Managing Emergency Traffic Evacuation With a Partially Random Destination Allocation Strategy: A Computational-Experiment-Based Optimization Approach

Yisheng Lv, Xiqiao Zhang, Wenwen Kang, and Yanjie Duan

***Abstract*—Natural or man-made disasters can cause huge losses of human life and property. One of the effective and widely used response and mitigation strategies for these disasters is traffic evacuation. Evacuation destination choice is critical in evacuation traffic planning and management. In this paper, we propose a partially random destination allocation strategy for evacuation management. We present a metamodel-based simulation optimization method to design the strategy. The proposed method uses a quadratic polynomial as a metamodel, within which a degree-free trust region algorithm is developed to solve the proposed model. The performance of the proposed method is evaluated based on a subnetwork of Beijing with two different traffic demands. Computational experiments demonstrate that the proposed method can yield a well-performed strategy, leading to reduced network clearance times.**

***Index Terms*—Computational experiment, evacuation control, metamodel, simulation-based optimization.**

I. Introduction

In recent years, natural or man-made disasters like hurricanes, chemical or nuclear accidents, bush fires, have increased and caused huge losses of human life and property worldwide. One of the effective and widely used response and mitigation strategies for these disasters is traffic evacuation. It has drawn a great deal of research efforts. There are two lines of evacuation analysis, modeling, management and control: Simulation-based methods and analytical methods.

Traffic evacuation is a process full of nonlinearities, combinatorial relationships and uncertainties, which make it too complex to be effectively modeled analytically. Traffic simulation becomes a preferred tool in these settings. Traffic simulation methodology has been extensively used in analyzing, managing and controlling traffic evacuation. Those simulation-based methods can mimic traffic evacuation dynamics better than analytic-based methods [1]. Based on the level of details, traffic simulation models are classified into macroscopic, mesoscopic and microscopic simulation. Compared to macroscopic and mesoscopic simulation, microscopic traffic simulation can represent real world traffic conditions in great details. It can account for social and environmental impacts, individual traffic behavior such as departure time choice, route choice, destination choice, response to real-time traffic information, car following and lane changing behavior. Thus, microscopic traffic simulators can yield rich description of dynamics of traffic evacuation process and provide more accurate network evacuation performance estimates.

Unfortunately, microscopic traffic simulation runs are computationally expensive, and it is hard to use microscopic traffic simulation for evacuation strategy optimization. Microscopic traffic simulation is usually applied to do what-if scenario analysis, in which one or several predetermined scenarios are simulated and evaluated. However, developing a method to use microscopic traffic simulation for evacuation strategy optimization is important and desirable. Simulation-based optimization is a tool to achieve this goal, which bridges the capability of microscopic traffic simulation and optimization methods.

A well-prepared evacuation plan and procedure is critical to the successful implementation of evacuation operations, which ensures the efficient and safe utilization of time and transportation network. There is increasing recognition that explicit consideration of accurate behavioral assumptions on the endangered population is required for evacuation planning [2]. Evacuees can make their own decisions on when to depart, which route to follow, what to ride, and where to go. Their behavior has a significant impact on evacuation efficiency [3], [4] and is most probably not system optimum [5]. It is straightforward to think of improving emergency evacuation efficiency by intervening evacuees' behavior besides traditional evacuation management and control strategies such as contraflow management, traffic signal control. In this paper, we focus on evacuees' destination choice behavior.

To improve upon the state of practice, we propose a partially-random destination allocation strategy to manage evacuation process, which has the potential to improve evacuation

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efficiency. The aim of this paper is to address the following key questions: 1) What if some portion of evacuees' destinations is randomly allocated and these evacuees are assumed to follow the allocation? Can it improve evacuation efficiency? 2) If so, what is the optimum proportion of evacuees that should be informed to direct to random destinations? With regard to the first question, we used an artificial transportation system called TransWorld to model the whole traffic evacuation process including evacuation management and control strategies, dynamic traffic supply, dynamic traffic demand, and road traffic dynamics, etc. With TransWorld, we can quantitatively analyze emergency evacuation management and control strategies. To address the second question, a metamodel-based simulation optimization method is developed to determine the optimum proportion. Specifically, a metamodel in the form of quadratic polynomials is constructed through computational experiments, and a degree-free trust region algorithm is developed to search the optimal solution.

Contributions of this paper are threefold: i) we develop a new and simple partially-random destination allocation strategy for evacuation operations. ii) A metamodel-based simulation optimization method is proposed to design the strategy. iii) A degree-free trust region algorithm is developed to solve the model. Research findings show the beneficial impact of intervention and guidance of evacuees' destination choice behavior on improving evacuation efficiency, which demonstrates the feasibility, direction, and need to design new strategies for evacuation management in addition to traditional methods like signal control and staged evacuation.

This paper is structured as follows. Section II reviews the studies on emergency traffic evacuation modeling and management strategies. Section III presents the proposed metamodel based simulation optimization method for managing destination choice. Section IV discusses the numerical analyses. Concluding remarks are given in Section V.

II. Related Work

During the past few decades, considerable efforts have been made to develop methods on modeling and managing traffic evacuation operations for various disasters such as hurricanes, tornadoes, fires, earthquakes, and terrorist attacks. As early as 1970s, studies focused on hurricane evacuation. After the Three Mile Island reactor incident in 1979, research interests switched to nuclear power plant emergencies. Then, emphasis returned to hurricane evacuation because a number of extremely devastating hurricanes pummeled the United States in the 1990s, as well as in 2005. Since the horrifying events of September 11, 2001, there is an increasing attention on mass evacuation due to terrorist attacks within the transportation research community.

Existing traffic evacuation models can be classified into two categories: simulation models and analytical models. An analytical model is typically a set of functions with good mathematical properties. Derivatives of the model are usually available, and the optimal solutions can be obtained. Analytical models can be further divided into static analytical models and dynamic analytical models. Static analytical models assume static traffic states on road networks or use static traffic information. Examples of static models can be found in [6]–[8]. Dynamic analytical models consider the evolution of road traffic states and traffic demand, and they usually take advantage of dynamic traffic assignment approaches. Work of Lin [9], Chen and Xiao [10], and Xie and Turnquist [11], belongs to dynamic analytical models.

With great advances in computing power, more and more evacuation studies are conducted using traffic simulation methodology, because traffic simulation models can better capture aggregate or disaggregate behavior of evacuees and traffic flow dynamics. Traditional traffic simulation models for evacuation modeling and planning are typically macroscopic. Sheffi *et al.* developed a macroscopic simulation model named NETVACI, which was motivated by estimating network clearance time for evacuation due to nuclear power plant disasters [12]. DYNEV was also a macroscopic simulation model to develop evacuation plans for nuclear power plants [13]. MASSVAC used macroscopic traffic flow simulation models for evacuation planning [14]. Pel *et al.* proposed a macroscopic evacuation traffic simulation model EVAQ to predict traffic flow conditions on a road network for a wide range of emergencies [3], [15]. Xie *et al.* presented a cell-based evacuation network optimization-simulation model [1].

A large number of emergency evacuation simulation models are microscopic traffic simulation models which are capable of modeling the whole evacuation process more realistically involving decisions and actions of individual agents in a created artificial transportation system. Stern and Sinuany-Stern proposed a microscopic simulation model for radiological evacuation, in which they incorporated behavioral factors including the diffusion time of the evacuation instructions and individual's evacuation decision time. They claimed that the proposed model is more realistic than the purely engineering-type models [4]. The traffic simulation model of OREMS developed in Oak Ridge National Laboratory (ORNL) is based on CORSIM. OREMS can be applied to estimate evacuation times, assess traffic management and control strategies, identify evacuation routes, etc. [16]. Cova and Johnson developed a method to test neighborhood wildfire-induced evacuation plans using a microscopic traffic simulator named Paramics [17]. Han and Yuan applied VISSIM to simulate regional traffic evacuation in the event of a major nuclear power plant accident [18]. Jha *et al.* used MITSIMLab to evaluate emergency plans for the entire region that includes all technical areas within the Los Alamos National Laboratory and the towns of White Rock and Los Alamos, New Mexico [19]. Actually, there have been many similar traffic evacuation studies using microscopic traffic simulation technologies in recent years, such as in the literature of Gu [20], Tagliaferri [21], Lim and Wolshon [22], Zhang *et al.* [23], Chen and Zhan [24], VanLandegen and Chen [25].

As a trade-off between computational demands and representation details of traffic behavior, mesoscopic traffic simulation models are applied to evacuation studies, such as that of Chiu [26], Balakrishna *et al.* [27], Noh *et al.* [28]. For more information on evacuation transportation modeling, readers are referred to reviews [29] and [30].

Current evacuation traffic management strategies mainly include vehicle routing, staged evacuation, signal control, intersection crossing elimination, and lane reversal. The vehicle routing strategy is to route people so as to utilize the available capacity of a road evacuation network more efficiently and reduce evacuation time. Dunn and Newton proposed two algorithms to identify optimum routes which maximize the flow through a capacity constrained network [31]. Campos *et al.* presented an algorithm to find k-optimal paths for allocating vehicle flow in emergency transportation planning. Cova and Johnson developed an optimal lane-based evacuation strategy that is formulated as a network flow model [32]. Chiu and Mirchandani proposed a behavior-robust feedback information routing (FIR) strategy which is based on the concept of closed loop control for mass evacuation [33]. Zheng proposed a mixed-integer model for bus routing during an emergency evacuation [34].

Staged evacuation is to schedule traffic demand into a road network over the allowable period of time. It can effectively limit traffic demand surge on the network and delay network degradation. Chen and Zhan used Paramics to investigate the effectiveness of simultaneous and staged evacuation strategies on three types of road network structures [24]. Chiu developed a mathematical model for evacuation scheduling to minimize the total travel time [26]. Sbayti and Mahmassani proposed an iterative heuristic procedure to solve the bi-level formulation of the evacuation scheduling problem, where Dynasmart-P is used to propagate vehicles [35]. Chien and Korikanthimath developed an analytical method to model the evacuation staging process, and results showed that appropriately implemented staged evacuation can significantly reduce evacuation time and delay [36].

Signal control is believed to be an effective strategy to mitigate daily traffic congestion. During emergency evacuation, it also has a critical role to improve evacuation efficiency [37]. Sisiopiku *et al.* applied CORSIM to test the impact of signal timing optimization on evacuation efficacy. The optimal signal timing plan was established with SYNCHRO which is a signal timing program [38]. Chen *et al.* investigated four different signal timing plans for two evacuation corridors of Washington, D. C. [39]. Liu and Luo proposed a bi-level model for configure signalized and uninterrupted flow intersections for emergency evacuation operations [40].

Basically, intersections are bottlenecks of a traffic network. Cova and Johnson argued that most traffic delays occur at intersections during regional evacuations. They proposed using the lane-based routing strategy for intersection crossing elimination so as to reduce these delays [32]. Lane reversal operation, also known as contraflow design, is to reverse one or more danger-bound lanes for use in the safety-bound direction in order to increase the capacity of evacuation traffic network. Lim and Wolshon used CORSIM to assess and compare the operational characteristics of contraflow evacuation termination point designs during catastrophic storms [22]. Tuydes and Ziliaskopoulos developed a tabu-based heuristic algorithm to determine optimal contraflow design for urban evacuations [41]. Kim *et al.* proposed a macroscopic method for contraflow network design which incorporates road capacity constraints, multiple sources, congestion, and scalability [42].

Combination of different control strategies can improve the evacuation network performance better than either of them solely. Kalafatas and Peeta [43], Xie *et al.* [1], Xie and Turnquist [11], investigated the combined intersection crossing elimination and Lane reversal strategies, respectively. Liu proposed a system incorporating different evacuation control strategies [37].

In summary, microscopic traffic simulation models can represent evacuation transportation processes with the most details, and appropriate management and control strategies can significantly improve evacuation efficiency. It is arguable whether the management and control strategies are optimal if a model cannot properly describing human behavior and traffic flow propagation. There is a need to develop a method to optimize evacuation strategies with microscopic traffic simulation efficiently.

III. Methodology

A. Overview and Problem Formulation

The evacuation process can be seen as the interaction of individuals, emergencies, authorities, and third parties. There are many kinds of man-made or natural disasters which may cause the necessity to evacuate the affected area. The authority distributes warning information of disasters, issues evacuation instructions, organizes transportation systems, provides shelters, etc. to minimize the loss of property and life. Apart from the information offered by the authority, nowadays many third parties give traffic and hazard conditions. Individuals make their own decisions on whether to evacuate upon receiving the evacuation order. All the information obtained from the authority, third parties, and even other individuals clearly affect evacuee's pre-trip and en-trip behavior. The evacuation traffic flow is results of all individual behavior which are departure time choice behavior, destination choice behavior, route choice behavior, car following behavior, lane changing behavior, response to information behavior, etc. Fig. 1 shows the interaction of the listed aspects.

In the context of evacuations, destination choice is critical in evacuation traffic planning and management, because the results of destination choice will impact the trip and traffic flow distributions which are two of determinants on evacuation efficiency in the transportation network. Previous studies identify that separate evacuees choose their destination in different ways and suggest the destination choice as 1) the closest safe destination outside the at-risk area (in terms of distance); 2) the soonest safe destination outside the at-risk area (in terms of time); 3) the safe destination with the minimum perceived cost (in terms of established perceived cost); or 4) the prespecified safe destination according to the prepared evacuation plan [2], [44]. Aggregate and disaggregate models for evacuation destination choice have been developed to estimate trip distributions, such as in [45]–[47].

It is not system optimum if letting evacuees choose their destinations freely. Reallocating some portion of evacuees'

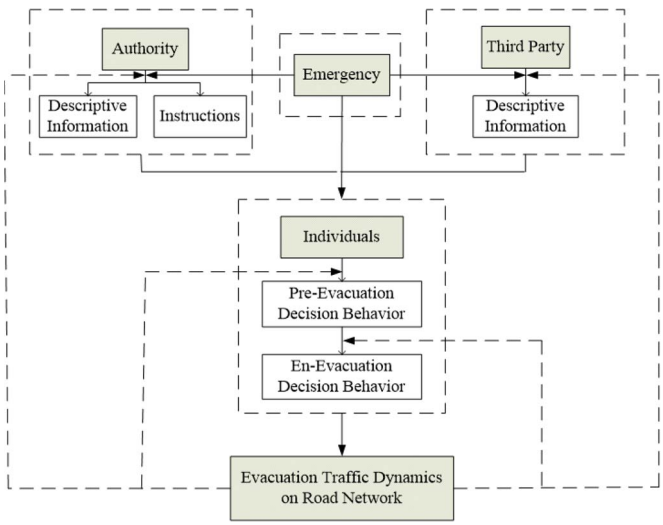

Fig. 1. Evacuation process.

destinations could improve system performance. One simply and easily implemented strategy is to randomly allocate destinations to some evacuees. The question now is to determine the best percentage of evacuees that should be informed to go to random destinations. Here, we call this problem as Partially-random Destination Allocation for Evacuation Management (PDAEM).

The PDAEM problem can be formulated as follows:

$$\min_{x\in\Omega} f(x,w). \tag{1}$$

Subject to

$$\sum x_i = 1, \quad i = 1, 2, \cdots, l \tag{2}$$

$$0 \le x_i \le 1, \quad \forall i \tag{3}$$

$$\text{Other constraints} \tag{4}$$

x_i is the ratio of evacuees choosing destination in the ith pattern. l is the number of destination choice patterns, such as random destination choice, the closest destination choice. w is a vector of exogenous parameters. $f(x,w)$ is a performance measure function. The objective is to minimize $f(x,w)$.

A fundamental breakthrough in concepts and techniques for emergency transportation studies is required to improve the current state-of-the-practice of modeling, experiments, management and control of emergency transportation systems. The theoretical challenges are twofold. First, it requires detailed modeling of emergency traffic process, including hazard information, traffic information and evacuation instructions provided by authorities and third parties, individual responses and decisions, road traffic dynamics, etc. Second, it requires a computational mechanism to optimize emergency traffic management and control strategies. As described in [48], we can use a tailored microscopic traffic simulator which can grow artificial traffic behavior from bottom to up, to model emergency traffic process, and use simulation-based optimization techniques to address the computational optimization challenge.

B. Simulation-Based Optimization Framework

The simulation-based optimization method bridges the use of detailed microscopic traffic simulators and optimization tasks, which enable simulators to go beyond of what-if analysis mostly for testing and evaluating scenarios. Recently, Osorio *et al.* proposed a simulation-based optimization framework for urban transportation problems [49], and they have applied this framework to address traffic signal control optimization problems, where the results are superior and promising [49]–[51].

The problem of simulation-based optimization on emergency traffic management can be stated as follows:

$$\min_{x\in\Omega} f(x,w) = \mathrm{E}\left[F(x,w)\right]. \tag{5}$$

The problem has a stochastic objective. F corresponds to a stochastic performance measure of interest. The objective function f is the expected value of F. x is a decision vector, and w is a parameter vector. Here, we focus on the case that the decision vector x is continuous bounded, i. e., $\Omega = \{x \in R^n : a < x < b\}$. a and b are the lower and upper bounds for x, respectively.

Given w and x, $F(x,w)$ can be evaluated via a single simulation run. Assume we perform R runs for a given w and x, denoted as $F_1(x,w), F_2(x,w), \ldots, F_R(x,w)$, the underlying objective function can be computed by taking an average over the sample runs

$$\hat{f}(x,w) = R^{-1}\sum_{i=1}^{R} F_i(x,w). \tag{6}$$

Further, the estimation of $f(x,w)$ via simulation is often computationally expensive especially when R is large.

Many approaches, such as direct search methods, gradient-based methods, heuristic methods, and metamodel-based methods, have been proposed to address simulation optimization problems. In many cases it is unavailable or unreliable to get derivatives with microscopic traffic simulators due to high computational cost. Direct search methods are derivative-free. However, they generally need performing quite a lot of simulation runs. Heuristic methods also require a large number of simulated evaluations to obtain adequately good solutions. In this paper, we focus on metamodel-based methods.

A metamodel is also known as a surrogate model. The idea of metamodel-based optimization methods is to construct a mathematical model m to approximate the underlying function based on a sample of simulation outputs. m is usually less accurate but cheaper to evaluate. Given the form of a metamodel m, the main procedure for performing metamodel optimization is 1) fit m via a set of simulated observations, 2) use m to perform optimization instead of simulation models and derive a trial point, 3) conduct simulation experiments on the trial point and refit the metamodel m. Iterate 2) and 3) until the stop criterion of the procedure is met. Fig. 2 depicts the optimization process. The model $m(\cdot)$ can be fitted by minimizing the difference

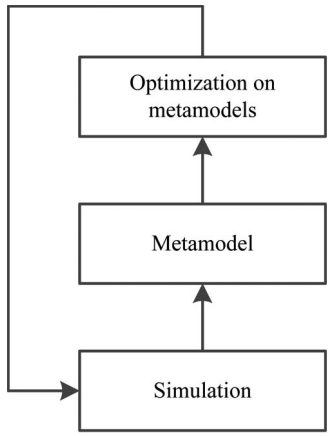

Fig. 2. Metamodel based simulation optimization framework.

of $m(\cdot)$ and the function$F(x, w)$ over a representative set of points $\mathcal{S}$:

$$\begin{aligned} \min \quad & \sum_{x_i \in S} \Theta(F(x_i, w_i) - m(x_i)) \\ \text{s.t.} \quad & m(x_i) \in \mathcal{M} \end{aligned} \tag{7}$$

$\Theta(\cdot)$ is a merit function. Typically it is chosen as an l^2—norm. The set $\mathcal{M}$ is a class of functional forms. The most popular options of $\mathcal{M}$ are general-purpose models, such as polynomials, which can be used to approximate any objective function.

We used a computer program called TransWorld to simulate the traffic evacuation process. TransWorld is an ongoing project developed at the Institute of Automation, Chinese Academy of Sciences. TransWorld is an agent-based microscopic traffic simulation tool. The features of TransWorld are: 1) It can create artificial transportation environment and micro-simulate traffic dynamics. 2) It is flexible and agent-based. 3) It is a computational experimental platform for the analysis and synthesis of transportation systems. TransWorld is composed of network construction module, artificial population generator module, disaster generation module, route planner module, microscopic traffic simulation module, computational results analysis module, two-dimensional and three-dimensional animation module, feedback module. More information on TransWorld can be found in [14]–[19].

C. Quadratic Metamodel

A quadratic polynomial is one of most common functional forms for a metamodel. The quadratic metamodel is fitted based on sample sets from microscopic traffic simulation runs.

Given the following basis of the space of polynomials of degree at most 2 in $\mathbb{R}^2$,

$$\phi(x) = \left(1, x_1, \ldots, x_l, x_1^2, x_2^2, \ldots, x_l^2, x_1x_2, x_1x_3, \ldots, x_{l-1}x_l\right)^{\mathrm{T}}, \tag{8}$$

which has $(l+1)(l+2)/2$ elements. The quadratic model can be defined as $m(x) = \alpha^{\mathrm{T}}\phi(x)$.

Powell shows that on trust region methods quadratic polynomials with diagonal second derivative matrices are often more efficient than full quadratic models [52]. Therefore, we choose quadratic polynomials with a diagonal second derivative matrix as the metamodel, which is shown as:

$$\phi(x) = \alpha_0 + \sum_{i=1}^{l} \alpha_i x_i + \sum_{i=1}^{l} \alpha_{i+l+1} x_i^2 \tag{9}$$

where α_i is a parameter, l is the dimension of x, and x_i is the ith component of x.

In this paper, we use a trust region derivative-free algorithm to find the optimum solution. The key points of a trust region algorithm are how to compute the trial step of the trust region and how to decide whether to accept a trial step or not. At each iteration of a trust region algorithm the metamodel approximates the objective function in a region that the approximate model is trusted. A trust region is a neighborhood of the current iterate. The metamodel is built based on simulated observations obtained at the current iteration and previous iterations. It is fitted via solving a least squares problem. Assuming that a set of n_k separate points $\{x^1, x^2, \ldots, x_k^n\}$ have been simulated until the iteration k, we can easily compute the estimates of the objective function on each point, denoted as $\{\hat{f}(x^1), \hat{f}(x^2), \ldots, \hat{f}(x_k^n)\}$. The least squares problem is stated as follows.

$$\min_{\alpha} \sum_{i=1}^{n_k} \left[\hat{f}(x^i) - m(x^i)\right]^2. \tag{10}$$

D. Solution Algorithm

In this section we give the trust region algorithm which is based on the work of Conn *et al.* [53]. The convergence analysis of the solution algorithm is referred to [49] and [53].

Step 0. Initialization: For a given iteration k, let m_k as the metamodel, x_k as the iterate, $\triangle_k$ as the trust region radius, α_k as the vector of metamodel parameters, n_k as the sample size, u_k as the number of successive trial points rejected, and ε_k as the measure of stationarity evaluated at x_k.

Given an initial model m_0,

Choose

- An initial point x_0.
- An upper bound for the trust region radius $\triangle_{\max} > 0$.
- An initial trust region radius $\triangle_0 \in (0, \triangle_{\max}]$.
- The maximum number of function evaluations permitted $n_{\max}$.
- The parameters $\eta_1, \gamma, \gamma_{inc}, \varepsilon_c, \bar{\tau}, \bar{d}, \bar{u}$ such that $0 < \eta_1 < 1, 0 < \gamma < 1 < \gamma_{inc}, \varepsilon_c > 0, 0 < \bar{\tau} < 1, 0 < \bar{d} < \triangle_{\max}$.

Set $k = 0$.

Step 1 Criticality Step: If $\varepsilon_k \leq \varepsilon_c$, then proceed as follows. Attempt to certify whether the model m_k is fully linear on $B(x_k; \triangle_k)$or not. If the model m_k is not fully linear on $B(x_k; \triangle_k)$, or if $\triangle_k > \mu\|g_k\|$, then apply the criticality step algorithm (described below) to construct a model $\tilde{m}_k(x_k + s)$, which is fully linear on the ball $B(x_k; \tilde{\triangle}_k)$, for some $\tilde{\triangle}_k \in \mu\|\tilde{g}_k\|$ given by the criticality step algorithm. Set $m_k = \tilde{m}_k$ and $\triangle_k = \min\{\max\{\tilde{\triangle}_k, \beta\|\tilde{g}_k\|\}, \triangle_k\}$. Otherwise m_k and $\triangle_k$ remain unchanged.

Step 2 Step Calculation: Compute a step s_k that reduces the model m_k and such that $x_k + s_k \in B(x_k; \triangle_k)$.

Step 3 Acceptance of the Trial Point: Compute $f(x_k + s_k)$ and define

$$\rho_k = \frac{f(x_k) - f(x_k + s_k)}{m_k(x_k) - m_k(x_k + s_k)}. \tag{11}$$

If $\rho_k \geq \rho_1$, then accept the trial point $x_{k+1} = x_k + s_k$; otherwise, reject the trial point, $x_{k+1} = x_k$, $u_k = u_k + 1$.

Include the new iterate into the sample set, and fit the new model m_{k+1}. Set $n_k = n_k + 1$.

Step 4 Model Improvement: Compute

$$\tau_{k+1} = \frac{\|\alpha_{k+1} - \alpha_k\|}{\|\alpha_k\|} \tag{12}$$

If $\tau_{k+1} < \bar{\tau}$, then improve the model by sampling a new point x, compute f at x. Include this point in the sample set. Set $n_k = n_k + 1$. Update m_{k+1}.

Step 5 Trust Region Radius Update: If $\rho_k \geq \rho_1$, then increase the trust region radius. Set $\triangle_{k+1} = \min\{\gamma_{inc}\triangle_k, \triangle_{\max}\}$.

If $\rho_k < \rho_1$ and $u_k \geq \bar{u}$, then $\triangle_{k+1} = \gamma\triangle_k$, $u_k = 0$. Otherwise, $\triangle_{k+1} = \triangle_k$.

Set $n_{k+1} = n_k$, $u_{k+1} = u_k$.

Set $k = k + 1$.

If $n_k < n_{\max}$, then go to Step 1. Otherwise, stop.

Criticality Step Algorithm:

1. Initialization: Set $i = 0$, and $m_k^{(0)} = m_k$.
2. Repeat

$i = i + 1$. Use the model-improvement algorithm to improve the previous model $m_k^{(i-1)}$ until it is fully linear on $B(x_k; \theta^{i-1}\triangle_k)$. Denote the new model by $m_k^{(i)}$. Set $\tilde{\triangle}_k = \theta^{i-1}\triangle_k$ and $\tilde{m}_k = m_k^{(i)}$.

Until $\tilde{\triangle}_k \leq \mu\|g_k^{(i)}\|$.

IV. Computational Experiments

We perform simple computational experiments to evaluate and illustrate the proposed method. The study is based on a road network within the Zhongguancun area, which is located in Haidian, Beijing, China. We built the artificial transportation system of the study area via TransWorld. The extracted network covers 15. 3 km2, west to Wanquanhe Road, east to Xueyuan Road and Xitucheng Road, north to North 4th Ring Road, and south to 3rd Ring Road. It contains forty two roads and eighteen intersections (see Fig. 3.). Details regarding the Zhongguancun sub-network are described in [54].

We consider two different demand scenarios. One is that 5000 vehicles are supposed to be evacuated, and the other has a higher demand that 10000 vehicles are assumed to be evacuated. We assume that all the evacuees choose a closest safe destination. We use network clearance time as the performance measure. We compare the proposed empirical cumulative distribution function (cdf) of the network clearance time over three separate ratios of evacuees choosing a safe destination (i.e., three different destination choice strategies), which are: 1) a ratio derived by the proposed method, 2) a random ratio which is uniformly drawn from [0, 1], 3) 0, which means all evacuees choose a closest safe destination. We run 50 replications of the simulation model for each destination choice strategy to build the empirical cdf. We set the maximum number of simulation runs as 100.

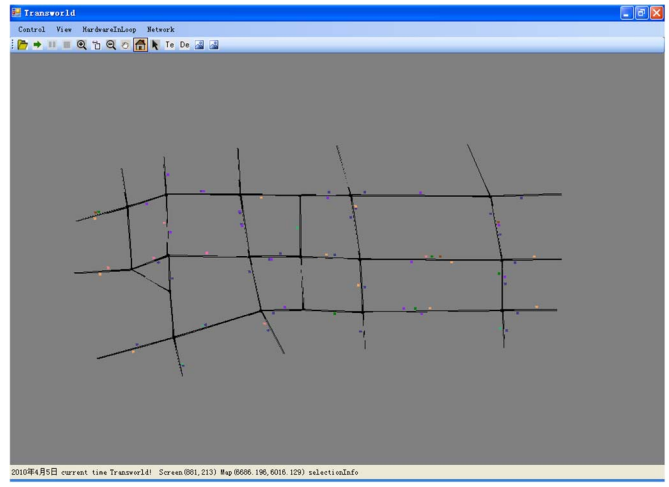

Fig. 3. Zhongguancun sub-network

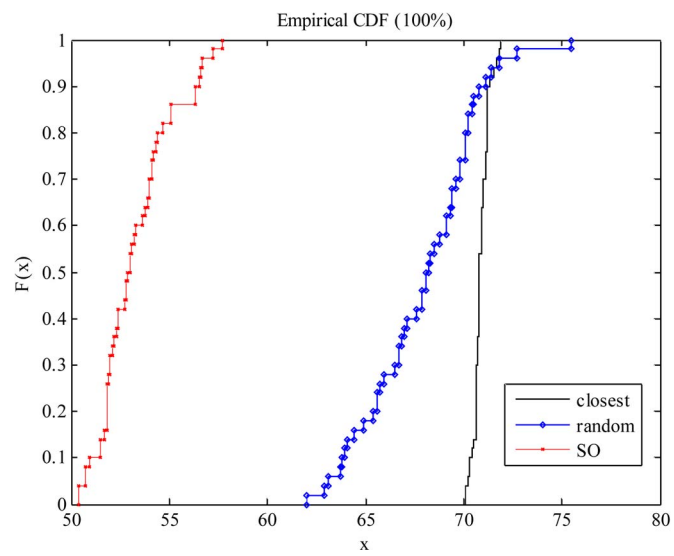

Fig. 4. Scenario 1: The cdf of network clearance time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

We firstly consider the Zhongguancun sub-network with traffic demand of 5000 vehicles. Fig. 4 displays the cdf of network clearance time for each strategy with traffic demand of 5000 vehicles. The proposed method yields a strategy with improved performance compared to the random ratio strategy and all having the closest destination strategy. We further investigate the cdfs of 25% evacuation time, 50% evacuation time and 75% evacuation time over the three methods, respectively. Herein, 25% evacuation time is the time to evacuate 25% of all the evacuees, 50% evacuation time is the time to evacuate 50%

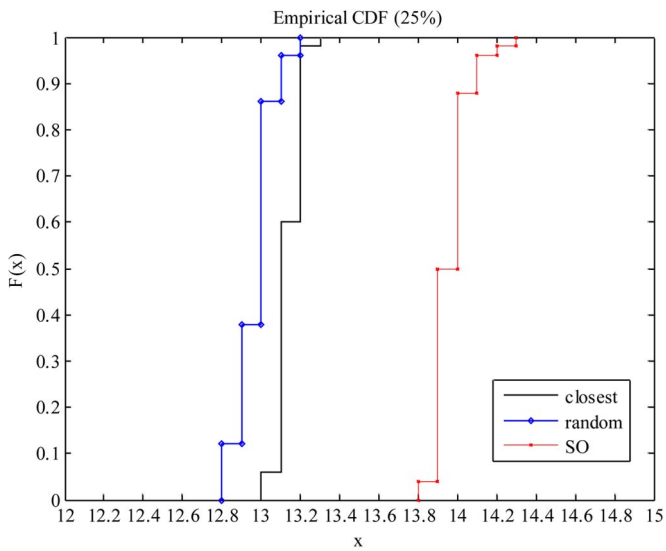

Fig. 5. Scenario 1: The cdf of 25% evacuation time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

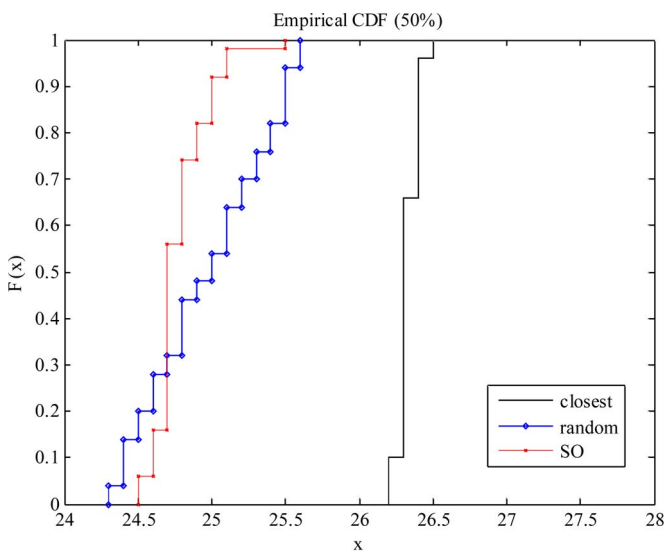

Fig. 6. Scenario 1: The cdf of 50% evacuation time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

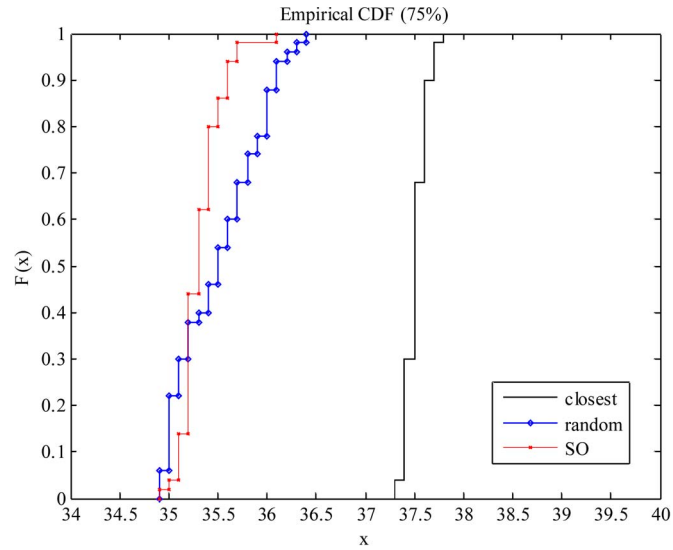

Fig. 7. Scenario 1: The cdf of 75% evacuation time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

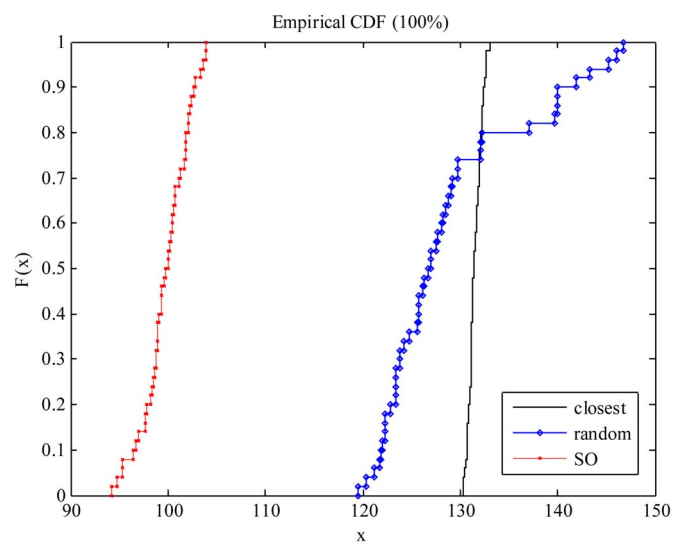

Fig. 8. Scenario 2: The cdf of network clearance time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

of all the evacuees, and 75% evacuation time is the time to evacuate 75% of all the evacuees. Fig. 5 displays the cdf of 25% evacuation time, Fig. 6 displays the cdf of 50% evacuation time, and Fig. 7 displays the cdf of 75% evacuation time. However, for 25% evacuation time, 50% evacuation time, and 75% evacuation time, the random ratio strategy and the all having the closest destination strategy have a similar performance and are a little bit better than the proposed method.

We then consider the Zhongguancun sub-network with traffic demand of 10000 vehicles. Fig. 8 displays the cdf of network clearance time for each strategy with traffic demand of 10000 vehicles. The proposed method leads to a strategy with improved performance compared to the random ratio strategy and all having the closest destination strategy. We also further investigate for the three methods the cdfs of 25% evacuation time, 50% evacuation time and 75% evacuation time, respectively. Fig. 9 displays the cdf of 25% evacuation time, Fig. 10 displays the cdf of 50% evacuation time, and Fig. 11 displays the cdf of 75% evacuation time. Although the proposed method has a better performance regarding the network clearance time compared to the other two methods, it is not the case for 25% evacuation time, 50% evacuation time and 75% evacuation time. For 25% evacuation time and 50% evacuation time, the random ratio strategy has a better performance than the other two methods. For 75% evacuation time, strategies derived by the random ratio generation method and the proposed method have a better performance than the all having the closest destination strategy.

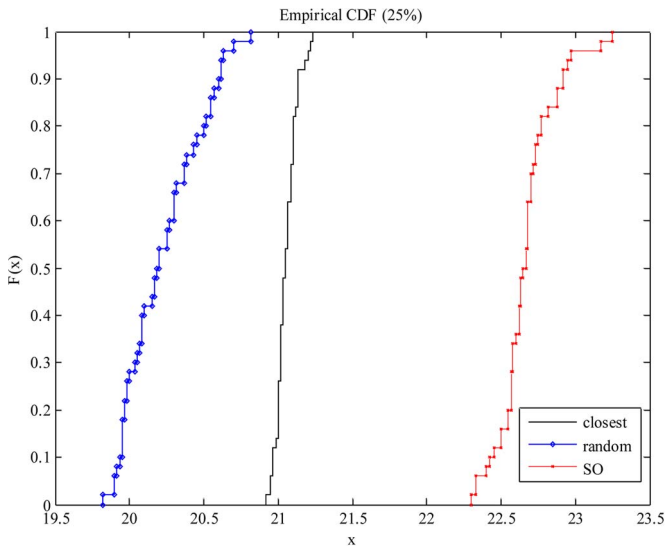

Fig. 9. Scenario 2: The cdf of 25% evacuation time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

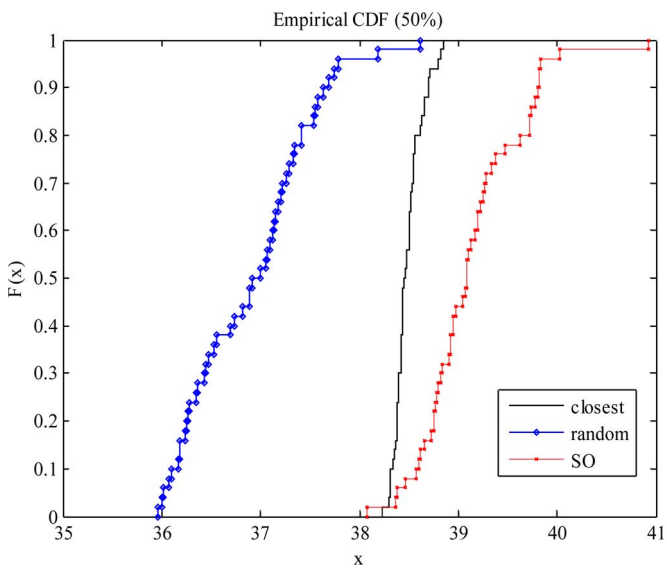

Fig. 10. Scenario 2: The cdf of 50% evacuation time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

V. Conclusion

This paper presents a partially-random destination allocation strategy for evacuation operations. A metamodel-based simulation optimization method is proposed to design the strategy. It uses a quadratic polynomial as a metamodel. A degree-free trust region algorithm is developed to solve the proposed model. The performance of the proposed method is evaluated based on a sub-network of Beijing with two different traffic demands. Computational experiments show that the proposed method can make a strategy with well improved performance in terms of network clearance time. However, it does not guarantee the corresponding intermediate evacuation time like 25% evacuation time, the 50% evacuation time, and the 75% evacuation time

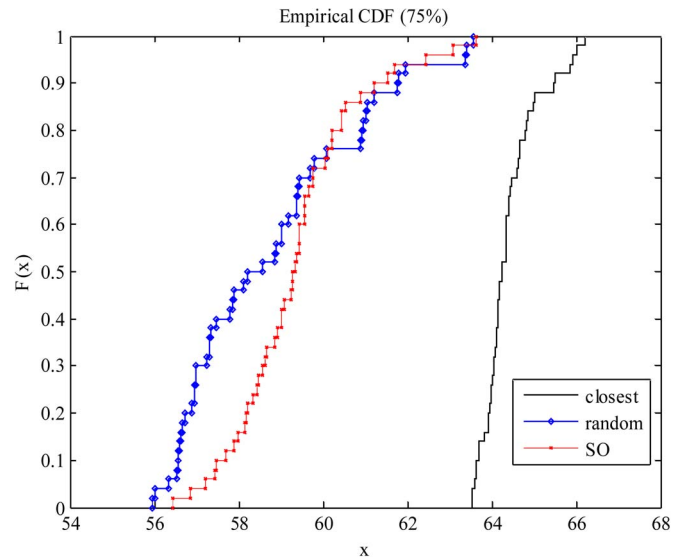

Fig. 11. Scenario 2: The cdf of 75% evacuation time for the proposed method, a random generation method uniformly drawn from [0, 1], and all evacuees choosing a closest safe destination, respectively.

will be reduced either. Investigating other forms of metamodels and designing new solution algorithms to improve the accuracy and the efficiency of the method are our future work.

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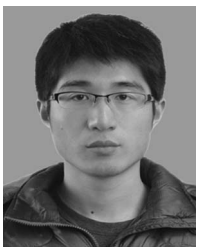

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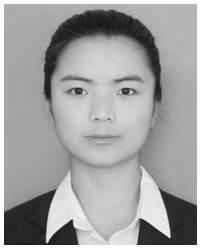

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