (Zhang et al., 2008; Lou et al., 2011) and simulation-based optimization (Hassan et al., 2013; Hashemi and Abdelghany, 2016; Gupta et al., 2016). Typically, the approaches (with a few exceptions) tend to ignore system-level interactions and are reactive in that they are based on only current network states and not predicted network states.

Given that the optimization framework for Smart Mobility needs to be adaptive and computationally efficient, responding in real-time to recurrent/

nonrecurrent transportation supply and demand fluctuations, the approach we propose utilizes short-term predictions of the multimodal transportation system within a rolling horizon framework. More specifically, within this framework, a simulation-based optimization problem is solved periodically (e.g., every 5 minutes) wherein different candidate strategies of the smart mobility service operation are evaluated using predictions of the transportation system over a short-term future horizon period (e.g., 1 hour). The predictions are generated by a real-time dynamic traffic assignment (DTA) model system and involve detailed behavioral and supply models, explicitly taking into account the responses of users to the strategies. Examples of such real-time DTA systems include DYNASMART-X (Mahmassani, 2001), DynaMIT2.0 (Ben-Akiva et al., 2010; Lu et al., 2015b), and DIRECT (Hashemi and Abdelghany, 2016).

2.2.1 Real-time DTA and rolling horizon framework

The proposed optimization approach is built upon the prediction methodology (Section 2.1) and therefore utilizes traffic state predictions from a real-time DTA system operating in a rolling horizon mode. Although in principle, any simulation-based or analytical DTA system could be applied, in the following description, we make use of DynaMIT2.0 (Lu et al., 2015b). Some distinguishing features of DynaMIT2.0 include the modeling of multiple modes (e.g., car, transit, on-demand services) and generation of guidance information that is consistent with actual network conditions that users will encounter when responding to the guidance.

DynaMIT2.0 is composed of two core modules, state estimation and state prediction, and operates within a rolling horizon mode. In the example shown in Fig. 12.3, at 8:00 a.m., an execution cycle begins with DynaMIT2.0 receiving real time data from various sources including surveillance sensors, traffic information feeds, special event websites, weather forecasts, social networks, etc. This data is used in conjunction with historical information to first calibrate or "tune" the demand and supply parameters of the simulator so as to replicate prevailing traffic conditions as closely as possible (termed online calibration or state estimation; refer Section 2.1 for more details) for the time interval from 7:55–8:00. Based on this estimate of the current network state, the state prediction module predicts future traffic conditions for a prediction horizon (8:00–9:00 a.m.) taking into account the response of the drivers to the provided travel time (or other) guidance information. The outputs of the prediction module are forecasts of network conditions that are consistent with the expectation of users when responding to the guidance. Within our approach, the optimization of smart mobility services utilizes the state prediction module iteratively to evaluate potential candidate strategies based on the multimodal network predictions from 8:00 to 9:00 a.m. These are then applied to the system for the time interval from 8:00–8:05 a.m. At 8:05

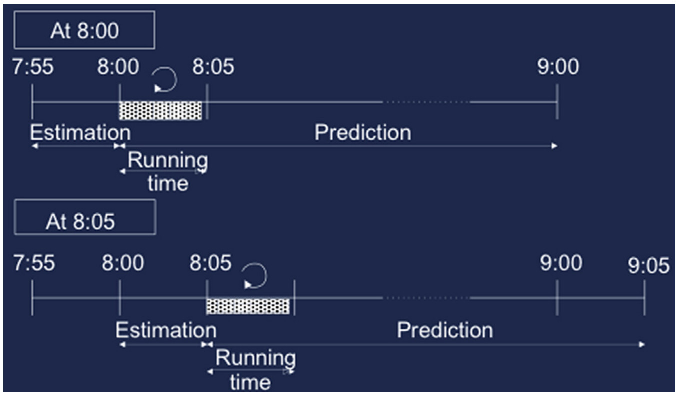

FIGURE 12.3 Rolling horizon framework.

a.m., the next execution cycle or "roll period" begins and the process repeats. The multimodal network predictions are based on behavioral models that incorporate the response of travelers to the smart mobility services.

2.2.2 Optimization formulation and solution approaches

In this section, we formally define the generic optimization problem applicable to the design/operation of any of the previously discussed "smart mobility" solutions. Consider a network $G(N, A)$, where N represents the set of n network nodes and A represents the set of m directed links and assume that the simulation period consists of $h = 1, \ldots, T$ estimation intervals of length t. Further, let the prediction horizon be K intervals, i.e., length to Kt, where each subinterval of length t within the prediction horizon is termed a prediction interval. Let $\boldsymbol{\theta_h} = \left(\boldsymbol{\theta_h^1}, \boldsymbol{\theta_h^2}, \ldots, \boldsymbol{\theta_h^K}\right)$ denote a vector of decision variables for the prediction horizon corresponding to estimation interval h that are to be optimized based on desired system or operator level objectives. The decision variables could involve pricing policies for smart mobility services, incentive allocation schemes, network tolls, etc. and are revised every estimation interval. For example, in Fig. 12.4, we have $K = 3$ prediction intervals and $\boldsymbol{\theta_h^1}, \boldsymbol{\theta_h^2}, \boldsymbol{\theta_h^3}$ represent the values of the decision variables for the three prediction subintervals in roll period h.

The state of the multimodal network over the prediction horizon associated with estimation interval h is denoted by a vector $\mathbf{x}$ which could include link flows, speeds, densities, bus/train dwell times, and so on. With this background, the optimization problem to be solved in roll period (i.e., estimation interval) h is formulated as follows:

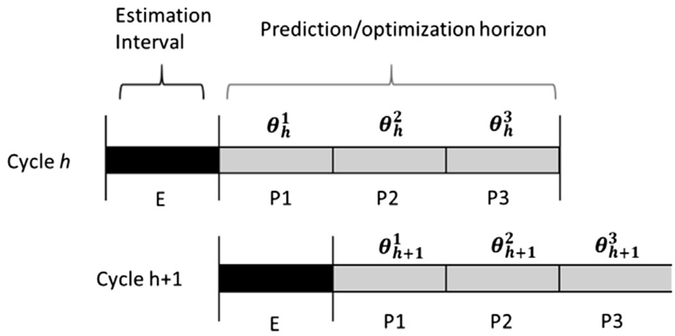

FIGURE 12.4 Notation for the rolling horizon approach.

$$Min_{\theta_h} Z = f(\boldsymbol{\theta_h}, \mathbf{x})$$

$$s.t \;\; S(\boldsymbol{\eta}, \boldsymbol{\theta_h}) = \mathbf{x}$$

where, $\boldsymbol{\eta}$ represents the forecasted demand and supply parameters for the prediction horizon, $S(.)$ represents the complex coupled demand and supply simulators of the DTA system and $f(.)$ represents the objective function of interest. The objective function could include the maximization of social welfare, minimization of energy, maximization of operator profits, fleet utilization, and so on. The objective function of optimization problem does not have a closed form and is the output of a complex simulator. Therefore, it is typically nonlinear and nonconvex. Solution approaches to solve this problem include meta-heuristics (Gupta et al., 2016; Hashemi and Abdelghany, 2016) which are amenable to the use of parallel and distributed computing and can achieve real-time performance. In the example application presented in the next section, we use a genetic algorithm approach that enables such parallelization. Nevertheless, the framework is flexible and already implemented with other solution algorithms including search heuristics.

2.2.3 Example application

In this section, we discuss the application of the framework to a dynamic toll optimization problem using a case study on the Singapore Expressway Network shown in Fig. 12.5 where there are 16 gantries. The decision vector $\boldsymbol{\theta_h}$ in this case is a vector of toll rates on those gantries to be determined for the prediction horizon. Note that, Singapore already has toll optimization in place through Electronic Road Pricing (ERP) in the form of time-of-day tolling (Seik, 2000).

The impact of the predictive optimization of network congestion is evaluated using a closed-loop setup wherein the DynaMIT2.0 system is interfaced with a traffic microsimulator MITSIM (Yang et al., 2000). MITSIM is run concurrently with DynaMIT2.0 and mimics the real network, providing sensor

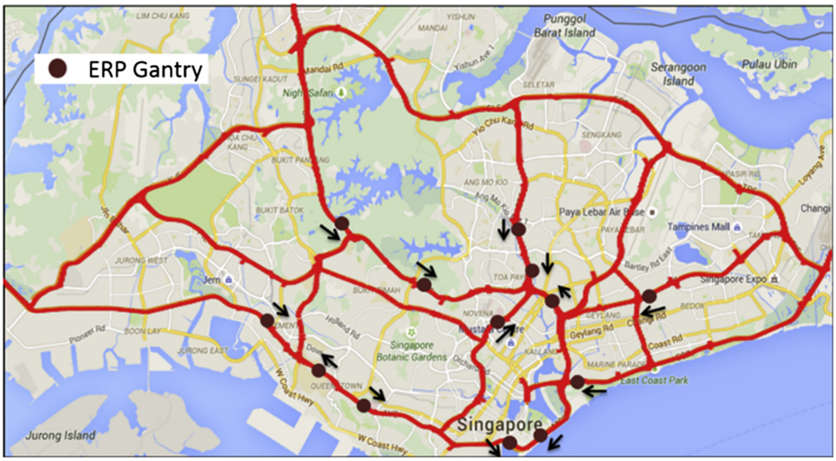

FIGURE 12.5 Singapore Expressway Network (map data: Google Maps, 2018).

counts (surveillance data) to DynaMIT2.0, which in turn provides predictive guidance and optimized tolls to MITSIM. The impact of the guidance and optimized tolls is then examined by obtaining relevant performance measures from MITSIM. For the experiments, in order to obtain a realistic representation of demand and supply on the Singapore expressway network, an offline calibration is performed in two stages. In the first stage, MITSIM is calibrated against real-world sensor count data (for details see Prakash et al., 2017) and in the second stage, the demand and supply parameters of DynaMIT2.0 are calibrated against simulated outputs from the calibrated MITSIM system.

In the numerical experiments, the performance of the predictive optimization is examined against two benchmarks, a *no-toll* scenario and a *static-optimum*, where tolls are time-invariant and optimized offline using historical demands. Two demand scenarios are considered, a base demand (calibrated MITSIM demand) and a high demand scenario (base demand increased systematically by 20%). In both cases, the MITSIM demand is also randomly perturbed to represent recurrent demand fluctuations. The simulation period is 6:30 a.m. to 12:00 p.m., which includes the morning peak in Singapore, and the estimation interval and prediction horizon are 5 and 15 min, respectively. For each demand scenario, the closed-loop simulation is performed 20 times (to account for simulator stochasticity) and the performance measures (trip travel times) are averaged.

The average trip travel times (aggregated in 5-minute departure time windows) in the two demand scenarios are shown in Figs. 12.6 and 12.7 (the bands represent the standard deviation in the travel time estimates based on the 20 replications). The results show that predictive optimization can yield

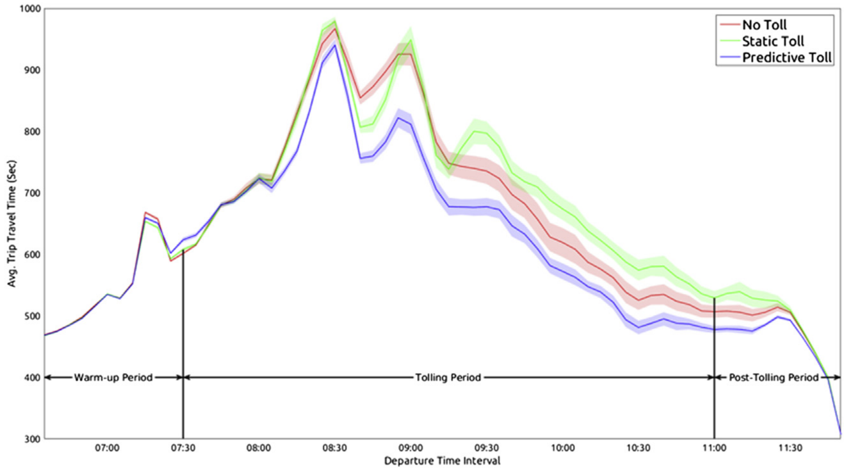

FIGURE 12.6 Average Travel Times (Base demand).

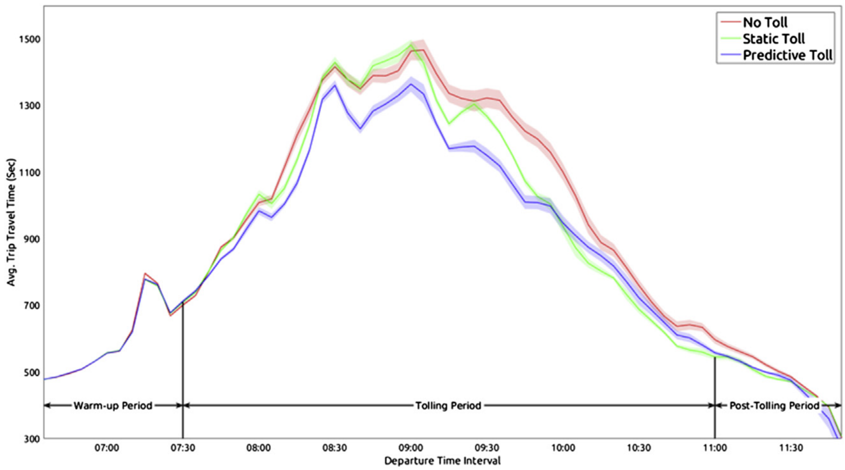

FIGURE 12.7 Average Travel Times (High demand).

statistically significant (at a 95% confidence level) travel time savings at the network level. The average trip travel times (across the entire tolling period from 7:30 to 11:00) in the case of the predictive optimized tolls are lower than the static-optimum and no-toll cases by 9.12% and 6.74% in the base demand case, and 4.00% and 8.38% in the high demand case.

There are several future promising directions related to real-time predictive optimization for improving transportation network conditions. An immediate direction is including more advanced demand models in the optimization framework in order to personalize the transport policies such as tolls, incentives, etc., and personalization methodology will be discussed in the next section.

2.3 Smart mobility: personalization

Travelers' needs are different and the preferences are heterogeneous across the population and across time. Smart Mobility solutions therefore need to present alternatives that are personalized in order to achieve long-term performance while ensuring that system-level objectives are met. For this purpose, we identify two main methodologies that make personalization possible: behavioral modeling and personalized menu optimization. First, behavioral modeling is the key to understand the heterogeneity across observations, and for Smart Mobility, the behavior of interest could be mode choice, route choice, departure time choice, etc. Second, user-specific optimization uses the behavioral information in order to optimize the Smart Mobility offer to be presented to the user. This optimization is represented by a menu optimization model that selects the optimal set of alternatives to be presented and this set of offered alternatives is referred as *menu*.

2.3.1 Behavioral modeling

Discrete choice methodology is well accepted to model behavior in various contexts (Ben-Akiva and Lerman, 1985). Different types of models have been developed and used in understanding behavior with various applications to travel behavior. Heterogeneity in behavior is particularly important to model and most of the literature focuses on heterogeneity across the population (inter-consumer heterogeneity). It is typically modeled as logit mixture (or mixed logit), and depending on the specification, simulation techniques are developed and used for the estimation (Train, 2009). More recently, researchers have investigated the heterogeneity across the choice situations (or menus) of the same individual (intraconsumer heterogeneity), especially when the data is collected over a long time with multiple observations for each individual (Cherchi et al., 2009; Hess and Rose, 2009; Ben-Akiva et al., 2019). This is especially relevant for Smart Mobility—based apps, where user data is likely to be available for multiple time periods.

Logit mixtures that account for both inter- and intraconsumer heterogeneity are estimated with maximum simulated likelihood (MSL) estimators (Hess and Rose, 2009). Building on the Allenby-Train procedure (Train, 2001), a Bayesian estimator is developed by Becker et al. (2018) for Logit mixtures with both levels of heterogeneity by extending the 3-step Allenby-Train procedure as a 5-step procedure. Population level, individual level, and menu level parameters are obtained with the proposed 5-step estimator. They compare the estimator to MSL and show that the proposed estimator retains the MSL estimates and is computationally 5 times less costly. Furthermore, based on the mentioned Bayesian methodology, the authors developed an offline–online update mechanism in order to continuously update the parameters as individuals make choices in the system (Danaf et al., 2019a). Therefore, our proposed approach is to use the Bayesian estimator and the update mechanism for Smart Mobility in order to estimate parameters that represent the heterogeneity across population and across choice situations accurately and also to keep the estimates up-to-date based on the recent observations.

We will now illustrate a typical logit mixture model with inter- and intraconsumer heterogeneity. We have population-level parameters given by μ, individual-level parameters represented by ζ_n for each individual n and menu-level parameters given by η_{mn} for menu m and individual n. Furthermore, we have the interconsumer covariance matrix Ω_b and the intraconsumer covariance matrix Ω_w. We assume that ζ_n and η_{mn} are normally distributed as follows:

$$\eta_{mn} \sim \mathcal{N}(\zeta_n, \Omega_w) \tag{12.6}$$

$$\zeta_n \sim \mathcal{N}(\mu, \Omega_b) \tag{12.7}$$

Consider the following utility function for individual n alternative j in menu m:

$$U_{jmn} = V_{jmn} + \varepsilon_{jmn} = X_{jmn}\eta_{mn} + \varepsilon_{jmn} \tag{12.8}$$

where V_{jmn} is the systematic utility and X_{jmn} represents alternative attributes. In the context of Smart Mobility, those attributes are typically travel time, cost, frequency, reliability, level of service, etc. Assuming that the error term ε_{jmn} follows the Gumbel distribution and the choice set for individual n for menu m is represented by J_{mn}, the choice probability of alternative j is given as:

$$P_j(\eta_{mn}) = \frac{\exp(V_{jmn}(\eta_{mn}))}{\sum_{j'=0}^{J_{mn}} \exp\left(V_{j'mn}(\eta_{mn})\right)} \qquad \forall j \in J_{mn} \tag{12.9}$$

Such models with advanced level of heterogeneity needs appropriate datasets with multiple observations for individuals together with the contextual information. For achieving the data needs, we utilize the Future Mobility Sensing (FMS) platform that was developed by the intelligent transportation system (ITS) Lab at MIT and SMART (Cottrill et al., 2013; Zhao et al., 2015). FMS is mainly used to collect high-resolution mobility data in the form of activity diaries through a smartphone app, where users can validate their entire set of trips and activities during a day. As users are typically asked to use the app for a few weeks, multiple choices of mode, route, departure time, etc., are observed. The users also provide socioeconomic information when installing

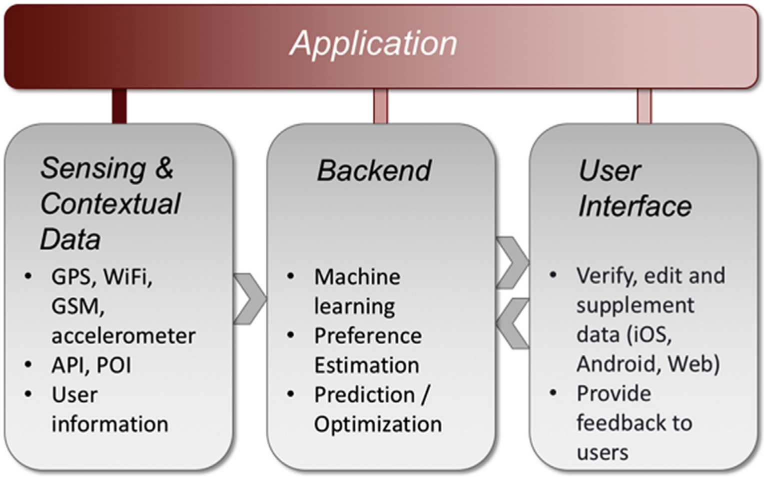

FIGURE 12.8 FMS platform overview (Zhao et al., 2018).

the app. Therefore, FMS enables the collection of rich datasets and the development of individual-level choice models.

Fig. 12.8 provides an overview of the FMS platform. FMS collects location, accelerometer, and contextual data continuously making use of the available sensors on smartphones. The FMS backend system processes the collected data through machine learning algorithms. The web and app interfaces allow the users to access the information about their trips and activities and also to validate them. The machine learning techniques are continuously being improved in order to reduce the burden on the user, i.e., minimize the need for the user to correct trip and activity information on their diaries. Note that, FMS is extended with stated preferences capability for understanding the behavior toward new mobility services (Atasoy et al., 2018; Danaf et al., 2019b) and it can be used for obtaining reasonable parameter values in the early phases of the Smart Mobility solution (in a simulation environment or real-life) before any estimation is possible based on observed choices.

2.3.2 Personalized menu optimization

In order to provide a personalized menu of travel options for Smart Mobility, differentiation of individuals and choice situations need to be taken care of with an appropriate behavioral model. Therefore, a logit mixture model with inter- and intraconsumer heterogeneity described above is the building block for personalized menu optimization. Given the logit mixture model, the personalized menu optimization will choose an M-size menu out of *C* many available alternatives for individual n in order to maximize an objective function of interest. It can be maximization of revenue, consumer surplus, a combination of the two, etc. In recommender systems for mobile apps, it is common to have a menu-size constraint to avoid information overload (Zhuang et al., 2011).

Personalized menu optimization is closely related to the assortment optimization, where the goal is similarly to select a subset of items to offer to the user from a universe of substitutable items. The objective is typically to maximize the revenue under random choice behavior of users. To represent the user behavior, different choice models are used in the literature such as multinomial logit, nested logit, and logit mixture (Davis et al., 2013, 2014; Feldman and Topaloglu, 2015). We refer to Kök et al. (2008) for a review of assortment optimization literature together with industry practice.

Here, we present a personalized menu optimization with revenue maximization, where p_j is the revenue of alternative $j \in C$. This revenue may be the monetary value or energy savings or any other benefit brought by the Smart Mobility system. The model for each individual n, with binary decision variables x_j that decide whether alternative j will be in the menu or not, is then provided as follows:

$$\max_{x_j{}' j=1,\ldots,C} \sum_{j=1}^{C} p_j \frac{x_j \exp(V_{jmn}(\eta_{mn}))}{\sum_{j'=1}^{C} x_{j'} \exp(V_{j'mn}(\eta_{mn})) + \exp\left(V_n^{opt}\right)} \tag{12.10}$$

subject to

$$\sum_{j=1}^{C} x_j \leq M_n \tag{12.11}$$

$$x_j \in \{0, 1\}, \forall j \in \{1, \ldots, C\} \tag{12.12}$$

where the objective function (10) is a function of binary decision variables through the choice probability that is given by the behavioral model introduced in the previous section. V_n^{opt} denotes the utility of opt-out alternative (not choosing anything on the menu) for individual n. We include the opt-out alternative in order to represent the fact that the user is not captive and may leave the Smart Mobility system and this utility may be different across individuals. Constraint (11) is the menu-size constraint and it is given by M_n, as in principle the size of the menu could also be personalized.

The above-presented model (10−12) represents a complex problem as it has a nonlinear objective function and binary decision variables. There are ways to simplify the problem under different assumptions. We refer to Song (2018) for a discussion of those cases and also for different versions of the model with an objective function of consumer surplus.

2.3.3 Example application

We applied the personalization approach with a real data set from Massachusetts Travel Survey (MTS) which includes travel diaries for 33,000 individuals from 15,000 households collected between June 2010 and November 2011. The individuals reported travel diaries for a preassigned weekday and provided transport mode, arrival/departure times, activity location, etc. We used a sample of 5154 individuals who made at least one trip during the specified day. The choice set for those trips was constructed by using Google Maps API based on the origin, destination, and departure time information from MTS data. Considered modes are walk, bike, car, car-pool, and transit, and with different route options the choice set may include 4 to 16 alternatives. Note that more than 80% of the trips in the MTS data were performed by car/car-pool. For more details we refer to Song (2018) and Song et al. (2018) also used a smaller sample from this dataset for an earlier version of this work.

A logit mixture model is specified and the utility for individual n of alternative j for a given choice situation (menu) m is given by

$$U_{jmn} = \frac{\left(ASC_{mode} - \exp\left(\eta_{mn,Time}\right) Time_{jmn} - Cost_{jmn}\right)}{\exp\left(\eta_{mn,Cost}\right)}$$

where ASC_{mode} denotes the alternative specific constant for each of the five modes that are considered and it is set to zero for the walk mode. The utility is in willingness-to-pay specification (i.e., in monetary units) as it is normalized by the cost coefficient. ASCs are normally distributed; travel time and cost coefficients are introduced as exponential terms in order to have them log-normally distributed and to control their signs.

For the example application here, we consider 1733 individuals who performed at least nine trips during the specified day. The parameters are estimated based on the first eight trips with the previously mentioned Bayesian estimator and the menu is optimized for the ninth trip. In order to assess the benefits of personalization, we compare it to its *nonpersonalized* counterpart, which does not capture individual-level preferences. The comparison is done in terms of the *hit rate*, which is the proportion of the cases the optimized menu for trip nine includes the "true" choice. This analysis is carried out under two settings of the assumed consumer heterogeneity, first assumes inter-only heterogeneity and the second considers both inter- and intraconsumer heterogeneity.

Figs. 12.9 and 12.10 provide the comparison under inter-only and inter- and intraconsumer heterogeneity, respectively. For the analysis, different menu sizes are considered between 2 and 10 and as mentioned previously the choice set may be of size 4 to 16 across different observations. As expected, when menu size gets closer to the size of the choice set, the hit rate approaches 1 and the difference between personalized versus nonpersonalized menu optimization gets smaller. Fig. 12.9 shows that, for menu sizes of until 6,

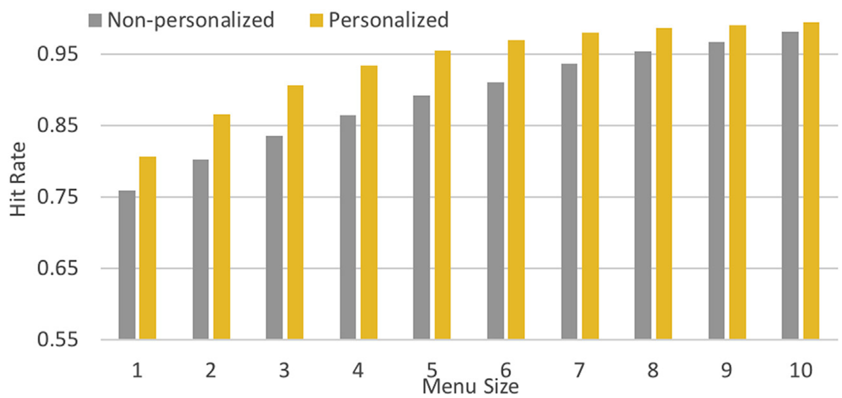

FIGURE 12.9 Comparison under inter-only heterogeneity.

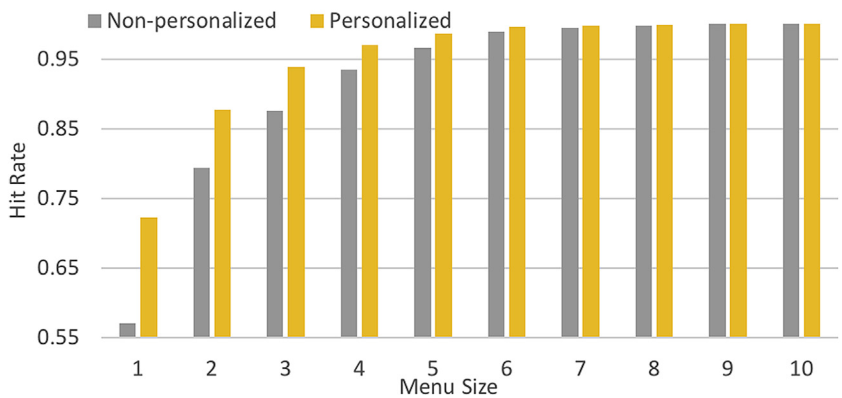

FIGURE 12.10 Comparison under inter- and intraconsumer heterogeneity.

personalization increases the hit rate by more than 5% under inter-only heterogeneity. When we look at the case under inter- and intraconsumer heterogeneity in Fig. 12.10, it is observed that the hit rate of both methods increased significantly in general which shows that the behavior can be captured much better with a more accurate representation of heterogeneity. The difference between personalized versus nonpersonalized menu optimization becomes very small as of menu size 6. Nevertheless, with smaller menu sizes, there is a significant benefit of personalization, e.g., for menu sizes of 1 and 2, personalization brings around 15% and 8% increase in hit rate, respectively, which are bigger differences compared to the inter-only case.

The presented results show the added value of more advanced behavioral models with detailed representation of consumer heterogeneity as well as the personalized menu optimization. It shows the potential for Smart Mobility solutions and will definitely be more powerful when the user history is tracked over a time horizon and several choices from the same individual is observed.

2.4 Simulation-based evaluation of smart mobility

Similar to other mobility solutions, Smart Mobility can be assessed by means of surveys, laboratory or field experiments, and simulations. When such solutions are not yet deployed in the field, analysts tend to resort to stated preference surveys for the assessment of demand impacts. Yet, insights from these are known to be unreliable in scenarios, where the context is too far from situations familiar to the subjects (see, for example, Choudhury et al., 2018 for the assessment of the willingness to pay for different smart mobility options). Laboratory experiments are usually useful for cognitive and other human factors issues associated with the interaction of a certain technology, thus providing even further insights into demand aspects. Field experiments on the other hand, allow for coupling insights on such demand impacts with reduced context bias together with limited supply characteristics of the Smart Mobility solution at stake. Such experiments are at the forefront of Smart Mobility assessment but are still constrained to a limited range of potential operational settings, either due to technology limitations or the associated experimental costs, thus limiting supply related insights. Harb et al. (2018), for example, collected pioneer insights on travel behavior patterns shifts for automated mobility by mimicking a privately owned self-driving vehicle with 60 h in 7 days of free chauffeur service for each of the study participants.

While the above methods are extremely useful for demand specific insights, system-level impact assessment, effects from demand-supply interactions or freedom of scenario testing have been recently tackled by means of simulation. With advances in computational power, the research community has been tackling the assessment of Smart Mobility impacts in large urban areas with integrated demand-supply complex simulators. These simulators are typically composed of several interconnected models for each of the dimensions of the transportation system: land-use, demographic, and economic model; travel (often activity-based) demand model; and a multimodal network supply assignment model. An example of current state-of-the art platforms targeting this aim are Polaris (Auld et al., 2016), CEMDAP + MATSim (Ziemke et al., 2015) or SimMobility (Adnan et al., 2016). For assessing the impacts of different operational settings for *prediction, optimization*, and *personalization,* simulation platforms require a set of features. We summarize in this section SimMobility's features for assessing Smart Mobility.

SimMobility is an integrated agent-based simulation platform used to evaluate a wide range of future mobility related scenarios (See Fig. 12.11). It is comprised of three integrated modules differentiated by the time-frame in which we consider the traveler behavior and operations of an urban system:

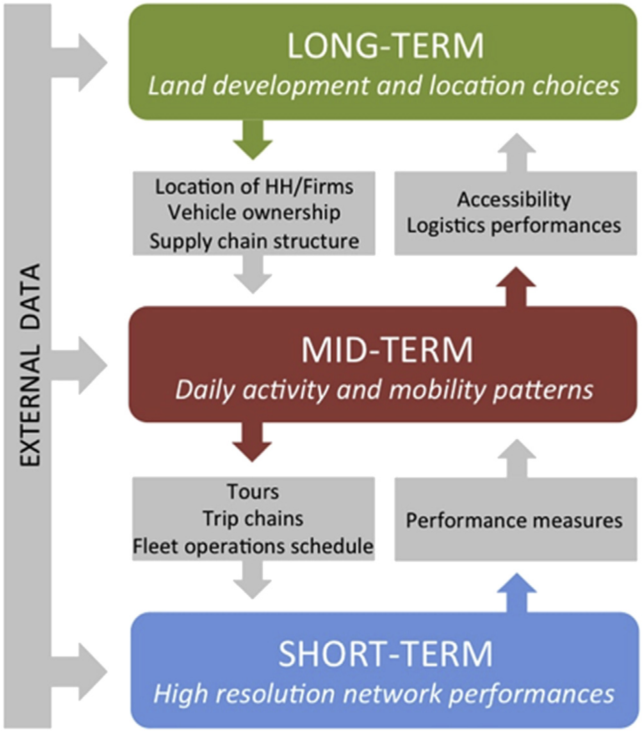

FIGURE 12.11 SimMobility framework (Adnan et al., 2016).

*short-term (*a microscopic mobility simulation, few hours simulated at 0.1-second time resolution), *mid-term* (an activity-based model integrated with a dynamic multimodal assignment simulator, daily simulation at 5-second resolution), and *long-term* (a land use and long-term behavioral model, at 6-month to 1 year resolution) (Adnan et al., 2016). The integrated nature of SimMobility enables consistency between the levels through a single database model which is used by all three levels. Thus, an agent's travel behavior and characteristics will be consistent across all levels. For example, the short-term uses trip chains generated by the mid-term model, which are also generated by using land use information from long-term. Demand in mid-term, vehicle ownership and the geographic distribution of the population in long-term rely on supply performance through a feedback loop. Introducing new mobility solutions in the simulation affects the aforementioned agents' choices, including mode choice. In this context, Smart Mobility is expected to directly influence an agent's preferences of mode choice due to the presentation of personalized and shared alternatives which have different characteristics such as travel time, schedule delay, and privacy.

SimMobility long-term is designed to simulate the interrelations between the transportation system and land-use mainly capturing the decision-making related to the household location choices, school and workplace choices, and vehicle ownership choices (Zhu et al., 2018). The main model is a housing market module simulating daily dynamics in the residential housing market and affecting the remaining long-term choices (e.g., vehicle ownership) together with overall transportation performance coming from the mid-term model in the form of utility-based accessibility measures. While the impact of different smart mobility scenario performances is already taken care of in long-term decision-making by means of accessibility changes, direct extensions to the current formulation of individual behavior are being implemented to reflect cost of vehicle ownership, such as subscription services (e.g., to new smart mobility services) and new modes such as personal mobility devices (Zhu et al., 2018).

It is at the level of the travel demand and network simulation, where critical smart mobility simulation features are required. In SimMobility, the travel behavior models are present in the mid-term simulator, which comprises two groups of behavioral models: preday and within-day (Lu et al., 2015a). The preday models follow an econometric day activity schedule approach, detailed in Hemerly Viegas de Lima et al. (2018), to decide on the initial overall daily activity schedule of the agent, particularly its activity sequence (including tours and sub-tours), with preferred modes, departure times by half-hour slots, and destinations. As the day unfolds, the within-day models are applied to the agents to transform the activity schedule (plans) into effective decisions, revise the preday patterns as needed, and decide on the routes for their trips (actions).

For a particular scenario and to accommodate the effects of Smart Mobility in the preday models, individuals from the synthetic population have access to the available Smart Mobility modes at stake in their choice set while constructing their activity schedules. The systematic utility of each mode in the combined mode and destination choice model of preday considers the key attributes of the Smart Mobility mode, individual, and context characteristics (such as *travel times*, *costs*, *trip purpose*, *vehicle ownership*, *smart mobility and other mode subscription, age*, *gender,* etc.). General assumptions on the generalized travel attributes of the Smart Mobility mode at stake need to be made usually based on related past literature, experiments, stated preferences, and/or proxy modes. Under this approach, the formulation of the remaining choices in preday's day activity schedule approach (e.g., activity participation, number of tours, etc.) would still rely on estimations from existing datasets and, if existing, additional calibrations using the Smart Mobility related data sets.

At the within-day level, user interactions with the daily operations of the Smart Mobility service at stake are simulated. Using SimMobility's event publish/subscribe mechanism (Adnan et al., 2016), travelers subscribe to the Smart Mobility service. For a planned trip under the Smart Mobility mode from the preday model, simulated travelers first have to choose if they access the actual Smart Mobility interface first during the simulation. This intermediate decision allows for changes in decision-making due to dynamic characteristics of the transportation system. When accessing the service, a second model decides on the service product within the Smart Mobility service to select (or rejection of all offers). Finally, if selecting a certain product, one may need to consider a potential rescheduling of the remaining day activity schedule, namely if the alternatives offered by the Smart Mobility service rely on drastic changes to the planned activities (e.g., significant trip delay, much longer travel times, etc.). Such feature is not yet available in SimMobility; currently, if travelers chose not to use the Smart Mobility service or reject all product offers, they act as nonusers and follow preday plans; if they select a product, they follow the choice for that particular trip and follow the remaining preday plans (for a detailed description, data for estimation and actual estimation procedure see Xie et al., 2019).

Finally, to allow the simulation of operations of Smart Mobility services, SimMobility introduced two new relevant agents at the supply level, both in mid-term and short-term: the service-driver and the Smart Mobility controller. Such current implementation is flexible to allow for the simulation of diverse Smart Mobility scenarios: (i) multiple service providers, (ii) service-drivers/vehicles subscribing to multiple service-providers, and (iii) flexible exchange of information between the service-providers and service-drivers/vehicles. First, as multiple service-providers can be simulated in tandem, we can replicate currently available services like Uber and Lyft and also test the impact of new competitors on the network. Second, as a service-driver/vehicle can subscribe to multiple service-providers, we are able to simulate the effect on the system of doing so. Third, the exchange of information between service-provider and service-driver/vehicle may channel travel information or control from the service-provider to service driver/vehicle and, vice-versa, transfer dynamic driver/vehicle specific data (e.g., location) to the service provider.

The Smart Mobility controller consists of three main components: i) initializer, ii) fleet/driver manager, and iii) service monitor. The initializer initializes any existing service fleet or drivers and their attributes. The manager deals with servicing the traveler after receiving his/her travel request. It processes the request, selects and offers the service products to the traveler, and services accordingly. For example, in an Uber-like scenario, vehicle-driver matching, pricing, dispatching, routing, and rebalancing algorithms are part of the manager. The service monitor component monitors the servicing, the dynamic attributes of service vehicle and driver assets and the spatial and temporal distribution of demand. The simulation of a wide range of Smart Mobility services in SimMobility can be found in the literature, such as (i) regular taxis (ii) ride on-demand (iii) ride-sharing, and (iv) information provision within SimMobility (Lima Azevedo et al., 2016; Adnan et al., 2017; Basu et al., 2018).

3. Smart mobility examples

In this section, we provide examples of Smart Mobility solutions that are designed based on the methodologies we presented above.

3.1 Flexible Mobility on Demand (FMOD)

FMOD is an app-based service that provides an optimized menu of travel options including taxi, shared-taxi, and minibus in real-time (Atasoy et al., 2015a). The traveler can select one option in the menu for their trip or reject all options. It is illustrated in Fig. 12.12 a user accessing the system through a smartphone app and receiving a menu including the three services with different attributes. FMOD taxi provides door-to-door service in a private vehicle, which is typically the highest priced service. FMOD shared-taxi serves multiple passengers in the same vicinity, and travel time may increase due to the pick-up and drop-off of other passengers. FMOD minibus runs along fixed stops but adapts to passengers' schedule and typically has the lowest fare. These different modes give a spectrum of services ranging from private to public transportation.

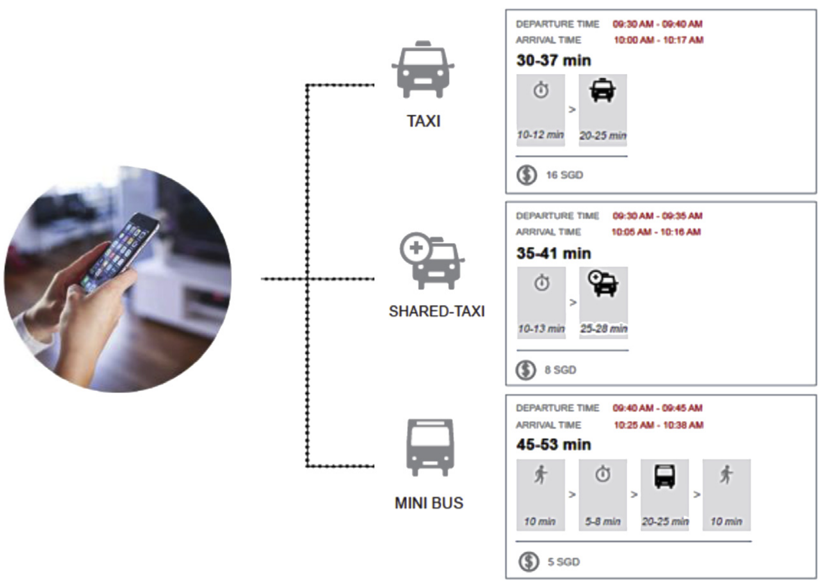

FIGURE 12.12 Flexible Mobility on Demand system.

The modeling framework for FMOD includes a behavioral model, a dial-a-ride problem, and a personalized menu optimization model. The behavioral model is a mode choice model that defines the utilities of the FMOD alternatives as well as the opt-out alternative. Considered attributes include travel time, cost, access/egress times (if any), and schedule delay.

When a user request is received, a dial-a-ride problem (refer to Cordeau and Laporte, 2007 for a review) is solved in order to generate a set of feasible transport alternatives that fit the request of the user (i.e., origin, destination and preferred departure/arrival time) and the capacity and existing schedules of the vehicles. Finally, a personalized menu optimization model is solved in order to get the optimal (e.g., maximum revenue and/or maximum consumer surplus) menu among the full set of feasible solutions. As described in Section 2.3, this personalized menu optimization model embeds the behavioral model that represents the choice probability toward FMOD alternatives and the opt-out alternative. For more details on the models and solution approach, we refer the reader to Atasoy et al. (2015a).

FMOD is evaluated in Singapore with the SimMobility platform introduced in Section 2.4. Fig. 12.13 indicates the simulated network and the shaded area is assumed to be the service area for FMOD. It is assumed that 10% of all the road users in the shaded area have access to FMOD (i.e., access FMOD app to make a travel request). For this experiment, the behavioral model is a rather simple logit mixture model that considers only interconsumer heterogeneity, i.e., the willingness-to-pay varies across the population but not across different choice situations of the same individual. Dial-a-ride problem is solved with insertion heuristics such that when a user request is received, the existing schedules of the potential vehicles are evaluated to see whether the requested trip can be inserted or not. For the personalized menu optimization model,

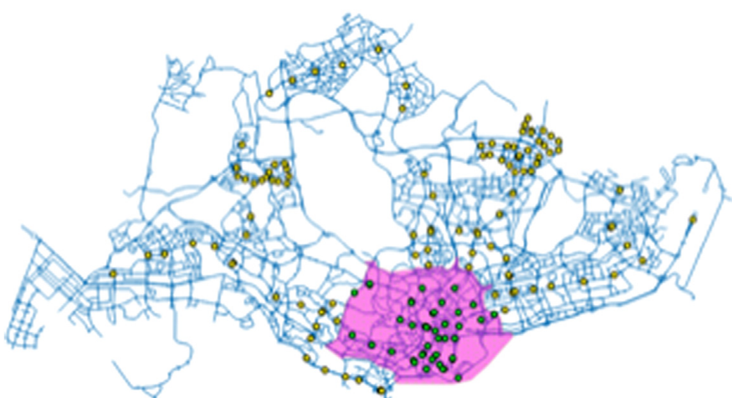

FIGURE 12.13 Singapore network, pink shaded area represents the central business district area, where FMOD is assumed to operate.

three versions are considered with the objectives of profit maximization, consumer surplus maximization, and both. The trade-off between operator's profit versus user benefit is analyzed under the different versions.

A base case is considered where there is no FMOD in the provided network. It is observed that when FMOD is introduced, 5% system-wide travel time reduction is obtained compared to the base case. Moreover, around 10% −20% reduction is obtained in volume-to-capacity ratio. Furthermore, the comparison of the three objective functions is provided in Table 12.2, where the base scenario is considered to be the consumer surplus maximization. The relative profit and consumer surplus of the two other scenarios are provided with respect to the base scenario. It is observed that when we maximize profit, we end up reducing the consumer surplus significantly which may in the long run mean that the users will not revisit the FMOD system and the envisioned profit may not be reached. When we optimize both profit and consumer surplus, it is observed that consumer surplus is regained without significant reduction in profit. Therefore, it is important to consider the benefit to both users and operators and FMOD framework enables that as a behavioral model is embedded in the menu optimization. FMOD is also evaluated for a network in Tokyo under different objective functions and scenarios (Atasoy et al., 2015a, 2015b).

Note that the presented application of FMOD focuses on the personalization aspect and it is evaluated by SimMobility. In principle and similarly to the case study presented in the next section, this Smart Mobility solution could also be developed in a predictive framework where the travel time in the network is predicted in real-time and the operation of the system is carried out based on the predicted traffic conditions. Furthermore, the prediction framework could be extended for the arrival of user requests such that, the number of requests that will be received in the near future is predicted and the resources are allocated more efficiently.

TABLE 12.2 Results for FMOD under different objective functions.

Scenario objective	Relative profit	Relative consumer surplus
Maximize consumer surplus	Base case	Base case
Maximize profit	+45%	−140%
Maximize total welfare	+40%	−31%

3.2 Tripod: sustainable travel incentives with prediction, optimization and personalization

Tripod is a smartphone-based system to influence individuals' real-time travel decisions by offering information and incentives with the objective of optimizing system-wide energy savings (Lima Azevedo et al., 2018). When starting a trip, travelers can choose to access Tripod's *personalized* menu via a smartphone app and are offered incentives in the form of tokens for a variety of *optimized* energy-reducing travel options (i.e., mode, route, departure time, driving style alternatives as well as the option of canceling the trip) (see Fig. 12.14). Options are presented with *predictive* information to help travelers understand the energy and emissions consequences of their choices. By accepting and executing a specific travel option, a traveler earns tokens that depend on the system-wide energy savings she or he creates, encouraging them to consider not only their own energy cost but also the impact of their choice on the system. Tokens can then be redeemed for services and goods from participating vendors and transportation agencies.

The Tripod system relies on the simulation-based multimodal network prediction system described in Section 2.2. As Tripod aims at maximizing system-wide energy savings, the prediction simulation framework was extended with (1) individual specific preferences toward different alternatives and incentives, (2) a simulated personalization which simulates the generation of the menu of alternatives shown by the Tripod app, and (3) TripEnergy (Needell and Trancik, 2018), a detailed model that estimates the energy impacts of multimodal travel.

Tripod's overall system-wide maximization of energy efficiency is achieved through a bilevel optimization approach with the system *optimization* as strategy (top level) and the app menu generation as the *personalization* (lower

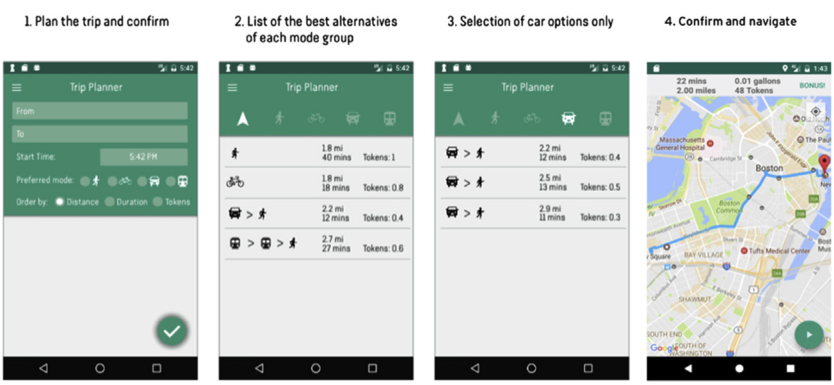

FIGURE 12.14 Tripod interface (Lima Azevedo et al., 2018).

level). The link between these two loosely coupled problems is achieved through the real-time computation of the token energy efficiency (TEE), defined as the amount of energy a traveler must save to earn one token (Araldo et al., 2019). The TEE is the key decision variable of the system optimization and is used in every menu personalization, then triggered by each trip request from a control point traveler, i.e., Tripod user. In this framework, there are two optimization cycles: the system optimization is triggered at every roll period and each individual menu for a trip request is personalized on an individual on-demand basis. The Tripod app also keeps track of Tripod users' preferences from their menu selections and informs the system optimization for better predictions. As previously mentioned, the response to different TEE and overall predicted demand is embedded in the prediction framework (for more information the reader is referred to Araldo et al., 2019).

Similar to the FMOD service presented in the previous section, Tripod's menu personalization in real-time maximizes a user-specific objective function based on the guidance from the obtained network predicted conditions as well as the TEE. The tokens associated with each option are determined before running the personalization based on the formula provided in Section 2.3.1., the optimal TEE and the estimated energy consumption for each potential menu alternative using TripEnergy (Needell and Trancik, 2018). The savings are the key variables to be maximized in Tripod. A reference energy value is computed for each trip request based on the expected energy consumption without tokens. The reader is referred to Lima Azevedo et al. (2018) and Araldo et al. (2019) for details on the formulation, implementation, and configuration of Tripod.

In preliminary assessments of different Tripod designs, a simulation-based evaluation, as in Section 2.4, was used. Results were obtained by implementing Smart Mobility features and the controls generated by Tripod in SimMobility, in an interactive manner. During each roll period, the following sequence of interactions occur: (1) Tripod *prediction* module obtains sensing information (e.g., counts and speed measurements) from SimMobility for the latest roll period, conducts online calibration of DynaMIT supply and demand simulators, performs the system optimization loop based on state prediction for the duration of the rolling horizon to find the optimal TEE for the current roll period, and passes the TEE and predictive traffic and energy information to the personalization module. (2) The latter receives Tripod requests from simulated users in SimMobility and generates personalized menu with tokens potentially assigned for each request using the latest TEE and predictive information. (3) SimMobility then simulates each Tripod user's responses to the personalized menu as well as all other travelers' choices and loads all travelers to the network. This closed-loop framework reflects how Tripod would work in real life where SimMobility is replaced by the real world.

The preliminary experiments on the route and departure time choice dimensions of Tripod were conducted on a simulation model of the Boston

FIGURE 12.15 Map of Boston CBD (Lima Azevedo et al., 2018).

Central Business District (CBD), in Massachusetts, United States (Fig. 12.15) with a network of 843 nodes, 1879 links, 3075 segments and 5034 lanes including both highways and arterials. The simulation period was from 6:00 a.m. to 9:00 a.m. with a roll period of 5 min and a rolling horizon of 15 min. The total number of travelers was 47,588.

The effectiveness of Tripod was evaluated by performing two simulations: with and without Tripod. In both simulations, all travelers receive real-time predicted information on network conditions and thus the difference in performance is only due to tokens. The performance measures were the average travel time and energy consumption per vehicle and the distribution of travel time and energy consumption.

In the preliminary tests, a budget of 2000 tokens per 5 min was used (a total of 72,000 over a 3-hour period and a monetary value of a token of $0.50). Since the models are not calibrated, our discussion focuses more on the relative magnitude of savings, instead of the absolute values.

As seen in Table 12.3, as the penetration rate of Tripod increases, the energy savings increase. The rate of increase, however, is not a monotonic function of the penetration rate, suggesting a highly nonlinear underlying

TABLE 12.3 Preliminary results with route and departure time choice in Boston CBD.

Penetration rate	Average energy consumption per Trip (MJ)	Energy savings per Trip	Average Travel time (seconds)	Travel time savings per Trip
0 (base case)	9.2	N/A	458	N/A
25%	9.0	2.1%	442	3.5%
40%	8.7	5.4%	409	10.7%
50%	8.7	5.4%	417	9.0%
60%	8.7	5.4%	413	9.8%
75%	8.6	6.5%	420	8.3%
80%	8.6	6.5%	420	8.3%

system, and specifically, an effect of saturation as the penetration rate gets close to 80%.

4. Discussion and conclusions

In this chapter, we provided an overview of three methodological components of smart mobility systems analysis: prediction, optimization, and personalization. These methodologies are designed to interact with each other during the operations of Smart Mobility. Predictions are critical so that the optimization of several policies (e.g., tolls, incentives) is done taking into account the real-time data in a predictive manner. Prediction and optimization both guide personalization such that the attributes of alternatives reflect the real-time conditions and the optimal policies when offering menus to individuals.

Those methodologies can be enhanced in several dimensions. First of all, the demand representation in prediction and optimization methods is typically at an aggregate level. Extending them with disaggregate models is a promising direction. This naturally may come at the expense of computational burden and efficient methodologies for prediction and predictive optimization need to be developed. The prediction is considered with a focus of predicting traffic conditions. Nevertheless, predicting user requests in the future is very important during the operation of Smart Mobility solutions in order to better allocate the resources across received requests. Furthermore, the presented methodologies have more of a model-driven nature even though high-resolution data is exploited from the behavioral perspective. Ways of effectively and efficiently combining model-driven and data-driven methodologies across prediction, optimization, and personalization need to be further investigated.

While this chapter illustrated the methodologies on two case studies, the approach is suitable for any type of Smart Mobility solution. Mobility as a Service (MaaS) is one example of an emerging integrated mobility platform that is amenable to this type of analysis. MaaS offers mobility bundles to users that combine urban public transport, taxi and on-demand services, shared bikes and personal mobility devices (e.g., e-scooters), and carshare and rental services. Ongoing research on MaaS demonstrates its benefits. For example, a stated preferences survey conducted by Matyas and Kamargianni (2017) deployed in Greater London found higher preference for flexible, mass-transited oriented plans. And field experiments with MaaS subscribers in Helsinki, where users can choose monthly subscription packages or pay-as-you-go schemes, indicate a significant increase in mass transit share and taxi trips per person as well as monthly public transport spending. Simulation of FMOD, as a special case of MaaS, also indicates the potential benefits of flexibility and personalization in MaaS: potential reduction of system-wide travel time by 5% and about 10%−20% reduction in volume-to-capacity ratio in Singapore network simulated through SimMobility. Such MaaS systems would be working more efficiently when integrated with prediction and optimization methodologies presented in this chapter.

Two issues not addressed in this chapter will likely influence the long-term impacts and the adoption of Smart Mobility solutions. The first is the interplay between on-demand mobility options and public transit. For example, a study by UC Davis indicated that ride hailing resulted in a decline in mass transit usage by 6% in the United States from 2014 to 2016. On the other hand, few cities have partnered with ridesourcing services to provide first-/last-mile connectivity to public transit (Shen et al., 2017; Lyft, 2015). If shared on-demand mobility is to replace mass transit, large fleet sizes will be required to meet demand resulting in additional congestion. For example, Basu et al. (2018) found that a scenario of automated mobility on demand (AMOD) substituting mass transit in Singapore would result in 50% higher in-vehicle travel times compared to a scenario where AMOD complements mass transit. Future research should study various integration scenarios of on-demand mobility with mass transit to assess their impacts on mass transit ridership and network performance.

Another factor that has helped in the quick adoption of on-demand mobility is shifting societal mobility preferences of millennials, i.e., those who were born between 1981 and 2000. Millennials are less likely to own cars and more likely to adopt a lifestyle of city living, environmental sustainability, and walking and cycling (Circella et al., 2015). They are also comfortable with information technology and services of the sharing economy including on-demand ride hailing services such as Uber and Lyft shared mobility (Mahmassani, 2016). It is unclear, however, whether these preferences are stable or whether millennials would revert to car-based modality styles as they enter the (delayed) child-rearing phase of their life. At any rate, the evolution of these preferences is likely to have an impact on the speed of uptake of on-demand shared mobility services of the future.

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