

Model Reference Adaptive Control Framework for Real-Time Traffic Management under Emergency Evacuation

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Abstract: Recent natural or man-made disasters around the world have provided compelling evidence that transportation system plays a crucial role in the emergency evacuation and have stressed the need for effective evacuation traffic management to maximize the utilization of the transportation system and to minimize fatalities and losses. This paper presents a model reference adaptive control (MRAC) framework for real-time traffic management under emergency evacuation. Distinct from the well-studied evacuation planning, real-time traffic management for evacuation aims to dynamically guide (control) traffic flow under evacuation in such a way that certain system objective (e.g., minimization of fatalities or property losses) could be achieved. The proposed framework is based on both dynamic network modeling techniques and adaptive control theory, by considering the traffic network under evacuation as a dynamic system. First, a prescriptive dynamic traffic assignment model is applied to predict, in a short-term and rolling-horizon manner, the desired traffic states based on certain system optimal objectives. This model will serve as a reference point for the adaptive control. Then, the adaptive control system integrates these desired states and the current prevailing traffic conditions collected via the sensing system to produce real-time traffic control schemes. Finally, these traffic control schemes are implemented in the field to guide the real-world traffic flow to evolve towards the desired states. Simulation studies provided in this paper show that the proposed framework based on MRAC can significantly improve the performance of real-time evacuation traffic management.

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Introduction and Motivation

Man-made or natural disasters, either predictable or not, could result in severe life losses and property damages. Emergency evacuation, a mass movement of people and their properties from disaster-impacted areas to safer ones, has been studied and practiced for decades as one means of countermeasures to mitigate these calamitous consequences. Existing evacuation research in transportation field has been mostly focusing on the planning stage, from various perspectives such as traffic management policies (Theodoulou and Wolshon 2004), origin-destination (OD) trip estimations (Mei 2002; Murray-Tuite and Mahmassani 2003; Fu and Wilmot 2004), and behavior analysis (Baker 1991;

Helbing et al. 2000; Fraser-Mitchell 2001). Moreover, due to the distinct features of different types of disasters, specific planning models have been developed for various evacuation scenarios, including nuclear plant crisis, hurricane, flooding, and fire, etc. For detailed discussions regarding evacuation planning modeling, we refer to reviews by Southworth (1991), Urbina and Wolshon (2003), and Alsnih and Stopher (2003).

Although evacuation planning is important for the emergency preparedness, it hardly gives good predictions of future evacuation scenarios due to the highly dynamic and uncertain features involved in such extreme events. Past experience has shown that ineffective traffic management under evacuation could result in severe traffic jams and life losses. Therefore, effective real-time traffic management for emergency evacuation is crucial to maximize the utilization of the transportation system and thus minimize fatalities and losses. As a result, there is an urgent need for emergency management agencies to look for ways to manage the evacuation traffic efficiently and effectively in real time. Interestingly, despite a long history of evacuation research in transportation field, only a few studies have been reported regarding real-time traffic management under evacuation (Barrett et al. 2000). However, these existing real-time models mainly rely on the dynamic network modeling technique which may not be sufficient to capture the highly dynamic and uncertain characteristics of traffic flows under evacuation. On the other hand, as one may only ascertain the current state of traffic (vehicles and people) under evacuation, effective real-time traffic management is expected to be highly dependent on the current traffic state and thus must be traffic *adaptive*.

In this paper, therefore, we propose a model reference adaptive control (MRAC) based real-time traffic management framework for evacuation, by integrating both dynamic network modeling

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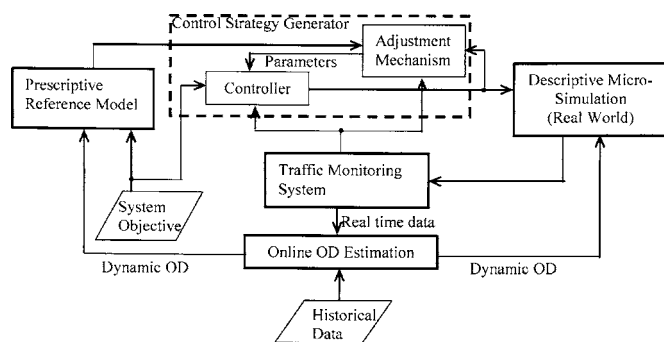


Fig. 1. Framework for adaptive control-based real-time evacuation traffic management

techniques and adaptive control theory. In the framework, the traffic network under evacuation is treated as a dynamic system. The states of the system can be collected through existing and emergently deployed sensing devices. A prescriptive dynamic traffic assignment (DTA) model is applied to predict, in a short-term and rolling-horizon manner, the desired traffic states based on certain system optimal objectives. This model will serve as a reference point for the adaptive control. Then, these desired states and the current prevailing traffic conditions collected via the sensing system are evaluated and fed into the adaptive control model to produce real-time traffic control schemes. These schemes will be finally implemented in the field to guide evacuation traffic flows to evolve toward the desired states. In such a framework, the prediction error of the prescriptive DTA could be minimized partially because the prediction is only short term and based on latest traffic conditions, and partially due to the fact that the adaptive control model could tolerate or even eliminate such errors. Simulation studies are also provided in this paper using the flooding scenario in the City of Logan, Utah. Results show that the proposed adaptive control based framework can remarkably improve the performance of real-time traffic management under evacuation in the sense that both the evacuation time and the possible fatalities could be significantly reduced.

This paper is organized as follows. The adaptive control based framework is proposed in the second section, with three major components identified and described, including the prescriptive DTA model, adaptive control model, and the real-world traffic model. Each of the three components is further discussed in the next three sections. In particular, we focus on key issues for designing these models by considering the distinct features of evacuation traffic flows. Simulation studies are provided in the next section, followed by concluding remarks and future study directions.

Adaptive Control-Based Framework for Real-Time Evacuation

In this section we present an integrated framework for real-time dynamic traffic management under emergency evacuation using MRAC, as depicted in Fig. 1. To cope with the dynamic and uncertain nature of evacuation traffic, the proposed framework adopts the following traffic management paradigm: “observe, evaluate, control and advise, cyclically and frequently,” so that the dynamic nature of evacuation can be captured and the unpredictable feature of the problem can be alleviated by the adaptive control. In the MRAC framework, the monitoring system takes

measurements to *observe* from the real-world traffic, the prescriptive model *evaluates* the current condition and provides a reference point for the desired traffic states to the feedback control system, and therefore strategies can be generated to *control and advise* the traffic toward the reference states to achieve certain system optimal objectives designated by the traffic management authorities. The procedure needs to be conducted *cyclically and frequently*, in a rolling horizon fashion. This framework is in contrast to traditional evacuation models which only include the descriptive traffic assignment or simulation model for the testing of fixed evacuation plans (Moeller et al. 1981; Cova and Johnson 2003; Yuan and Han 2004). In particular, this paper focuses on:

- The “prescriptive short-term prediction” model, i.e., reference model, to produce simultaneously the target or desired traffic states and perfect control to achieve such states. This reference model represents the desired response of the traffic under evacuation, based on the designated system objective from the traffic management authorities. Since in the highly uncertain and panicky driver-behavior evacuation scenario, only a short-term (few minutes) traffic forecasting is reliable enough; but that is all that is needed for a closed-loop feedback control approach.
- The “descriptive real-world” model which will adopt the control strategy (instead of a fixed “plan”) for evacuation; by strategy we mean a real-time traffic assignment procedure that provides, cyclically and frequently, a set of routes and traffic control advisories based on feedback of current observed state. We propose to use a microscopic traffic simulation model as a representation of “real world” for the testing and evaluation of this research.
- The design of the feedback control system, based on the difference of desired traffic states from the reference model and current prevailing traffic states collected from the traffic monitoring and sensing system. For MRAC, the adaptation law searches for parameters such as the response of the plant (real-world traffic flow) under adaptive control becomes the same as that of the reference model, i.e., the objective of the adaptation is to make the tracking error converge to zero.

Although the three aforementioned models are key components of the MRAC framework, online dynamic OD estimation and resource allocation are also important issues. However, to simplify our discussion, these two issues are not considered in this paper. In other words, we will assume the dynamic OD demands are given a priori and further assume that traffic sensing and control devices can cover all locations—the so-called “perfect sensing and control.” Meanwhile, since during evacuation, the primary goal of evacuees is to move to safer areas instead of a specific destination, in most cases, therefore, the “super zone” concept can be applied in which all the evacuation destination zones are combined as a “super destination zone” (Chiu et al. 2005). Under the super zone concept, we are essentially dealing with one destination zone, the safe area. Such an assumption will significantly reduce the dimension of the model and thus the computational efforts of the solution algorithm proposed in this paper.

Before discussing the three components (prescriptive model, descriptive model, and controller design) of the proposed framework in detail, we first study the properties of the dynamic system, i.e., the traffic network and flow under evacuation. The system dynamics describe the evolvement of the controlled system. For the traffic flows under evacuation, the dynamics can be expressed in two aspects: link dynamics and node dynamics.

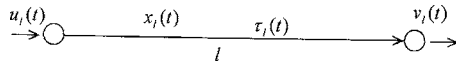


Fig. 2. Link dynamics

Link Dynamics

Link dynamics represent how the flow evolves along a single link. As described by Ran and Boyce (1996) and also shown in Fig. 2, the link dynamics can be expressed as follows:

$$\frac{dx_l(t)}{dt} = u_l(t) - v_l(t), \quad \forall l, t \quad (1)$$

and

$$\int_0^t u_l(t) dt = \int_0^{t+\tau_l(t)} v_l(t) dt \quad (2)$$

where $u_l(t)$, $v_l(t)$, and $x_l(t)$ denote, respectively, the link inflow rate, exit flow rate, and total number of vehicles for each link l at each time instant t and $\tau_l(t)$ =so-called link travel time for link l at time t . $\tau_l(t)$ can normally be modeled as a function of $u_l(t)$, $v_l(t)$, and $x_l(t)$, although the function form may not be easily determined.

As the control will usually be done in a discrete-time fashion, Eqs. (1) and (2) can be rewritten discretely as

$$x_l(k+1) - x_l(k) = u_l(k) - v_l(k) \quad (3)$$

$$u_l(k) = v_l(k + \hat{\tau}_l(k)) \quad (4)$$

where $\hat{\tau}_l(k) = \langle \tau_l(k)/h \rangle$ denotes the integer valued link travel time for link l at time k and h is the length of each time interval. The link inflow rate u , exit flow rate v , and total number of vehicles x for each link l at each time instant t represent the states of the dynamic system. As from Eqs. (3) and (4), these three variables are dependent and usually x and v can be determined by u , we only consider u as the system state for designing the controller. This can significantly simplify the design.

Node Dynamics

Node dynamics describe the interactions among links, especially on an intersection. Fig. 3 depicts a typical four-leg intersection, which has four incoming links and four outgoing links. Denote $u_{m,n}(k)$ the turning movement from link m to link n at time k which is also the inflow rate to link n from link m . Here

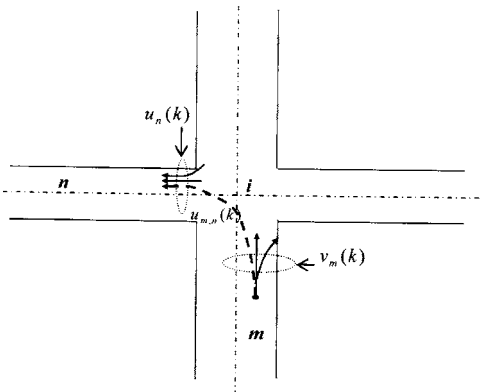


Fig. 3. Node dynamics

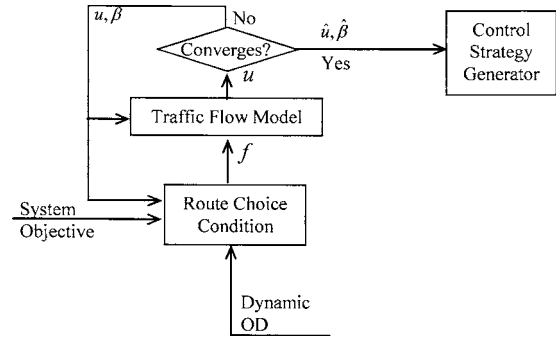


Fig. 4. Prescriptive DTA model

$H(m)=L(n)=i$ with $H(m)$ and $L(n)$ denoting, respectively, the head node and tail node of link m and n . Then we can define the splitting rate of the flow from link m to link n , denoted as $\beta_{m,n}(k)$, as follows:

$$\beta_{m,n}(k) = \frac{u_{m,n}(k)}{v_m(k)} \quad (5)$$

That is, at a given intersection (i in Fig. 3) and some instant k , splitting rate represents the proportion of traffic going to a particular outgoing approach (e.g., n in Fig. 3) among all traffic from a particular incoming approach (e.g., m in Fig. 3).

Apparently, if m and n are the only incoming and outgoing link of node i , we must have $u_{m,n}(k)=v_m(k)$ implying the splitting rate $\beta_{m,n}(k)=1$ in this case. Using Eq. (5), the turning movement volume can be determined given the total exit flow rate and the splitting rate of each incoming link of the intersection:

$$u_{m,n}(k) = v_m(k) \beta_{m,n}(k) \quad (6)$$

Further, the total inflow rate for each outgoing link n can be determined as

$$u_n(k) = \sum_{m \in A, H(m)=L(n)} v_m(k) \beta_{m,n}(k) \quad (7)$$

where A denotes the set of links in the network. Eqs. (5)–(7) represent the node dynamics at a given node i . Notice that the time-dependent turning movement volume $u_{m,n}(k)$ or the splitting rate $\beta_{m,n}(k)$ can be used to determine the signal timing plan for fixed time signals. Therefore, $\beta_{m,n}(k)$ is the control variable of our proposed MRAC framework. In MRAC, the desired states of the system (u) and the associated control schemes (β) will be first generated by the prescriptive DTA model. These desired states and control are fed into the controller, together with prevailing traffic states collected from the field, to generate designated control schemes. These schemes are then applied to the field to guide the real-world traffic to evolve toward the desired traffic states.

Prescriptive Short-Term Prediction Model

In this section, we will depict the prescriptive short-term prediction model which generates the desired traffic states, e.g., traffic inflows and splitting rates, based upon the given system objective via the traffic management authorities. As shown in Fig. 4, the prescriptive model is a short-term one (in minutes) and implemented in a rolling horizon manner (Peeta and Mahamassani 1995). At the start of each horizon, the dynamic OD demands are fixed temporarily using the latest estimated ones. Then certain system optimal objective is used to derive the route choice con-

dition from which the dynamic route flows can be computed. These route flows are fed into the traffic flow model and the time-dependent link inflows can be finally generated.

Under emergency evacuation, the prescriptive model is to produce the target or desired traffic states and to seek the traffic control to achieve such states simultaneously. In this model, we assume all intersections are controlled by traffic officers, and evacuees will follow their guidance, i.e., the “perfect sensing and control.” Therefore the question becomes “how can we determine the splitting rates at all intersections to achieve the system objective.” Mathematically, we can describe the prescriptive model as the following nonlinear programming problem (NLP). $\min_{f,u,\beta} F(f,u,\beta)$ subject to

$$\begin{aligned} H(f,u,\beta) &= 0 \\ G(f,u,\beta) &\geq 0 \end{aligned} \quad (8)$$

where $f = (f_p^{rs}(k))_{\forall p,r,s,k}$ = vector of time-dependent path flows with $f_p^{rs}(k)$ denoting the path flow for path p from origin r to destination s at time interval k , and $u = (u_{m,n}(k))_{\forall m,n,k}$ and $\beta = (\beta_{m,n}(k))_{\forall m,n,k}$ the vector of link inflows and splitting rates. In Eq. (8), $F(f,u,\beta)$ is the objective, and $H(f,u,\beta)$ and $G(f,u,\beta)$ the equality and inequality constraints (refer to Ran and Boyce 1996, Chap. 4), respectively. $F(f,u,\beta)$ is determined by the system objective imposed by the traffic management authorities. For example, if the total clearance time is required, $F(f,u,\beta)$ can be more specifically expressed as follows:

$$F(f,u,\beta) = \sum_{rs} \sum_p \sum_k \eta_p^{rs}(k) f_p^{rs}(k) \quad (9)$$

in which $\eta_p^{rs}(k)$ denotes the travel time for path p from origin r to destination s at time interval k . Please note that the splitting rate $\beta_{m,n}(k)$ is treated as defining variables of the prescriptive model, and will be determined simultaneously with the path flows and link inflows according to the desired system objective. Therefore, the desired splitting rate can be used as a reference when designing the control strategy.

Descriptive “Real-World” Model

The purpose of the descriptive real-world model is to describe, in a short-term fashion, the real-world dynamic traffic flow pattern under evacuation as accurate as possible. Most of the existing evacuation models have focused on developing such a descriptive model. Due to the complexity of modeling traffic flows under evacuation, various topics have been proposed and studied in this regard such as OD estimations, behavior analysis, contra flow management (Jenkins 2000; Tuydes and Ziliaskopoulos 2004; Lim and Wolshon 2005), and traffic network modeling (Barrett et al. 2000; Chiu et al. 2005). In this research, however, because of the highly unpredictable feature of evacuation traffic flow, we propose to use a microscopic traffic simulation model to implement the short-term traffic control strategy at the decision nodes based on the splitting rates. In particular, we adopt one of the commercial microscopic simulation models, PARAMICS (PARAllel MICROscopic Simulation), as our evaluation tool. PARAMICS is a scalable and high-performance microscopic traffic simulation package developed in Scotland (Smith et al. 1994). To implement the adaptive control strategies, the capabilities of PARAMICS have to be extended to enable its use. Particularly, we will develop a route choice model based on the splitting rate

(generated by the controller) at each intersection. This will be accomplished using the PARAMICS’ application programming interface library through which users could customize and extend many features of the underlying simulation model (Chu et al. 2003).

Ideally, if traffic officers can be deployed at each intersection to guide the traffic under evacuation, the proposed descriptive model will be straightforward—traffic flows diverge at each intersection according to the designated splitting rate. This is the so-called “rigid control.” Then using the micro-simulation model, the actual traffic states can be represented. However, in reality, two issues invalidate such an ideal scenario. First, besides “rigid” control, there are many other “soft” traffic controls such as traffic advisory radio and changeable message signs, etc. We need to consider the compliance of evacuees towards these control strategies. This is because, soft controls can not strictly divert the traffic (according to the desired splitting rate) and thus certain compliance rate has to be imposed. Therefore issues on driver compliance need to be investigated. The second issue is, due to resource limitations, it is possible that control devices can only cover portion of the network intersections, rather than all of them. This will raise a resource allocation problem (Ibaraki 1988), namely, under resource limitations, which device should be deployed at which intersection. Detailed discussions regarding compliance and resource allocation will be provided in subsequent papers.

Model Reference Adaptive Control

The MRAC system produces real-time traffic control strategies (particularly, the splitting rate at each intersection), based on the difference between the desired traffic states from the prescriptive reference model and prevailing traffic states from the descriptive real-world model. For MRAC, the desired behavior of the system is specified by a reference model, and the parameters of the controller are adjusted based on the error, which is the difference between the outputs of the closed-loop system and the model. Therefore the system has an ordinary feedback loop composed of the plant and the controller and another feedback loop that changes the controller parameters (Slotine and Li 1991).

In the transportation field, feedback control theories have already been applied in dynamic network modeling (Kachroo and Ozbay 1998, 1999; Papageorgiou 1990; Hawas and Mahmassani 1995; Mammara et al. 1996; Pavis and Papageorgiou 1999; Wang et al. 2003). However, due to the fact that the traffic flow pattern under evacuation is highly dynamic and uncertain, the parameters for designing the feedback controller may not be determined easily and have to be adjusted accordingly in a timely manner. Therefore, distinguished from all previous studies, we explicitly introduce a prescriptive reference model, which represents the desired behavior of the system, to adjust the controller parameters dynamically to better guide the evacuation traffic. The objective of the adaptation is to make the tracking error converge to zero.

As depicted in Fig. 5, two major components can be identified for an MRAC system, namely, the ordinary feedback controller and the adjustment mechanism. The feedback error, which is the difference between the output of the system (i.e., link inflows or splitting rates from the descriptive real-world model) and the output of the reference model (i.e., link inflows or splitting rates from the prescriptive model), can be used for changing the parameter. The mechanism for adjusting the controller parameters

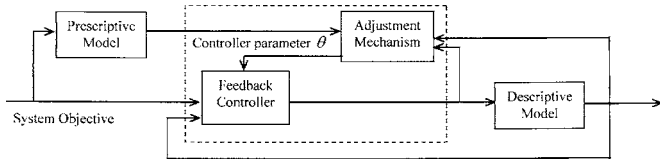


Fig. 5. MRAC model for generating traffic control strategies

for MRAC can be achieved in two ways: by using a gradient method or by applying the stability theory.

In this paper, the controller is designed as a proportional and integral (PI) controller whose parameters are updated by the MRAC scheme using the gradient method. The PI controller can be expressed as follows:

$$\beta_{m,n}(t) = \beta_{m,n}(t-1) + K_{m,n}^P e_{m,n}(t) + K_{m,n}^I \int_0^t e_{m,n}(t) dt, \quad \forall m, n \in A, H(m) = L(n) \quad (10)$$

where $e_{m,n}(t) = u_{m,n}(t) - \hat{u}_{m,n}(t)$ = error term with $u_{m,n}(t)$ denoting the actual turning volume from link m to link n at time t and $\hat{u}_{m,n}(t)$ = desired one generated by the prescriptive DTA. Due to the highly dynamic nature of traffic flow under evacuation, the parameters in Eq. (10), $K_{m,n}^P$ and $K_{m,n}^I$, are not constant; rather, they will change over the time. This is the reason why the MRAC scheme is applied in our framework. Using the gradient method, we can define a loss function (Astrom and Wittenmark 1995)

$$J_{m,n}(\theta_{m,n}) = \frac{1}{2} e_{m,n}^2, \quad \forall m, n \in A, H(m) = L(n) \quad (11)$$

where $\theta_{m,n} = [K_{m,n}^P \ K_{m,n}^I]^T$. Then, the parameters can be determined in such a way that the loss function is minimized. For most of the times, it is reasonable to change the parameters in the direction of the negative gradient of J (the so-called MIT rule), i.e.

$$\frac{d\theta_{m,n}}{dt} = -\gamma_{m,n} \frac{\partial J_{m,n}}{\partial \theta_{m,n}} = -\gamma_{m,n} e_{m,n} \frac{\partial e_{m,n}}{\partial \theta_{m,n}}, \quad \forall m, n \in A, H(m) = L(n) \quad (12)$$

where $\gamma_{m,n}$ is called the “adaptation gain” which should be determined by the controller designer and $\partial e_{m,n} / \partial \theta_{m,n}$ the “sensitivity derivative” of the system which indicates how the error is influenced by the adjustable parameter. After solving Eq. (12), the time-variant controller parameters $\theta_{m,n}$ can be obtained which in turn can be applied in designing the feedback controller in Eq. (10).

Case Studies

Model Development

To test the proposed framework, we have developed a prototype system which includes three key components of MRAC, namely, the prescriptive model, the descriptive model, and the controller. The dynamic OD matrix is assumed to be given and fixed during the evacuation process. We also assume perfect sensing and control such that the resource allocation problem is temporarily ignored.

The reference model is implemented as an analytical dynamic system optimal (DSO) model, aiming to minimize the total system travel time, as illustrated in

$$\min \sum_{k=1}^{K'} \sum_{a \in A} x_a(k) \tau_a(k) \quad (13a)$$

$$st. \ x_{as}(k+1) - x_{as}(k) = u_{as}(k) - v_{as}(k), \quad \forall a, s, k \quad (13b)$$

$$\sum_{a \in A(j)} u_{as}(k) = d^{js}(k) + \sum_{b \in B(j)} v_{bs}(k), \quad \forall j, s, k; \quad j \neq s \quad (13c)$$

$$u_{as}(k) = v_{as}(k + \hat{\tau}_a(k)), \quad \forall a, s, k \quad (13d)$$

$$u_{as}(k) \geq 0, \quad v_{as}(k) \geq 0, \quad x_{as}(k) \geq 0, \quad \forall a, s, k \quad (13e)$$

$$x_a(k) = \sum_{s \in S} x_{as}(k), \quad u_a(k) = \sum_{s \in S} u_{as}(k) \quad (13f)$$

$$v_a(k) = \sum_{s \in S} v_{as}(k), \quad \forall a, k \quad (13g)$$

$$x_a(1) = 0, \quad \forall a \quad (13g)$$

Note that in model (13), $x_{as}(k)$, $u_{as}(k)$, and $v_{as}(k)$ denote, respectively, the number of vehicles, inflow rate, and exit flow rate of link a with respect to destination s at time k ; K' = total number of time intervals; $d^{js}(k)$ = travel demand from node j to destination s at time k ; and $A(j)$ and $B(j)$ = set of outgoing links and incoming links to node j , respectively. Therefore, the objective of the DSO model (13a) aims to minimize the total system travel time, and Eq. (13b) is the so-called mass balance constraint, Eq. (13c) is the flow conservation constraint, Eq. (13d) is the flow propagation constraint, and Eqs. (13e)–(13g) are the nonnegativity, definition, and boundary conditions, respectively.

As the model is a NLP problem, it can be readily solved by existing NLP solvers. In our study, we applied CONOPT (Drud 1992) which is proved to be very efficient for solving the DSO problem. In order to improve the prediction accuracy of the DSO, it is solved in a rolling horizon manner. In particular, DSO is solved for every 30 min and only predictions for the first 10 min (rolling period) are used as input to the controller. After current prevailing traffic states are fed into DSO, the system will roll to next stage and DSO is solved once again.

The descriptive real-world model is implemented in PARAMICS in order to simulate detailed traffic dynamics during evacuation. Route choice is modeled by the splitting rate (from the controller) at each intersection. In particular, we assume each intersection is signal controlled and calculate the green time for each movement based on the splitting rate. Note that under evacuation, this control scheme is feasible due to the super zone concept. Current prevailing traffic states will be generated by real-world model and fed back to DSO model for calibrating the prediction during the rolling horizon process.

The MRAC controller is designed based on Eqs. (10)–(12). In particular, for the ease of computer implementation, we use a discretized version of Eqs. (10)–(12). First, the increment of the splitting rate from link m to n at time interval k is

$$\Delta \beta_{m,n}(k) = \Delta P_{m,n}(k) + \Delta I_{m,n}(k), \quad \forall m, n \in A, L(m) = H(n) \quad (14)$$

where

$$\Delta \beta_{m,n}(k) = \beta_{m,n}(k) - \beta_{m,n}(k-1)$$

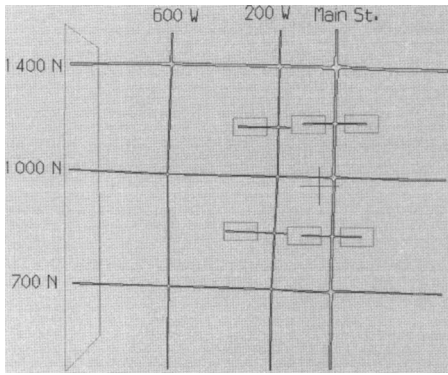


Fig. 6. The testing Logan network

$$\begin{aligned}\Delta P_{m,n}(k) &= P_{m,n}(k) - P_{m,n}(k-1) \\ \Delta I_{m,n}(k) &= I_{m,n}(k) - I_{m,n}(k-1)\end{aligned}\quad (15)$$

$\forall m, n \in A, L(m) = H(n)$, in which

$$P_{m,n}(k) = K_{m,n}^P e_{m,n}(k)$$

$$I_{m,n}(k) - I_{m,n}(k-1) = h K_{m,n}^I e_{m,n}(k)$$

$$\begin{aligned}\beta_{m,n}(k) &= \beta_{m,n}(k-1) + K_{m,n}^P [u_{m,n}(k) - \hat{u}_{m,n}(k) - u_{m,n}(k-1) \\ &\quad + \hat{u}_{m,n}(k-1)] + h K_{m,n}^I [u_{m,n}(k) - \hat{u}_{m,n}(k)]\end{aligned}\quad (16)$$

and the parameters are updated using

$$\theta_{m,n}^j(k) = \theta_{m,n}^j(k-1) - \gamma_{m,n} e_{m,n}(k) \frac{e_{m,n}(k-1) - e_{m,n}(k-2)}{\theta_{m,n}^j(k-1) - \theta_{m,n}^j(k-2)}\quad (17)$$

where $\theta_{m,n}^j = K_{m,n}^I$ or $K_{m,n}^P$.

Testing Network

To test the performance of our proposed adaptive control-based evacuation framework, an example network was built based on a portion of traffic network of City of Logan, Utah, for the purpose of flooding evacuation. The microsimulator we chose is the Paramics V5.

The network shown in Fig. 6 is a well calibrated network coded in Paramics. It has 71 nodes and 148 links with 6 origin zones on the right and one super destination zone on the left. We assume the vehicle will be safe once it arrive the destination zone. One-hour with 10 min extra warm-up demands are assigned in the network to represent the demand pattern in evacuation. Testing is carried on a desktop with one 2.8 GHz CPU processor and 1 GB RAM, and the operating system is Microsoft Windows XP Professional.

To obtain the dynamic OD matrix, a two-step procedure is preformed. First, the population distribution for the testing area is obtained from City of Logan. Based on this, the total evacuation demand for each origin zone is estimated. Then, a departure curve is postulated to simulate the departure choice of evacuees, based upon past evacuation experiences.

Results Analysis

For comparison purposes, we utilize three performance measures, namely, the total system travel time, clearance time, and the num-

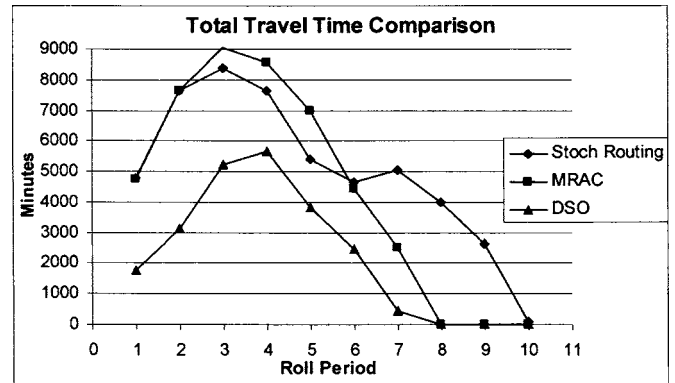


Fig. 7. Comparison of total system travel time

ber of victim vehicles, in our simplified framework implementation. The clearance time is the longest time for the last evacuee to move to a safe place. And the number of the victim vehicles represents the number of vehicles that still present in the network after certain time budget once the evacuation starts.

The performances of three scenarios are computed and compared. These scenarios include the DSO, the MRAC control scheme, and the stochastic route choice. DSO is the best possible performance we can obtain in real-world evacuation. The MRAC scheme is the evacuation scenario resulting from our proposed control strategy, while the stochastic route choice represents the actual evacuation without the proposed MRAC control. Fig. 7 depicts the comparison of total travel time for the three scenarios. Note that in this figure, the horizontal axis represents the roll periods of the rolling horizon method for solving the prescriptive model. Each rolling horizon is 30 min and will be moved 10 min forward once it finishes current period. Therefore, the time difference between two consecutive periods in Fig. 7 is 10 min. It is obvious from the figure that at the very beginning of the evacuation, the results of MRAC scheme are far from DSO. However, as evacuation evolves, the controller will guide the real-world evacuation process towards the DSO states. This can be clearly seen from that fact that the MRAC and DSO curve in Fig. 7 becomes closer for later times. We can also see from Fig. 7 that, without adaptive control, the stochastic route choice scenario will be far away from DSO states for the entire evacuation. Further, although starting with the same state, the stochastic method outperforms the MRAC model at the beginning of the evacuation. This is due to the fact that the feedback controller in MRAC needs to be adjusted to closely fit the real-time traffic states. Therefore, it starts with relatively degraded performance. But as it gradually converges, its performance will be greatly improved as well.

Table 1 further shows the clearance time and number of victim vehicles for each scenario. Note that the time budget for computing the number of victim vehicles is set to 65 min, the clearance time of DSO. It is obvious from this table that the proposed MRAC control scheme can generate shorter clearance time and less victim vehicles compared with traditional stochastic route

Table 1. Clearance Time and Victim Vehicles

| Scenarios | DSO | MRAS | Stochasitc route choice |
|----------------------|-----|------|-------------------------|
| Clearance time (min) | 65 | 84 | 92 |
| Victim vehicles | 0 | 630 | 917 |

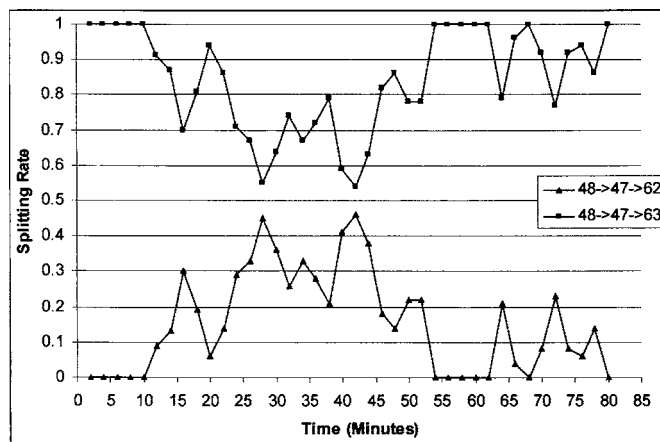


Fig. 8. Splitting rates at Intersection 47

choice scenario. These preliminary testing results demonstrate the benefits of applying the MRAC control scheme in actual traffic management under emergency evacuation. Fig. 8 depicts the change of splitting rates over time for intersection 47 from one incoming approach (48→47) to two outgoing approaches (47→62 and 47→63). It is clear from the figure that although the splitting rates change pretty significantly over the time, the summation of these two approaches equals to 1 which guarantees the flow conservation.

Concluding Remarks and Future Studies

In this paper we propose a MRAC framework for real-time traffic management under emergency evacuation, with a prediction model to generate desired traffic states to achieve optimized system objectives, a real-world traffic model to simulate actual evacuation traffic flows, and an adaptive control model to produce actual traffic control schemes. Distinct from previous planning models, the proposed framework aims to operate in a real time, dynamic, and feedback fashion so that current prevailing traffic states can be utilized to more effectively guide traffic under evacuation. Simulation studies showed that the proposed framework can significantly improve the performance of traffic management under evacuation.

For future study, a number of research directions can be identified based on current framework and our simplified implementation. First, we assumed perfect and rigid control in the simplified framework. However, in reality, soft control devices are widely deployed, e.g., VMS, HAR, etc. Therefore, the compliance of evacuees towards these devices remains a crucial and challenging question, provided the complicated traffic conditions under evacuation. We will investigate the compliance rate of evacuees with respect to different control devices in future study.

Second, this paper assumes the dynamic OD demand matrix is given and fixed during the entire evacuation process. Due to highly dynamic feature of evacuation, dynamic OD demands will very likely change as the evacuation evolves. With the traffic monitoring and sensing system in place for the proposed MRAC framework, prevailing traffic information, especially real-time traffic volumes, is expected to be available during the evacuation process. Therefore, there is a potential to dynamically update evacuation OD demands based upon real-time collected traffic data.

Third, we assumed perfect control in this paper and the resource allocation problem will be studied in detail in future study. Depending on different perspectives, resource allocation can be categorized into static and dynamic ones. Static resource allocation aims to simultaneously determine the optimal locations of control devices together with the optimal splitting rate for each controlled intersection, prior to or at the very beginning of the evacuation. This can be treated as the initial setup for the evacuation. However, due to the dynamic nature of the evacuation traffic, it is very likely that the initial setup becomes inappropriate as evacuation evolves. For example, it is possible that an initially controlled intersection (e.g., by a police officer) may have very light traffic later on. In this case, it would be more beneficial to re-deploy the device to other more congested intersections. Hence, in order to improve the performance of the evacuation process, we need to dynamically determine and re-deploy if necessary control devices.

Last but not least, the proposed framework is a unified one which can be applied for all evacuation scenarios. However, due to the distinctive characteristics for different types of evacuation, the proposed framework needs to be further tailored to better fit into various evacuation scenarios.

References

- Alsnih, R., and Stopher, P. R. (2003). "A review of the procedures associated with devising emergency evacuation plans." *Proc., 82nd Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.
- Astrom, K. J., and Wittenmark, B. (1995). *Adaptive control*, 2nd Ed., Addison-Wesley, New York.
- Baker, E. J. (1991). "Hurricane evacuation behavior." *Int. J. Mass Emerg. Disasters*, 9(2), 287–310.
- Barrett, B., Ran, B., and Pillai, R. (2000). "Developing a dynamic traffic management modeling framework for hurricane evacuation." *Transportation Research Record*, 1773, Transportation Research Board, Washington, D.C., 115–121.
- Chiu, Y. C., Korada, P., and Mirchandani, P. B. (2005). "Dynamic traffic management for evacuation." *Proc., 84th Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.
- Chu, L., Liu, H., and Recker, W. (2003). "Development of the capability-enhanced PARAMICS simulation environment." *Presented at the 82nd Transportation Research Board Annual Meeting*, Washington, D.C.
- Cova, T. J., and Johnson, J. P. (2003). "A network flow model for lane-based evacuation routing." *Transp. Res., Part A: Policy Pract.*, 37A(7), 579–604.
- Drud, A. (1994). "CONOPT—A large-scale GRG code." *ORSA J. Comput.*, 6(2), 207–216.
- Fraser-Mitchell, J. (2001). "Simulated evacuations of an airport terminal building, using the CRISP model." *2nd Int. Symp. in Human Behavior in Fire*, Boston, 89–100.
- Fu, H. Q., and Wilmot, C. (2004). "A sequential logit dynamic travel demand model for hurricane evacuation." *Proc., 83rd Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.
- Hawas, Y. E., and Mahmassani, H. S. (1995). "A decentralized scheme for real-time route guidance in vehicular traffic networks." *Steps Forward: Proc., 2nd World Congress on Intelligent Transport Systems*, Vol. 4, 1956–1963.
- Helbing, D., Farkas, I., and Vicsek, T. (2000). "Simulating dynamical features of escape panic." *Nature*, 407(6803), 487–490.
- Ibaraki, T. (1988). *Resource allocation problems: Algorithmic approaches*, MIT Press, Cambridge Mass.
- Jenkins, R. (2000). "Lessons learned about transportation operations dur-

- ing major evacuations—South Carolina.” *Technical Presentation to the FHWA Transportation Operations during Major Evacuations: Hurricane Workshop*, Atlanta.
- Kachroo, P., and Ozbay, K. (1998). “Solution to the user equilibrium dynamic traffic routing problem using feedback linearization.” *Transp. Res., Part B: Methodol.*, 32B(5), 343–360.
- Kachroo, P., and Ozbay, K. (1999). *Feedback control theory for dynamic traffic assignment*, Springer, New York.
- Lim, E., and Wolshon, B. (2005). “Modeling and performance assessment of contraflow evacuation termination points.” *Proc., 84th Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.
- Mammar, S., Messmer A., Jensen P., Papageorgiou M., Haj-Salem H., and Jensen L. (1996). “Automatic control of variable message signs in Aalborg.” *Transp. Res., Part C: Emerg. Technol.*, 4C(3), 131–150.
- Mei, B. (2002). “Development of trip generation models for hurricane evacuation.” Master’s thesis, Louisiana State Univ., Baton Rouge, La.
- Moeller, M. P., Urbanik, T., and Desrosiers, A. E. (1981). “CLEAR (calculated logical evacuation and response): A generic transportation network model for the calculation of evacuation time estimates.” *Prepared for the Nuclear Regulatory Commission Rep. No. NUREG/CR-2504*, Pacific Northwest Laboratory.
- Murray-Tuite, P. M., and Mahmassani, H. S. (2003). “Model of household trip chain sequencing in an emergency evacuation.” *Transportation Research Record. 1831*, Transportation Research Board, Washington, D.C. 21–29.
- Papageorgiou, M. (1990). “Dynamic modeling, assignment, and route guidance in traffic networks.” *Transp. Res., Part B: Methodol.*, 24B(6), 471–495.
- Pavis, Y., and Papageorgiou, M. (1999). “Simple decentralized feedback strategies for route guidance in traffic networks.” *Transp. Sci.*, 33(3), 264–278.
- Peeta, S., and Mahmassani, H. S. (1995). “Multiple user classes real-time traffic assignment for online operations: A rolling horizon solution framework.” *Transp. Res., Part C: Emerg. Technol.*, 3C(2), 83–98.
- Ran, B., and Boyce, D. E. (1996). *Modeling dynamic transportation networks: An intelligent transportation systems oriented approach*, 2nd Ed., Springer, New York.
- Slotine, J. E., and Li, W. (1991). *Applied nonlinear control*, Prentice-Hall, Englewood Cliffs, N.J.
- Smith, M., Druitt, S., Cameron, G., and MacArthur, D. (1994). “Paramics final report.” *Technical Rep. No. EPCC-PARAMICS-FINAL*, Univ. of Edinburgh, Scotland, U.K.
- Southworth, F. (1991). “Regional evacuation modeling: A state-of-the-art review.” *Rep. Prepared for the U.S. Department of the Army, Centre for Transportation Analysis*, Oak Ridge National Laboratory, Oak Ridge, Tenn.
- Theodoulou, G., and Wolshon, B. (2004). “Modeling and analyses of freeway contraflow to improve future evacuations.” *Proc., 83rd Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.
- Tuydes, H., and Ziliaskopoulos, A. (2004). “Network re-design to optimize evacuation contraflow.” *Proc., 83rd Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.
- Urbina, E., and Wolshon, B. (2003). “National review of hurricane evacuation plans and policies: A comparison and contrast of state practices.” *Transp. Res., Part A: Policy Pract.*, 37A(3), 257–275.
- Wang, Y., Papageorgiou, M., and Messer, A. (2003). “A predictive feedback routing control strategy for freeway network traffic.” *Proc., 82nd Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.
- Yuan, F., and Han, L. D. (2004). “Evacuation modeling and operations using dynamic traffic assignment and most desirable destination approaches.” *Proc., 83rd Annual Meeting of the Transportation Research Board* (CD-ROM), Washington, D.C.