Online Calibration of an Integrated Framework for Information-Based Evacuation Operations

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Abstract: This study seeks to online calibrate the parameters of aggregate evacuee behavior models used in a behavior-consistent information-based control module for determining information strategies for real-time evacuation operations. It enables the deployment of an operational framework for mass evacuation that integrates three aspects underlying an evacuation operation: demand (evacuee behavior), supply (network management), and disaster characteristics. To attain behavior-consistency, the control module factors evacuees’ likely responses to the disseminated information in determining information-based control strategies. Hence, the ability of the behavior models to predict evacuees’ likely responses is critical to the effectiveness of traffic routing by information strategies. The mixed logit structure is used for the aggregate behavior models to accommodate the behavioral heterogeneity across the population. An online calibration problem is proposed to calibrate the random parameters in the behavior models by using the least square estimator to minimize the gap between the predicted network flows and unfolding traffic dynamics. Background traffic, an important but rarely studied issue for modeling evacuation traffic, is also accounted for in the proposed problem. Numerical experiments are conducted to illustrate the importance of the calibration problem for addressing the system consistency issues and integrating the demand, supply and disaster characteristics for more efficient evacuation operations.

Keywords: Evacuation operation; Evacuee behavior model calibration; Behavior-consistent information-based control; Background traffic.

1. INTRODUCTION

The evacuation problem, aiming to avoid/mitigate the potential loss of life due to disasters, is shaped by the associated demand, supply, and disaster characteristics. It addresses the movement of population (demand) from the affected or potential threatened region (disaster characteristics) to areas of safety using the available transportation system (supply). In an operational context, the disaster impact may evolve spatiotemporally and result in time-dependent effects on both the demand and supply sides. Under the effects of the disaster impact, the interactions between the demand and supply sides lead to the unfolding traffic dynamics of the evacuation network and link to the progress of the evacuation operation. Hence, it is critical for disaster response operators, to understand and account for the behavioral responses of the demand side to supply, and disaster characteristics [1-5].

To implement an evacuation operation over the affected/threatened region, it is critical to incorporate the time-dependent effects of and the interactions between the demand, supply, and disaster aspects in the determination of the associated evacuation strategies within a deployable framework. Hsu and Peeta [6] proposed a stage-based framework which is capable of integrating these three aspects in the context of online operations. Within this framework, information-based

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control strategies, including evacuation recommendation and route guidance, are disseminated to
the associated individuals to enhance the evacuation network performance, thereby enabling more
efficient operations. A key component of the proposed framework is a control module, labeled the
behavior-consistent information-based (BCIB) control module, which determines information-
based control strategies by factoring the likely responses of the potential evacuees. This enhances
the consistency between the control objective and the traffic flow pattern resulting from the
predicted evacuee responses. Also, it reflects the interactions between the demand (potential
evacuees) and supply (network control strategies) sides. To capture the likely demand-side
responses to the disseminated information, Hsu and Peeta [7] developed two behavior models for
no-notice evacuations, to predict the decisions of potential evacuees at an aggregate level in terms
of whether to evacuate when recommended to do so and their evacuation routes to take, labeled the
evacuation decision model and the evacuee route choice model, respectively.

In the proposed evacuation operations implemented with the BCIB control, the prediction
capabilities of the two behavior models are particularly important as the consistency between the
control objective and the predicted evacuee responses to the control is key to the operational
efficiency. Thereby, if the behavioral prediction of the demand-side responses is significantly
erroneous, the disseminated information-based control strategies can even negatively impact the
traffic conditions in the evacuation network. Since the demand pattern in the evacuation network
dynamically changes as the evacuation operation progresses, there is the need to develop an
approach to calibrate the behavior models online using data available in the operational context.

In control systems, a calibration problem seeks to minimize systematic inconsistencies based on
the gap between the predicted and actual (observed) system states. In the context of dynamic
traffic assignment (DTA), online calibration problems have been formulated based on unfolding
network traffic states over several potential sources of inconsistencies, including traffic flow
modeling (e.g. [8–10]) and Origin-Destination (O-D) demand estimation (e.g. [11–14]). More
recently, behavioral aspects in terms of driver route choices under information provision were
modeled and incorporated in an online calibration process seeking the adaptability of the
prediction models and thereby ensuring meaningful prediction of the evolving network traffic
states [15–17].

Evacuation traffic management, as a potential application of DTA, however involves different
operational contexts of data availability and information deployment characteristics, and
additionally subject to the uncertainty related to disaster impact [18,19] and demand-side
responses [20–22]. Hence, to attain effective BCIB control for evacuation operations, this study
constructs an online calibration process within a stage-based framework to minimize the
inconsistency associated with evacuee behavior prediction while addressing related operational
characteristics. More specifically, we seek to calibrate the parameters of the behavior models using
the observable real-time link traffic flows. Thereby, for the evacuee behavior models developed by
Hsu and Peeta [7], which entail a mixed logit structure to account for behavioral heterogeneity at
an aggregate level, a least squares estimation problem is proposed to calibrate the random
parameters in the mixed logit models. The formulation of this online calibration problem and the
development of its solution approach represent a primary contribution of this study, which enables
disaster response operators to track the dynamics of evacuee behavior within the proposed
stage-based framework and thereby enhancing the effectiveness of the deployed information
strategies.

To calibrate the parameters in the behavior models based on the observed link traffic flows,
another key issue is the background traffic existing in the network at the start of the evacuation
operation. The background traffic can affect the network traffic flows in the initial stages of the evacuation operation. Accordingly, the calibrated parameters can be biased, if the effect of the background traffic is ignored. However, in the evacuation-related literature, explicit discussion of the background traffic in the operational context is comparatively rare in terms of how its effect can be tracked and factored in network flow dynamics. Hence, another key issue of this study is to model and incorporate background traffic in formulating the online calibration problem, thereby more robustly accounting for its effects in predicting evacuation network traffic states.

The remainder of the paper is organized as follows. The next section introduces the integrated framework for evacuation operations using behavior-consistent information, where the roles of the two behavior models are further highlighted and summarized. Based on the introduced framework and behavior models, the problem of calibrating the random parameters in the behavior models is described. The modeling aspects related to the background traffic are also discussed in this section. Next, the calibration problem is formulated and a solution method is developed. It is followed by numerical experiments that illustrate the importance of the calibration problem to the operational performance. The final section provides some practical insights and concluding comments.

2. PROBLEM BACKGROUND

2.1. Integrated framework for evacuation operations using BCIB control

Figure 1 conceptually illustrates the stage-based framework for an evacuation operation that uses behavior-consistent information for traffic management, where the entire operational horizon is divided into stages to respond to the dynamics of the evacuation network by periodically monitoring/updating the evacuation-related aspects of the operation. In addition, the stages also define the time point for the implementation of traffic management strategies which have to be adaptive to the evolving evacuation network. That is, the changing conditions of the evacuation network are updated at the beginning of each stage, and the management strategies are determined accordingly and implemented to the network. The process repeated over the stages forms the loop shown in Figure 1, until the end of the operation.

In real-world operations, the information of evacuation recommendation and route guidance can be disseminated through personalized communications (such as cell phone and onboard GPS navigation) and public media (such as television, radio, and roadside message signs). To deploy the information-based strategies, the disaster response operators need to first identify to whom the information should be disseminated. Hsu and Peeta [6] suggested providing evacuation recommendations to the population in an evacuation risk zone (ERZ), a spatially bounded subzone of the disaster-affected region that encloses the population with the highest evacuation risk in the current stage. All evacuees within the ERZ should be provided route guidance to the safe areas as well. The ERZ for a stage is determined primarily based on evacuation risk which reflects the dynamics of disaster evolution and demand-supply interaction; it also factors practical issues related to traffic management and the available resources for deploying the evacuation operation. For more details of ERZ determination, please see Hsu and Peeta [6].

We assume the population initially in the ERZ can be known from regional surveys and/or relevant studies at the planning stage. Under the disseminated evacuation recommendations, an evacuation decision model (Figure 1) is used to aggregately forecast the number of decisions to evacuate made within the ERZ. These aggregate quantities across all locations in the ERZ represent the evacuation demand for that stage, and these evacuees can potentially be influenced
by route guidance provision.

In the proposed framework, the determination of route guidance information factors the operator’s objective and the predicted evacuees’ responses to the provided information. The operator’s objective is represented by some desired traffic flow pattern to effectively evacuate the affected region. It can be translated into a routing scheme as the desired proportions of evacuation demand taking a set of routes associated with each origin. The evacuation objectives may differ due to the nature of disasters and the relevant operational conditions, for example, minimizing total evacuation time [3,23], network clearance time [24], and exposure to the threat [25], or maximizing arrivals at safe areas within a given time period [26]. This research adopts the total evacuation time minimization as the operational objective. The associated routing scheme is obtained by solving a system optimal dynamic traffic assignment (SO-DTA) problem which includes the consideration of traffic condition projection.

The route guidance is determined so that the predicted route choice proportions based on the evacuee route choice decisions at each origin are as close as possible to the desired (SO) proportions. This entails the need for an evacuee route choice model that can forecast how evacuees make route choice decisions in response to the route guidance provided. In Figure 1, the behavior-consistent information-based (BCIB) control module contains this evacuee route choice model and a fuzzy-based control model of information strategies that interact with each other to determine the route guidance information strategies while predicting the likely responses of evacuees simultaneously. It is to note that in the BCIB control module, the operational objective is translated into the desired route choice proportions. Hence, this framework and the calibration problem to be formulated in this study can be employed for any operational objective but not limited to the SO objective.

In this study, we consider information-based control for no-notice evacuation, and the evacuation decision and evacuee route choice models developed in [7] are utilized in the framework shown in Figure 1 (the two gray-shaded boxes). In the context of no-notice evacuation, we assume that the major concern for evacuees is to leave the disaster-affected areas as early as possible in a comparatively shorter operational horizon. After arriving at safe places outside the affected areas and being secure, they can further move toward their final destinations. Hence, the focus is on routing to a safe location in the shortest time, rather than the final destination. However, the framework can be further extended to incorporate the related consideration as a separate decision or a joint route-destination decision.

The evacuation recommendation and the determined route guidance are collectively disseminated to each origin in the ERZ. The evacuees then start moving towards safe areas using the available roadway system, and the operation advances to the next stage under the evolving disaster impact characteristics and network traffic conditions. It is also assumed that en-route choices rarely occur due to the pressure, panic, and uncertainty regarding ambient traffic conditions that evacuees may experience in the context of no-notice evacuation. Once their evacuation routes are decided, they are less likely to repeatedly re-evaluate other alternatives along their journey and switch routes accordingly. However, if there is unexpected congestion (for example, link capacity reduction due to traffic accidents or disaster impact), we can still apply the evacuation route choice model to all the vehicles at the relevant nodes, including en-route vehicles and the vehicles just loading onto the network, so as to determine the route choice proportions from those nodes.

The stage-based operational framework described heretofore is implemented using a rolling
horizon approach, conceptually illustrated in Figure 2. In a rolling horizon approach, each stage is divided into a roll period and a tail period. The information-based control strategies are deployed for the evacuation demand generated in the roll period of a stage, but are computed based on a stage-wide operational objective. That is, the strategies seek to minimize the total travel time of the evacuees for the duration of the associated stage. Thereby, the SO-DTA problem is solved for the entire stage based on the evacuation demand generation during that stage forecasted by using the evacuation decision model. By leveraging the lengths of the stage and roll period, the rolling horizon approach can enable real-time or quasi-real-time operation [27]. In this study, the lengths of a stage and its roll period are set as 20 minutes and 10 minutes, respectively.

2.2. Evacuation decision and evacuee route choice models

This section provides relevant summaries of the evacuation decision and evacuee route choice models used to formulate the online calibration problem in this study. For comprehensive details of these two behavior models, please see [7].

The behavior models, shown as the two gray-shaded boxes in Figure 1, are used to predict the likely evacuation demand and route choice proportions under information provision at an aggregate level. The prediction capabilities of these models can be critical to the modeling of network traffic dynamics and affect the effectiveness of the information strategies determined thereupon. For example, if the evacuee route choice model underestimates the responses related to complying with the route guidance, the information determined from the BCIB control module may try to direct more evacuees to some routes and thereby result in congestion on them. Hence, there is the need to calibrate the two behavior models over time to ensure their robust prediction capabilities as the evacuation operation progresses. This entails the online calibration problem for the proposed operational framework, shown as the dashed-line box in Figure 1.

The two behavior models are developed as discrete choice models; with binary choices (“to evacuate” or “not to evacuate”) in the evacuation decision model, and multiple choices of evacuation routes in the evacuee route choice model. Due to the limitations of data availability in real-world evacuation operations, both models are developed at an aggregate level where explanatory variables are measurable in the operational context. To accommodate the behavioral heterogeneity across individuals in the context of aggregate modeling, a mixed logit structure is employed [28,29]. The systematic components of the utility functions of the two models are as follows.

Evacuation decision model:

\[
V_{E_s} = \alpha_o + \sum_i \alpha_i(\phi)x_{E_s}^i = \alpha_o + \alpha_{PR}(\phi)PR_s + \alpha_{ER}(\phi)ER_s + \alpha_{HB}(\phi)HB_s + \alpha_{SD}s
\]

Evacuee route choice model:

\[
V_{R_{sk}} = \beta_{sk} + \sum_j \beta_j(\phi)x_{R_{sk}}^j = \beta_{sk} + \beta_{TT}(\phi)TT_{sk} + \beta_{LF}(\phi)LF_{sk} + \beta_{FB}(\phi)FB_{sk} + \beta_{RG}(\phi)RG_{sk} + \beta_{HB}(\phi)HB_{sk}
\]

\[V_{E_s}\] is the systematic part of the utility for the choice to evacuate in the evacuation decision model, and \(\alpha_o\) is the associated constant term. \(\beta_{sk}\) is the route-specific constant term in the systematic utility function \(V_{R_{sk}}\) for route \(k\) from origin \(s\) (except for the route selected as the base route). \(x_{E_s}^i\) and \(x_{R_{sk}}^j\) are the aggregate-level measurable variables (and proxy variables) in the evacuation decision model and evacuee route choice model, respectively, for origin \(s\) and route \(k\), and \(\alpha_i\) and
\(\beta_j\) are the associated parameters. \(\alpha_\phi (\phi)\) and \(\beta_\varphi (\varphi)\) represent the random parameters following distributions with parameters \(\phi\) and \(\varphi\), respectively.

In the evacuation decision model, the variables are: (a) \(PR\), evacuation risk, perceived from the perspective of whether the people at a location (origin) can successfully evacuate before the disaster impacts it, which is computed as the difference between the lead time and clearance time of the node [6], (b) \(ER\), evacuation recommendation provided to an origin by the disaster response operators, which may range from voluntary to mandatory, (c) \(HB\), herding behavior, implying the phenomenon that people tend to follow the actions of others due to panic and the limited time to evaluate alternatives [30,31], and the proportion of individuals deciding to evacuate in the previous time interval is used as the proxy variable for it, and (d) \(SD\), state dependence, which captures the propensity to evacuate varying over time. In no-notice evacuation, upon an evacuation recommendation, if an individual does not evacuate in the interval, his/her propensity to evacuate increases in future time intervals, as he/she should ultimately evacuate. Hence, it is justifiable to assume that such propensity monotonically increase until the evacuation decision is made and thereby can be surrogated by the number of non-evacuation decisions made up to the current time interval (from the interval when a recommendation to evacuate is made). It can be also associated with the accumulated information reception and time pressure for decision-making [32] as disaster impact approaches, while the effect may be varied in different disaster contexts. According to the aforementioned consideration, the more the non-evacuation decisions made by individuals in no-notice evacuation, generally the higher the accumulated pressure on them to make a decision to evacuate in the current time interval. Comparatively, in short-notice evacuation, the time of day over a longer operational horizon (one to three days) may have a significant influence, in addition to the accumulated time pressure [33].

The variables in the evacuee route choice model include: (a) \(TT\), route travel time estimated by evacuees, (b) \(LF\), risk of link failure along a route due to potential disaster impact, (c) \(FB\), freeway bias, indicating that freeway is considered more reliable and preferable in disaster situations [3], (d) \(RG\), evacuation route guidance provided to evacuees, and (e) \(HB\), herding behavior, manifested as some evacuees making route choice decisions by following the ambient traffic flows they observe.

Based on the potential effect of each variable on decision-making, some parameters are specified with certain distributions. \(\alpha_{ER}(\phi)\), \(\alpha_{LF}(\phi)\), \(\beta_{FB}(\varphi)\), \(\beta_{RG}(\varphi)\), and \(\beta_{HF}(\varphi)\) (for \(ER\) and \(HB\) in the evacuation decision model, and \(FB\), \(RG\), and \(HB\) in the evacuee route choice model) are assumed to follow normal distributions, as the associated variables may influence the attractiveness of an alternative both positively and negatively across individuals. For example, individuals may intend to follow or not to follow the received evacuation recommendation and route guidance, depending on the levels of their trust in the information. Log-normal distributions are considered for \(\alpha_{PR}(\phi)\), \(\beta_{TT}(\varphi)\), and \(\beta_{LF}(\varphi)\) (for \(PR\) in the evacuation decision model, and \(TT\) and \(LF\) in the evacuee route choice model), because the associated variables should influence all individual decisions in the same direction. For instance, evacuation risk is generally perceived negatively. For these random parameters, the online calibration needs to be performed for both the mean and variance of the corresponding distributions. \(\alpha_{SD}\), the coefficient of \(SD\), is specified to be a fixed parameter. This allows to reflect the aspect that the probability of the decision to evacuate is higher in the latter stages of the evacuation operation due to the accumulated pressure to evacuate, compared with earlier stages, if all else is equal.

It is important to note here that these two models seek to capture evacuee behavior in the ERZ, as
they receive evacuation recommendation and route guidance information. However, from the perspective of modeling traffic dynamics in the evacuation network, these models can also be extended to represent the behavior of the individuals outside the ERZ. In such a context, the variables of evacuation recommendation and route guidance are removed from the models. Nevertheless, a certain proportion of individuals outside the ERZ may also be aware of the occurrence of the disaster and decide to evacuate, even without receiving an evacuation recommendation. To address this aspect, in the evacuation decision model the effect of the state dependence variable commences from the time interval that individuals become aware of the occurrence of the disaster.

3. ONLINE CALIBRATION PROBLEM

3.1. Consistency between predicted and actual network traffic states

The behavior-consistent information strategies are disseminated to the forecasted evacuation demand so that the route choice proportions for each origin can approach the desired proportions. The network traffic states over time can be predicted based on the forecasted demand and the associated route choice proportions. However, in the real world, the potential evacuees may not behave as predicted, in terms of their evacuation decisions and route choices. Thereby, the actual unfolding network traffic may not be consistent with the predicted states.

The consistency issue related to the traffic flow pattern prediction has been discussed in the context of deploying a DTA system for traffic management under information provision [9]. Several potential factors are identified, which can contribute to the inconsistency between the predicted and actual network traffic states, including: (i) incorrect prediction of time-dependent O-D demand, (ii) unexpected traffic incidents, (iii) incorrect traffic flow modeling, (iv) incorrect driver behavior modeling, (v) incorrect assumptions on system related parameters, (vi) noise/sparsity of measurements, and (vii) failure of Advanced Traveler Information Systems (ATIS) components. In the disaster-related evacuation problem, another potential source of the inconsistency can be the incorrect prediction of the evolving disaster characteristics and the associated impact on the traffic network; for example, link/node failure or capacity reduction. As this study focuses on behavioral responses to the information strategies deployed for an evacuation operation, to calibrate the evacuee behavior over time, it assumes that the inconsistency arises primarily due to inaccurate behavior modeling so as to isolate its effect from other potential factors.

A calibration problem of an online system is a process to fine tune the system-related devices or models so that the output measurements from these devices or models conform to actual observations or some standard values. In this manner, system operators can ensure that these devices or models work properly so that the associated measurements can be reliably used. To formulate a calibration problem, the system operators need to identify the model(s) of concern and the relevant parameter(s) to be calibrated. Also, they need to consider the measurements to be compared, which have to be observable based on the system operation characteristics and can be linked to the parameter(s) to be calibrated. Since this study focuses on calibrating the behavior models under information provision for evacuation operations, the parameters to be calibrated are $\alpha$ and $\beta$ in Eqs. (1) and (2). The link traffic flows are selected to represent the state of the evacuation network, as they are measurable at an aggregate level. It is to note that online data acquisition of the link traffic flows can be challenging due to the failure of connection and associated facilities under disaster impact. This research does not focus on this aspect, while
several approaches to address missing data or partial observations of network flows have been proposed in previous studies (e.g. [34,35]) and can be referred to.

3.2. Background traffic
To formulate the online calibration problem for this study, there is the need to factor link traffic flows into the likely route flow patterns. In this study, we assume that the traffic flow resulting from the evacuation demand can be tracked by the calibrated behavior models. However, other than the evacuation demand that enters the traffic network during the evacuation operation, there is background traffic that exists in the network at the start of the evacuation operation. The background traffic also contributes to the link traffic flows, especially in the initial stages of an evacuation operation. If the effect of the background traffic is not adequately incorporated, it can be another source of inconsistency in predicting network traffic states.

In the evacuation-related literature, background traffic is generally included in simulation-based models for evacuation planning. However, in the problem context of online control for evacuation operations, few studies have modeled the flows of background traffic and factor their effects in network traffic dynamics. Zheng et al. [36] proposed the optimal zone-based vehicular evacuation strategy by considering background traffic which is defined as the trips with origins and destinations outside the evacuation zone. By contrast, the traffic existing within the evacuation zone at the beginning of evacuation operations is not explicitly accounted for. Ren et al. [22] developed a bi-level programming model for evacuation routing and traffic signal optimization; although background traffic is considered and its uncertainty is formulated as a likelihood region, emergency evacuation routes are planned exclusively for particular evacuation demand (stadium evacuation in their case study). That is, the background traffic is not included within the evacuation traffic, and its effect is minimized to meet the operational objective of evacuating a certain group of evacuees merely.

In this study, we address how the vehicles in the background traffic may behave after the start of the evacuation operation and consequently affect the network traffic states, by assuming that the number of vehicles on each link at the start of the evacuation operation can be observed or inferred (for example, from sensors and/or historical data). In the context of modeling the responses to the information strategies, the drivers in the background traffic can be primarily characterized by two factors: \( v \), the percentage of drivers who receive route guidance, and \( \kappa \), the percentage of drivers who are familiar with the network. The matrix shown in Table 1 summarizes the behavioral characteristics of these drivers with respect to these two factors.

In the matrix, we define four classes of drivers in the background traffic, A to D, based on their behavioral characteristics related to information accessibility and network familiarity. Let \( N_a \) denote the number of background traffic vehicles on link \( a \). Then the number of drivers in each class can be identified by the definitional values of \( v \) and \( \kappa \). As these drivers are already in the network at the start of the evacuation operation, the behavioral focus is related to their route choice decisions. The matrix illustrates the route choice behavior for each class of background traffic in terms of the systematic utility function and the potential choice set. If drivers are familiar with the network and receive route guidance (Class A), their behavior can be similar to the behavior of the evacuees who enter the network after receiving an evacuation recommendation. For the drivers who do not receive any information, there is no effect of route guidance on their route choice behavior. Also, as they do not receive any information (such as the start of the evacuation operation), they are not aware of potential link failures on their routes due to a disaster. Hence, these terms are removed from the associated utility functions (Classes C and D). Drivers who are
not familiar with the network are more likely to follow the route guidance (if they receive it) and/or others’ actions. Accordingly, for Classes B and D, the means of the associated random parameters are increased by adding certain values ($\Delta_{RG}^b$, $\Delta_{HB}^b$, and $\Delta_{HB}^n$) which need to be estimated as well.

The pre-planned routes for the vehicles in the background traffic can potentially be estimated from the historical traffic data or relevant travel surveys. It is pertinent to note here that the background traffic outside the ERZ does not receive route guidance as guidance information is only provided for locations within the ERZ. Instead, in the corresponding models, the variable of route guidance ($RG_{sk}$) is replaced by a variable that denotes receiving the information on the disaster occurrence and a notice that the roads into the ERZ are blocked. If the trips of vehicles which receive that notice are destined to locations within the ERZ, the trips are cancelled. The option of staying on the pre-planned routes is removed, and replaced by alternatives that involve returning back to their origins.

Both $\nu$ and $\kappa$ are individual-level attributes that are difficult to observe in real-time operations. In the real world, $\nu$ can potentially be identified from regional surveys on the use of information systems, and $\kappa$ can be determined after estimating the percentage of through (non-local) traffic in the region based on regional planning data. In the study experiments, insights are obtained by conducting sensitivity analyses on these two parameters.

4. CALIBRATION OF BEHAVIORAL PARAMETERS

4.1. Problem formulation

The problem for online behavioral parameter calibration is mathematically formulated in this section. It seeks to update the random parameters in the mixed logit behavior models so as to ensure reliable prediction capabilities as the evacuation operation progresses. The problem is formulated based on a comparison between the predicted and actual (observed) link traffic flows. Thereby, the objective is to minimize the difference between the predicted and actual link traffic flows, and the least square estimator is used. Towards the end of stage $\sigma$ (Figure 1), to calibrate the behavior models to be used for the next stage, the problem is formulated as follows:

\[
\text{Minimize} \left[ \sigma^{p(\sigma)} - \hat{\sigma}^{p(\sigma)} \right]^2
\]

where $\sigma^{p(\sigma)}$ is the vector of actual link traffic flows for roll period $\rho(\sigma)$, and $\hat{\sigma}^{p(\sigma)}$ is the vector of predicted link traffic flows for the same period. $\sigma^{p(\sigma)}$ is obtained directly from the traffic system measurements, while $\hat{\sigma}^{p(\sigma)}$ is determined through the following process:

\[
\hat{\sigma}^{p(\sigma)} = \sigma^{p(\sigma)} + E\left[ Y^{p(\sigma)} \right]
\]

where $\sigma^{p(\sigma)}$ is the flow contribution from the evacuation traffic which has not reached the safe destinations by the end of roll period ($\sigma - 1$). $E\left[ Y^{p(\sigma)} \right]$ is the expected link traffic flows contributed from the evacuation demand loaded onto the network in roll period $\rho(\sigma)$. As $\sigma^{p(\sigma)}$ can be tracked using the model of network traffic flows and the data observed from previous stages, the focus of the calibration problem lies in the modeling of $E\left[ Y^{p(\sigma)} \right]$. To determine the expected values of link traffic flows due to the newly loaded evacuation demand in the associated roll period, the expected route flows from origin $s$ for time interval $\tau$ in roll period $\rho(\sigma)$ are represented as:

\[
E\left[ f_{sk}^{\tau} \right] = v_{sk}^{\tau} p_{ks}^{l}(\alpha) p_{ks}^{h}(\beta)
\]

For notational simplicity, hereafter let $\alpha$ and $\beta$ denote the entire sets of parameters to be calibrated.
in the evacuation decision model and evacuee route choice model, respectively. \( v \) is the remaining vehicular demand which has not evacuated up to \( \tau \), \( p_{E_\alpha}^t(\alpha) \) and \( p_{R_\alpha}^t(\beta) \) are the associated evacuation rate and route choice proportion on route \( k \) predicted by the evacuation decision and evacuee route choice models, parameterized by \( \alpha \) and \( \beta \), respectively. Modeled using the mixed logit structure, \( p_{E_\alpha}^t(\alpha) \) and \( p_{R_\alpha}^t(\beta) \) can be represented as:

Evacuation decision:

\[
p_{E_\alpha}^t(\alpha) = E[L_{E_\alpha}^t(\alpha)] = \int L_{E_\alpha}^t(\alpha)g_\phi(\alpha)d\alpha \tag{6}
\]

Evacuee route choice:

\[
p_{R_\alpha}^t(\beta) = E[L_{R_\alpha}^t(\beta)] = \int L_{R_\alpha}^t(\beta)h_\phi(\beta)d\beta \tag{7}
\]

where \( L_{E_\alpha}^t(\alpha) \) and \( L_{R_\alpha}^t(\beta) \) are the probabilities computed in the regular binary and multinomial logit model based on \( V_{E_\alpha} \) and \( V_{R_\alpha} \) in (1) and (2) evaluated at fixed values of \( \alpha \) and \( \beta \) for time interval \( \tau \), respectively:

\[
L_{E_\alpha}^t(\alpha) = \frac{\exp[V_{E_\alpha}(\alpha)\phi]}{1+\exp[V_{E_\alpha}(\alpha)\phi]} \tag{8}
\]

\[
L_{R_\alpha}^t(\beta) = \frac{\exp[V_{R_\alpha}(\beta)\phi]}{\sum_{\gamma} \exp[V_{R_\alpha}(\beta)\phi]} \tag{9}
\]

\( g_\phi(\alpha) \) and \( h_\phi(\beta) \) are the density functions of \( \alpha \) and \( \beta \) over the distributions (termed mixing distribution in the mixed logit model) conditioned on \( \phi \) and \( \phi \).

Due to the integrals in (6) and (7), there is no closed form for estimating the models. Instead, simulation-based methods are commonly used to approximate the integral in the mixed logit model by making random draws over the associated mixing distribution. Here, (6) and (7) can be approximated by the simulated probabilities as:

Evacuation decision:

\[
p_{E_\alpha}^t(\alpha) \approx \frac{1}{l_E} \sum_{i=1}^{l_E} L_{E_\alpha}^t(\alpha_i) \tag{10}
\]

Evacuee route choice:

\[
p_{R_\alpha}^t(\beta) \approx \frac{1}{l_R} \sum_{i=1}^{l_R} L_{R_\alpha}^t(\beta_i) \tag{11}
\]

where \( l_E \) and \( l_R \) are the numbers of draws made on \( \alpha \) and \( \beta \), respectively.

Representing the route flows in a vector form, \( F^t = \{F^t_k\} \), then we can write the expected values of in the vector as \( E[F^t] = V^t \cdot P^t(\theta) \), where \( V^t = \{v^t\} \) and \( P^t(\theta) = \{p_{E_\alpha}^t(\alpha)p_{R_\alpha}^t(\beta)\} \), and \( \theta \) is the vector containing behavior model parameters \( \alpha \) and \( \beta \). To construct the relationship from route flows to the expected link traffic flows for roll period \( \rho(\sigma) \), \( F^{\rho(\sigma)} \), \( V^{\rho(\sigma)} \), and \( P^{\rho(\sigma)}(\theta) \) are specified as the matrices containing the vectors \( F^t, V^t, \) and \( P^t(\theta), \forall \tau \in \rho(\sigma) \). The expected link traffic flows for roll period \( \rho(\sigma) \) can be derived as:

\[
E[F^{\rho(\sigma)}] = \Lambda^{\rho(\sigma)} \cdot E[F^{\rho(\sigma)}] = \Lambda^{\rho(\sigma)} \cdot E[F^{\rho(\sigma)} | P^{\rho(\sigma)}(\alpha, \beta)]
\]

\[
= \Lambda^{\rho(\sigma)} [V^{\rho(\sigma)} P^{\rho(\sigma)}(\alpha, \beta)] = (\Lambda^{\rho(\sigma)} \cdot V^{\rho(\sigma)}) P^{\rho(\sigma)}(\theta) \tag{12}
\]

\( \Lambda^{\rho(\sigma)} \) is the matrix describing the link-route incidence relationship for the route flows generated in \( \tau, \forall \tau \in \rho(\sigma) \). \( \Lambda^{\rho(\sigma)} \) is obtained based on the SO-DTA solution for the previous stage that is adjusted with the network traffic conditions under the new evacuation demand in the current stage.

Define \( \varepsilon \) as the difference between the predicted and actual link traffic flows, \( \varepsilon = \tilde{\sigma}^{\rho(\sigma)} - \hat{\sigma}^{\rho(\sigma)} \).

Accordingly:
\[ \varepsilon = \sigma^{(\phi)} - \left( \sigma^{(\phi)} + E[Y^{(\phi)}] \right) = \left( \sigma^{(\phi)} - \sigma^{(\phi)} \right) - E[Y^{(\phi)}] \]  

(13)

By definition, \( Y^{(\phi)} = \sigma^{(\phi)} - \sigma^{(\phi)} \). Letting \( V_{\lambda}' = \Lambda' \cdot V' \), the objective (3) for the least square estimator can be re-written as:

\[ \text{Minimize } Z = \varepsilon' \varepsilon = \left( Y^{(\phi)} - E[Y^{(\phi)}] \right)' \left( Y^{(\phi)} - E[Y^{(\phi)}] \right) = \left( Y^{(\phi)} - V^{(\phi)} \bar{P}^{(\phi)}(\theta) \right)' \left( Y^{(\phi)} - V^{(\phi)} \bar{P}^{(\phi)}(\theta) \right) \]  

(14)

As \( p^i_{\lambda}(\alpha) \) and \( p^i_{\lambda}(\beta) \) are probabilities derived using the discrete choice models based on (10) and (11), their values are strictly within [0, 1]. Additionally, the random parameters in the developed behavior models are either normally or log-normally distributed. Hence, the requirement of non-negativity for the variances in the associated distributions induces supplementary constraints in this calibration problem.

4.2. Solution method

The proposed problem to calibrate the behavioral parameters online is highly complex, as it involves the nonlinearity inherent in both the dynamics of network traffic flows and the mixed logit structure used for modeling evacuee behavior. Hence, this study proposes a heuristic solution method to address it, conceptually represented as an iterative search process shown in Figure 3.

The process starts (iteration 1) with an initial set of behavioral parameters, and the random draws (100 draws using Latin hypercube sampling in this study) are made over \( \alpha \) and \( \beta \) based on the relevant distributions (normal or log-normal). In the proposed solution method, coefficients derived from survey-based data are input as the initial parameters for the first stage, while in the following stages, the behavioral parameters calibrated from the previous stage are used as the initial parameters for the subsequent stage. Thereby, the distributions for the associated random parameters can be approximated with sets of points, or more specifically, randomly drawn values of \( \alpha \) and \( \beta \). Following (10) and (11), by averaging \( I^i_{\lambda}(\alpha) \) and \( I^i_{\lambda}(\beta) \) over the sets of different points of \( \alpha(\phi) \) and \( \beta(\phi) \), the simulated probabilities, \( p^i_{\lambda}(\alpha) \) and \( p^i_{\lambda}(\beta) \) are obtained. Accordingly, the predicted link traffic flows \( \hat{\sigma}^{(\phi)} \) can be further determined (4) and compared with the actual observations \( \sigma^{(\phi)} \). The difference between the observed and predicted values using the random parameters of the current iteration is evaluated using pre-specified convergence criteria. If the criteria are satisfied, the random parameters of the current iteration are output as the calibrated parameters; otherwise, the search process advances to the next iteration by updating the random parameters. In this study, the process terminates and outputs the parameters of the associated iteration if the improvement in reducing the square of the difference between \( \sigma^{(\phi)} \) and \( \hat{\sigma}^{(\phi)} \) is within 5% for 20 consecutive iterations.

The search direction for updating the random parameters is governed by the first-order gradient of the square of the difference \( Z \) over the parameters. By expanding (14):

\[ Z = \left[ Y^{(\phi)} \right]' Y^{(\phi)} - \left[ P^{(\phi)}(\theta) \right]' \left[ V^{(\phi)} \right]' Y^{(\phi)} - \left[ V^{(\phi)} \right]' V^{(\phi)} \bar{P}^{(\phi)}(\theta) + \left[ \bar{P}^{(\phi)}(\theta) \right]' \left[ V^{(\phi)} \right]' V^{(\phi)} \bar{P}^{(\phi)}(\theta) \]  

(15)

Taking the first-order gradient of \( Z \) over \( \theta \):

\[ \frac{\partial Z}{\partial \theta} = \frac{\partial Z}{\partial P^{(\phi)}(\theta)} \frac{\partial P^{(\phi)}(\theta)}{\partial \theta} = \left( -2 \left[ V^{(\phi)} \right]' Y^{(\phi)} + 2 \left[ V^{(\phi)} \right]' V^{(\phi)} \bar{P}^{(\phi)}(\theta) \right) \frac{\partial P^{(\phi)}(\theta)}{\partial \theta} \]  

(16)

Herein, for each entry in \( P^{(\phi)}(\theta) \),

\[ p^{i}(\theta) = p^{i}_{\lambda}(\alpha) p^{i}_{\lambda}(\beta) = \left[ \frac{1}{E} \sum_{n=1}^{N} I^i_{\lambda}(\alpha_{m}(\phi)) \right] \left[ \frac{1}{R} \sum_{n=1}^{N} I^i_{\lambda}(\beta_{n}(\phi)) \right] \]  

(17)
Following this search direction, the random parameters will be updated as:

\[
\theta^{(n+1)} = \theta^{n} - \lambda^{n} \left( \frac{\partial Z}{\partial \theta_{p,\alpha,\beta}} \right)
\]  

(18)

\(\lambda^{n}\) is the step size for the search over the first-order gradient direction. We let \(\lambda^{n} = 1\), which may incur a few more iterations but significantly benefit computational simplicity within each iteration.

It is pertinent to note that \(\nu^{n}\), the number of people remaining at the beginning of each associated time interval, is dependent on the number of evacuation decisions made in the previous time interval. Also, the route choice proportions can affect the time-dependent link-route flow incidence relationships, as the result of intricate flow interactions. To precisely factor these relationships and the associated estimation can substantially increase the complexity to calculate the gradient of \(Z\). However, the derived improvement in solution quality and computational efficiency can be limited for the online operational problem, as the criteria are defined based on the value of \(Z\) but not its gradient. Hence, the search direction to the iterative search process is determined here based only on the gradient of \(p\) over \(\theta\). As a heuristic method, its iterative search along the first-order gradient may lead to some local minimum. However, the random draws over the distribution of \(\alpha\) and \(\beta\) can also allow some probability to explore larger solution space. In addition, more strict criteria can be adopted to attain better quality for the solution depending on how the network operators can leverage the trade-off between effectiveness and their computing power.

The formulation and solution method discussed focus on the calibration for a generic stage. It is relevant to note again that for the first stage, the effects of the background traffic on the network traffic flows can be introduced based on the modeling approach proposed in Section 3.2.

5. NUMERICAL EXPERIMENTS

Numerical experiments are conducted to illustrate several important issues/aspects that are addressed by the proposed operational framework for mass evacuation and the calibration problem formulated in this study. These issues/aspects are discussed in several dimensions in terms of the integration of demand, supply, and disaster aspects in the stage-based operational framework. First, the disaster characteristics are factored through the ERZ concept so that the deployment of evacuation strategies is adaptive to the dynamics of the disaster impact and network traffic states. Second, the demand-supply interactions are accounted for by incorporating the likely demand-side responses in the determination of behavior-consistent information-based evacuation strategies. Third, the evacuation operation is implemented within a stage-based framework through the online calibration of the behavior models. This captures the spatial and temporal evolution of the evacuation network as the behavioral parameters are calibrated based on the observation of the unfolding network traffic flow pattern.

5.1. Experimental setup

5.1.1. Study network and disaster characteristics. The Borman Expressway Network (Figure 4), located in Northwest Indiana, is used as the study network and includes 197 nodes and 460 links. 60 nodes, (roughly) uniformly spread over the network, are selected as origins with potential evacuation demand. Two disaster impact scenarios are created with the dynamics of disaster spreads specified as:

- Disaster impact A: A chemical plant accident occurs near the center of the network (see Figure
4), and the disaster impact uniformly spreads through the network in a radial pattern (with circular impact contours) with a speed of 1.0 mile/hr.

- Disaster impact B: The disaster event is the same as in Scenario A; however, the disaster impact spreads under a 0.2-mile/hr directional wind from west to east.

5.1.2. Actual evacuee behavior. In the absence of empirical data on evacuation traffic, the actual evacuee behavior in the experiments is represented using two bi-level lexicographic decision-making processes for evacuation decision and evacuation route choice, respectively [7]. In these two decision-making processes, the data of evacuation traffic are synthesized at an individual level, where each individual is randomly assigned perceived values of the relevant factors based on the designed experimental scenario following pre-specified normal distributions, which reflects behavioral heterogeneity across the population. In each time interval of the roll period, each individual in the ERZ who is still at his/her origin first faces the decision of whether to evacuate or not. If an individual decides to evacuate in a time interval, he/she has to further choose the evacuation route to take. Otherwise, he/she will remain at the origin and go through the same decision-making processes in the next time interval. In each bi-level lexicographic decision-making process, individuals are again randomly assigned to several behavioral classes related to the factors specified in the associated behavior model, for example, PR class for evacuation decision and TT class for evacuation route choice. At the first level, each individual evaluates alternatives based only on the factor of his/her behavioral class with his/her perception (randomly assigned), and the alternative which meets a pre-specified threshold or is significantly better off in terms of this factor will be selected. For example, an individual in the behavioral class of route travel time (TT) will select a route with significantly shorter travel time regardless of other factors. If alternatives are seemingly competitive in terms of the factor associated with an individual’s behavioral class, the decision cannot be made at the first level. This individual then moves to the second level and evaluates alternatives based on an assumed utility function by considering all the relevant factors. The details of the two bi-level decision-making processes are provided in [7].

The synthesized decisions are propagated using a mesoscopic traffic simulator, DYNASMART-P, to generate evacuation traffic for the experiments. DYNASMART-P is a DTA analysis tool which is capable of simulating the dynamics of network flow patterns based on Wardrop's first and second principles, or designated flow allocation mechanisms associated with time-varying demand and network conditions. It illustrates the interactions of traffic flows at a mesoscopic level, where vehicles are moved using aggregate flow-speed-density relationships over links for better computational efficiency, and includes the formation and dissipation of congestion. These are particularly important in an evacuation operation. More detailed information and methodological aspects can be found in [37].

It is important to note here that the structures/mechanisms of the two behavior models and the bi-level decision-making processes to synthetically generate actual behavior are different, though the same set of factors are considered for each decision. Thereby, the bi-level decision-making processes are only used to generate “actual” evacuee behavior at individual level. The disaster response operators do not know these decision-making processes but only observe the synthesized data at an aggregate level akin to observing empirical data on evacuation traffic if it were available.

5.1.3. Scenarios of evacuation operation deployment. To illustrate the importance of integrating the demand, supply, and disaster aspects within an operational framework that can be deployed
using the online calibration approach proposed in this study, five scenarios of evacuation operation deployment in terms of information-based control are analyzed:

- No information strategies deployed (NIF): No evacuation recommendation and evacuation route guidance are provided.
- Deployment with system optimal control (SO): The SO-DTA solution is computed and implemented for the entire evacuation time horizon. The associated flow pattern of evacuation traffic is viewed as the benchmark for ideal traffic management as all individuals are assumed to comply with the provided SO routes.
- ERZ-based deployment of non-behavior-consistent information (ERZ-NBC): Information strategies are deployed in synergy with stage-based ERZs. The linguistic route guidance information is determined by directly mapping SO assignment proportions with the triangular membership function [17] shown in Figure 5, but the likely responses of evacuees are not considered.
- ERZ-based deployment of behavior-consistent information (ERZ-BC): In contrast to ERZ-NBC, behavior-consistent information is determined by factoring the likely responses of evacuees using the proposed behavior models. However, the behavior models are not calibrated as the evacuation operation progresses.
- ERZ-based deployment of behavior-consistent information with calibrated behavior models (ERZ-BCC): In contrast to ERZ-BC, the behavior models used to determine behavior-consistent information are calibrated online using the approach proposed in this study.

For the deployment of ERZ-NBC, ERZ-BC, and ERZ-BCC, the rolling horizon approach is used to implement the evacuation operation. In the experiments, the lengths of a stage and the associated roll period are 20 minutes and 10 minutes, respectively.

5.2. Experiment Results and Analysis

5.2.1. Performance measure. The effectiveness of an evacuation operation is evaluated in terms of the network-related performance. This study uses two performance measures: (i) network clearance time (NCT), the time required to clear the network, and (ii) average evacuation risk exposure (AVRE), a measure that indicates the time margin for individuals to safely exit a location before it is impacted by the disaster. For each individual q, this measure is calculated as:

$$ R_q = \frac{\sum_{a \in K_q} (LT_a - ET_{aq})}{|K_q|} $$ (19)

where $K_q$ represents the set of nodes on the evacuation route that individual q takes, and a is the subscript for a node. $LT_a$ is the time point of the arrival of the disaster impact at node a. $ET_{aq}$ is the time point that individual q exits node a and moves to the next node on his/her evacuation route. The difference between $LT_a$ and $ET_{aq}$ is defined as the evacuation risk that individual q sustains at node a, which implies the spare time for the individual to evacuate from node a, and the negative sign indicates that evacuation risk is negatively valued. Eq. (19) averages the evacuation risk that individual q sustains along his/her evacuation route. $R_q$ is further averaged over the total evacuation demand to obtain the aggregate network-level performance. In (19), $LT_a$ reflects the disaster impact, and $ET_{aq}$ implies demand-supply interactions in terms of the movement of evacuee in the evacuation traffic flows. Collectively, the AVRE involves both disaster and network traffic aspects.
5.2.2. Comparison of evacuation operation deployment. Considering a demand of 67,200 vehicles, the experiments for different scenarios of the evacuation operation deployment under disaster impact A and B are summarized in Tables 2 and 3, respectively. In Table 2, the SO deployment, as the benchmark of idealized traffic control, outperforms others in terms of its performance on both the NCT and the AVRE. It results in the shortest NCT and the average longest time margin for evacuees to be safely evacuated from being impacted by the disaster. The third and fifth columns in Table 2 illustrate the improvement (in percentage) of the associated deployment scenarios relative to the NIF scenario in terms of NCT and AVRE, respectively. Compared to NIF, the deployment of ERZ-NBC can slightly improve network performance. However, ERZ-BC is significantly better off than ERZ-NBC, which indicates the importance of using behavior-consistent information. In the deployment of ERZ-BCC, where the behavior models are calibrated online, the network performance is further improved. In terms of the AVRE, ERZ-BCC performs very close to that of the idealized SO deployment, further highlighting the benefits of calibrating behavioral parameters online in a deployment framework.

Under disaster impact A, the directions of evacuation traffic propagation and the spread of disaster impact are synergistic to a certain degree. Table 3 displays the experiment results under disaster impact B, where more variability of the spread of disaster impact is created by introducing a directional wind. Under this variability, the performance in terms of NCT in each deployment scenario is worse off to a certain degree (1–6% increase of NCT), except the SO deployment, where we assume that evacuees fully comply with the provided SO routes and do not consider disaster impact in their route choice decisions. In terms of the performance of AVRE in each deployment under disaster impacts A and B, there are significant performance reductions in NIF and SO. However, in the deployment of ERZ-NBC, ERZ-BC, and ERZ-BCC, the performance of AVRE is reduced with comparatively smaller percentages (2–7%). This highlights the benefit of ERZ-based deployment in terms of AVRE due to its better adaptation to the variability in disaster impact dynamics. The ERZ-BCC deployment leads to the best performance in AVRE under disaster impact B, since it further accounts for the control aspects related to evacuee behavior dynamics as well.

5.2.3. Effectiveness of Online Calibration. As shown in Tables 2 and 3, ERZ-BCC outperforms ERZ-BC in terms of evacuation efficiency against disaster dynamics. This section further compares the two deployments to highlight the effect of online calibration on model prediction capabilities. Figure 6 plots the average prediction errors for both evacuation decision and evacuation route choice. The prediction error is computed as the proportion of choices which are wrongly predicted (in terms of the total number of wrong predictions at an aggregate level). For both models, prediction errors are decreasing along the stages if the online calibration is employed, which drop to around 10% after the 10th stage. By contrast, without the calibration, prediction errors remain above 20% for both behavior models. The difference between the trends of prediction errors under ERZ-BCC and ERZ-BC indicates the effect of the online calibration to factor behavioral dynamics on the demand side. In Figure 6, we also attach the calibrated random parameters (normally distributed) for evacuation recommendation and route guidance along the stages. The calibration results show that for the two normal distributions, both their means and variances present some decreasing trends. Such trends may imply the models capture the behavioral tendency that those who remain in the network till the later stages are less willing to follow the received information, particularly for evacuation recommendations (as what we design in the generation of synthetic data). Additionally, as people decide to evacuate along the stages, the
behavioral heterogeneity for those remaining in the network are decreasing as well.

Figure 7 illustrates the performance of each deployment with respect to the deviation from the desired SO route assignment proportions along the stages, and it particularly highlights the comparison between ERZ-BC and ERZ-BCC in terms of how much the associated information strategies can affect route choice proportions to approach the SO proportions. The performance is represented as the proportion of route choices deviated from the SO proportions at an aggregate level. A smaller percentage deviation of route choice proportions from the SO proportions implies that the derived traffic flow pattern is closer to the ideal SO solution. If the behavior models can more accurately predict the likely responses of evacuees to the disseminated information strategies, the information determined by the BCIB control module can more effectively direct the route choice proportions to approach the SO proportions. In Figure 7, the ERZ-BCC deployment gradually improves the prediction capabilities of the behavioral models, and the deviation from the SO proportions reduces to about 10% after the ninth stage. By contrast, without the online calibration of the behavioral parameters, the deviation in ERZ-BC remains above 20% throughout the operation. Figure 7 de facto shows the results similar to the error variation for evacuation route choice prediction in Figure 6. It is to note that the two models use the same set of initial behavioral parameters in both ERZ-BC and ERZ-BCC deployment, which can be estimated from a planning procedure (such as stated-preference or post-disaster surveys). Thereby, in Figures 6 and 7, both models start with the same performance in the first stage of the operation.

5.2.4. Analysis of background traffic. This section analyzes the effect of accounting for background traffic in the online calibration of the behavioral parameters. The effect of background traffic on network flows is factored using the matrix with behavioral specifications in the Background Traffic Section for the first stage. Here, the effects of addressing and not addressing background traffic are illustrated in Figure 8 for the ERZ-BCC deployment scenario with 67,200 vehicles under disaster impact A. Experiments with background traffic of 15% and 25% of the total demand are conducted, where 90% is used for the parameters \( \nu \) (percentage of drivers who receive route guidance) and \( \kappa \) (percentage of drivers who are familiar with the network). The deviation between the route choice proportions and the SO proportions is also analyzed to evaluate the effectiveness of the evacuation operations.

In Figure 8, the deviation gradually reduces with the progress of the evacuation operation in every experiment. This is partly because the online calibration (under ERZ-BCC) can generally improve the prediction capabilities of the behavior models. Further, the negative effect of not accounting for the background traffic also reduces as the associated vehicles are discharged from the network when they arrive at their destinations. In the experiments where the background traffic is considered, the magnitude and rate of reduction are greater; the reduction is about 15 percentage points throughout the operation as compared with 10 percentage points if the background traffic is not considered. In addition, a higher level of background traffic generally results in a higher deviation from the SO proportions, as it introduces more uncertainty in the system or more degrees of freedom to the calibration problem.

Table 4 summarizes the sensitivity analyses on the two parameters \( \nu \) and \( \kappa \) for the background traffic as 25% of the total demand. Pivoting on \((\nu, \kappa) = (90\%, 90\%)\), the experiments with different combinations of \((\nu, \kappa)\) are evaluated in terms of the NCT. Even with the background traffic of 25% of the total demand within the evacuation network, the effects of these two parameters are comparatively small. Under \( k = 90\% \), the change of \( \nu \) from 100% to 50% leads to only about 3% increase in the NCT. However, from the analyses, \( \nu \) in general has a more significant effect on the
efficiency of the evacuation operations than $k$ does. This may be because $\nu$, the percentage of drivers who receive route guidance, determines the scope of influence that the information-based control can attain. By contrast, for a driver in the background traffic who is unfamiliar with the network, as long as he/she receives the information disseminated, it can affect his/her route choice to a greater extent, compared with those who are familiar with the network.

5.2.5. Computational cost. The numerical experiments are implemented on a Windows 7 based PC equipped with a Core 2 Duo CPU T7500 processor running at 2.67 GHz. For a stage, the calibration problem can be solved in around a minute for the study network. Collectively with the other related processes (ERZ determination, SO-DTA solution, and behavior-consistent information determination), the computation time required for determining information-based evacuation strategies for a stage is around five minutes. Hence, the proposed operational framework can seamlessly be deployed within the rolling horizon approach for real-time operation.

6. CONCLUDING COMMENTS

Based on an information-based control framework for mass evacuation, this study seeks to deploy real-time evacuation operations by calibrating the behavioral parameters in two evacuee behavior models (evacuation decision model and evacuee route choice model) to integrate the dynamics of demand-supply interactions. The online calibration problem enhances the consistency between the observed (actual) and predicted network traffic states so as to ensure meaningful prediction by these behavior models in an operational context. Accordingly, the behavior-consistent information strategies determined by the BCIB control module can be more effective, as the determination of information strategies relies on the evacuees’ likely responses predicted by using these behavior models.

The two behavior models use variables observable at an aggregate level in light of the challenge to track the decisions made by each specific individual, and the mixed logit structure is employed to accommodate the behavioral heterogeneity across the affected population. This research primarily contributes the online calibration problem for the random parameters in these two behavior models, which preserves the mixed logit structure for computing aggregate evacuation decisions and route choice proportions. The problem is formulated by using the least square estimator to minimize the difference between the predicted and observed network traffic flows. A heuristic solution method embedded with random draws is proposed to iteratively search for the parameters that better represent the behavioral dynamics. The computational efficiency of the proposed heuristic method enables seamless incorporation of the calibration problem into the operational framework within a rolling horizon approach that executes the evacuation operation in a stage-based manner. Hence, the overall framework is deployable for real-world operations.

In addition, this study also contributes to accounting for the effect of background traffic on the network flow pattern. As the background traffic can also affect the factoring of network traffic, it can be directly related to the formulation of the online calibration problem and consequently degrade prediction capabilities of the calibrated behavior models. Hence, modeling the behavior of drivers in the background traffic is also essential to comprehensively factor the effect of behavioral aspects in the network flow pattern and improve the efficiency of network traffic management, especially in the earlier stages.

Numerical experiments of different deployment scenarios for evacuation operations are
implemented in the proposed operational framework which integrates the aspects related to the evolving disaster characteristics, demand-supply interactions, and the spatio-temporal evolution of the evacuation network resulting from the intricate traffic flow interactions. The experiment results highlight the importance of accounting for these aspects and the ability of the proposed framework to address them. Particularly, the online calibration problem plays an important role to capture the variation of evacuee behavior across time stages, which ensure behavior-consistency over time and enhance the effectiveness of the information-based evacuation control. The sensitivity analysis over background traffic also suggests that incorporating behavior modeling of background traffic in the online calibration problem can aid the determination of more effective information strategies.

More generally, the online calibration problem in this study enables the real-time operational deployment of the integrated framework of information-based control for disaster-related mass evacuation. The system consistency issues and the integration of relevant aspects are systematically addressed through several methodological perspectives within a unified framework. These perspectives are relative to system robustness with respect to the dynamics of the evacuation network and evolving disaster impact. While this study focuses on the inconsistency resulting from the dynamics of evacuee behavior, a future research direction is to extend the calibration problem to address other potential factors of system inconsistency, which can be non-trivial in the random and complex environments of real-world evacuation operations.

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REFERENCES

6. Hsu Y-T, Peeta S. Risk-based spatial zone determination problem for stage-based evacuation
operations. *Transportation Research C* 2014; **41**: 73–89.


Table 1. Behavioral characteristics of drivers in background traffic

<table>
<thead>
<tr>
<th>Familiar with network ( \kappa ) %</th>
<th>Receiving route guidance ( \nu ) %</th>
<th>Receiving no route guidance ( (1- \nu) ) %</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Drivers respond to route guidance akin to the evacuees who enter the network after receiving recommendations</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( U_{R,k} = \beta_{sk} + \beta_{TT}(\varphi)TT_{sk} + \beta_{Lx}(\varphi)LF_{sk} + \beta_{FB}(\varphi)FB_{sk} + \beta_{RG}(\varphi)RG_{sk} + \beta_{HB}(\varphi)HB_{sk} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C. Drivers may choose to:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Follow other vehicles</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Stay on pre-planned or preferred routes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( U_{R,k} = \beta_{sk} + \beta_{TT}(\varphi)TT_{sk} + \beta_{FB}(\varphi)FB_{sk} + \beta_{HB}(\varphi)HB_{sk} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B. Drivers may choose to:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Follow route guidance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Follow other vehicles</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Stay on pre-planned routes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( U_{R,k} = \beta_{sk} + \beta_{TT}(\varphi)TT_{sk} + \beta_{Lx}(\varphi)LF_{sk} + \beta_{FB}(\varphi)FB_{sk} + \beta_{RG}(\varphi)RG_{sk} + \beta_{HB}(\varphi)HB_{sk} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>D. Drivers may choose to:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Follow other vehicles</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Stay on pre-planned routes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( U_{R,k} = \beta_{sk} + \beta_{TT}(\varphi)TT_{sk} + \beta_{FB}(\varphi)FB_{sk} + \beta_{HB}(\varphi)HB_{sk} )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Experiment results under disaster impact A

<table>
<thead>
<tr>
<th>Deployment</th>
<th>NCT (min)</th>
<th>NCT improvement relative to NIF (%)</th>
<th>AVRE (min)</th>
<th>AVRE improvement relative to NIF (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIF</td>
<td>165.4</td>
<td>--</td>
<td>-30.9</td>
<td>--</td>
</tr>
<tr>
<td>ERZ-NBC</td>
<td>158.7</td>
<td>4.05</td>
<td>-32.8</td>
<td>6.15</td>
</tr>
<tr>
<td>ERZ-BC</td>
<td>145.8</td>
<td>11.85</td>
<td>-38.5</td>
<td>24.60</td>
</tr>
<tr>
<td>ERZ-BCC</td>
<td>140.9</td>
<td>14.81</td>
<td>-39.8</td>
<td>28.80</td>
</tr>
<tr>
<td>SO</td>
<td>130.2</td>
<td>21.28</td>
<td>-40.3</td>
<td>30.42</td>
</tr>
</tbody>
</table>

Table 3. Experiment results under disaster impact B

<table>
<thead>
<tr>
<th>Deployment</th>
<th>NCT (min)</th>
<th>Decrease in the performance of NCT relative to disaster impact A (%)</th>
<th>AVRE (min)</th>
<th>Decrease in the performance of AVRE relative to disaster impact A (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIF</td>
<td>174.9</td>
<td>-5.74</td>
<td>-24.8</td>
<td>-19.74</td>
</tr>
<tr>
<td>ERZ-NBC</td>
<td>163.1</td>
<td>-2.77</td>
<td>-30.5</td>
<td>-7.01</td>
</tr>
<tr>
<td>ERZ-BC</td>
<td>149.8</td>
<td>-2.74</td>
<td>-36.3</td>
<td>-5.71</td>
</tr>
<tr>
<td>ERZ-BCC</td>
<td>143.5</td>
<td>-1.85</td>
<td>-39.0</td>
<td>-2.01</td>
</tr>
<tr>
<td>SO</td>
<td>130.2</td>
<td>--</td>
<td>-35.7</td>
<td>-11.41</td>
</tr>
</tbody>
</table>

Table 4. Sensitivity analyses on \( \nu \) and \( \kappa \)

<table>
<thead>
<tr>
<th>NCT (min) for the experiments with background traffic of 16,800 vehicles (25% of total number of vehicles to be evacuated)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \nu = 90% )</td>
</tr>
<tr>
<td>161.7</td>
</tr>
<tr>
<td>( k = 90% )</td>
</tr>
<tr>
<td>163.2</td>
</tr>
</tbody>
</table>
Fig. 1. Conceptual framework for evacuation operations using information-based control

Fig. 2. Implementation of the rolling horizon approach
(both the roll period and tail period are specified to be 10 minutes in this research, and the total length of a stage is 20 minutes)
Fig. 3. Solution method for the online calibration problem
Chemical plant accident

Origin for evacuation demand

Fig. 4. Study network and disaster characteristics for numerical experiments

Φ₃: “The route is strongly recommended for evacuation”
Φ₂: “The route can be considered for evacuation”
Φ₁: “No specific guidance provided regarding the route”
Φ₀: “It would be better not to consider the route for evacuation”
Φ₋₁: “The route should not be used for evacuation”

Fig. 5. Membership functions used for linguistic messages
Fig. 6. Illustration of random parameters and effect of online calibration on prediction accuracy
Fig. 7. Comparison of experiment results in terms of deviation from SO proportions

Fig. 8. Experiment results with background traffic