Macroscopic network design for dynamic evacuation scheduling with MFD-based assignment using the recursive logit model

S. Masuda[a] and E. Hato[a,*]

[a] Department of Civil Engineering, The University of Tokyo, Tokyo, Japan
masuda@bin.t.u-tokyo.ac.jp, hato@bin.t.u-tokyo.ac.jp
* Corresponding author

Extended abstract submitted for presentation at the 11th Triennial Symposium on Transportation Analysis conference (TRISTAN XI)
June 19-25, 2022, Mauritius Island

April 3, 2022

Keywords: network design problem, macroscopic fundamental diagram, recursive logit model, graph neural network, Pareto frontier

1 INTRODUCTION

With climate change causing frequent disasters worldwide, there is an urgent need to develop effective evacuation plans. So & Daganzo (2010) proposed an optimal evacuation control method at freeway ramps on a single route. However, evacuation traffic is an interaction of individual decision-making on a network. Therefore, it is practical to repeatedly run traffic simulations to find a scenario that optimizes the objective function among many combinations of policy variables. Traffic microsimulation models can simulate detailed traffic conditions, but they are computationally expensive. Machine learning models can be computed quickly but have a problem with interpretation.

In this study, we propose a framework for the evaluation of a large number of evacuation planning scenarios by both reducing the computational cost of traffic simulation and representing evacuation behavior theoretically. Figure 1 shows the framework of this study.

To reduce the computational cost of traffic simulation, a region-based model is used, which divides a network into zones and considers traffic within and between zones. Knoop & Hoogendoorn

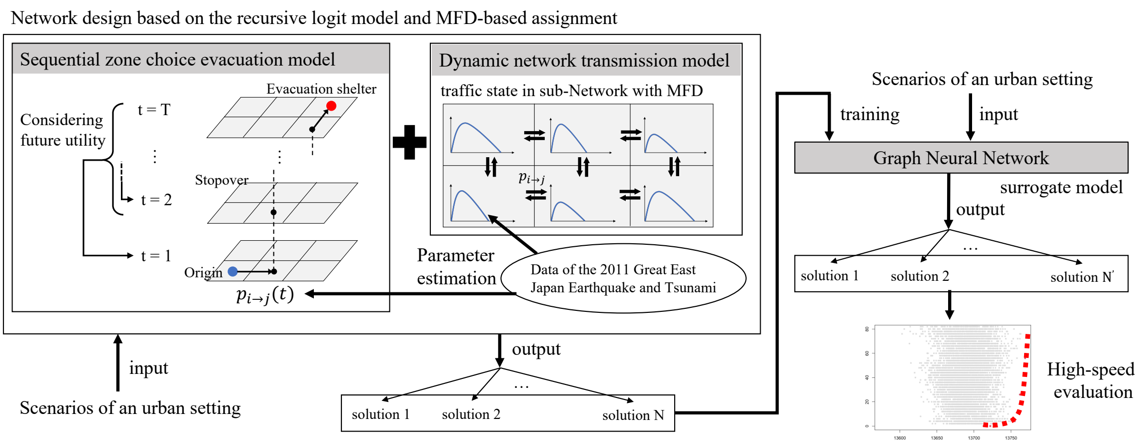

Figure 1 – *Framework of this study*

(2015) proposed the network transmission model (NTM) in which they calculated inter-zone traffic by the cell transmission model and intra-zone traffic with the macroscopic fundamental diagram (MFD). MFD (Daganzo, 2007) is an approach that describes the macroscopic traffic conditions of the network. Kim *et al.* (2018) applied the multinomial logit model to the NTM to model travel demand. However, no such region-based model incorporates a dynamic decision-making model. Since people choose their location based on the current conditions and future risks during the evacuation, a dynamic model that describes such scheduling behaviors is needed.

In this study, we formulate a sequential zone choice model using the discounted recursive logit (DRL) model (Oyama & Hato, 2017). The DRL model extends the recursive logit model (Fosgerau *et al.*, 2013) in which travelers sequentially choose the next link to maximize current and expected future utility. Oyama & Hato (2017) introduced the time discount rate into the recursive logit model and estimated the model using data from an actual disaster. They showed myopic decision-making during the disaster with a small time discount rate. We apply the DRL model to the NTM and call this the dynamic network transmission model (dynamic NTM).

In addition, a surrogate model that approximates the dynamic NTM is developed to speed up the simulation. The graph neural network (GNN) model, which can learn the graph structure of the input road network, is applied. The results under various planning scenarios (combinations of link capacities) are evaluated by the Pareto frontier consisting of the solutions that achieve the maximum number of successful evacuees and the minimum cost.

2 FRAMEWORK OF THE PROPOSED MODEL

2.1 Sequential zone choice model

A sequential zone choice model is formulated with the DRL model. Consider evacuees at state s_t, a combination of zone and time, transitioning to the next state $s_{t+1} \in A(s_t)$. $A(s_t)$ is the set of next states connected from s_t. We assume that evacuees choose the next state to maximize the sum of the instantaneous utility $u(s_{t+1} \mid s_t)$ and the expected maximum utility $V^d(s_{t+1})$ to the absorbing state d. $V^d(s_t)$ is formulated by the Bellman equation as follows:

$$\begin{aligned} V^d(s_t) &= \max_{s_{t+1} \in A(s_t)} E\left[\sum_{\tau=t}^{T} \beta^{\tau-t} u(s_{\tau+1} \mid s_\tau)\right] \\ &= E\left[\max_{s_{t+1} \in A(s_t)} \{v(s_{t+1} \mid s_t; \theta) + \beta V^d(s_{t+1}) + \mu\epsilon(s_{t+1})\}\right], \end{aligned} \tag{1}$$

where $v(s_{t+1} \mid s_t; \theta)$ is the deterministic utility component; θ is a parameter vector; $\epsilon(s_{t+1})$ is the random term following the i.i.d. Gumbel distribution with scale parameter μ; $\beta (0 \leq \beta \leq 1)$ is the time discount rate. By the assumption of the random term distribution, Eq.(1) is reformulated in the form of log sum, and the transition probability from s_t to s_{t+1} is formulated as follows:

$$p(s_{t+1} \mid s_t) = \frac{e^{\frac{1}{\mu}\left(v(s_{t+1}|s_t) + \beta V^d(s_{t+1})\right)}}{\sum_{s'_{t+1} \in A(s_t)} e^{\frac{1}{\mu}\left(v(s'_{t+1}|s_t) + \beta V^d(s'_{t+1})\right)}}. \tag{2}$$

2.2 Dynamic network transmission model

By the sequential zone choice model in **2.1**, the number of vehicle demands to move to each zone at each time step (vehicles on demand, VOD) is defined as follows:

$$n_{i \to j}^{\mathrm{VOD}} = p(s_{t+1} \mid s_t) \cdot n_i(t), \tag{3}$$

where $s_{t+1} = (j, t+1)$, and $s_t = (i, t)$. $n_i(t)$ is the number of vehicles in zone i at time t. Then, inter-zone traffic flow is calculated by $n_{i \to j}^{\mathrm{VOD}}$, the MFD of each zone, and boundary capacity. The detailed procedure for the NTM follows Kim *et al.* (2018). Thus, the dynamic evacuation behavioral model is incorporated into the NTM.

3 CASE STUDY

3.1 Parameter estimation

The case study is conducted in Ishinomaki City, Japan. We divided the city by 500m grids, and each grid corresponds to one zone in the dynamic NTM. The deterministic component of instantaneous utility in Eq.(2) is defined as follows:

$$v(s_{t+1} \mid s_t; \theta) = \theta_1 TT_{s_{t+1}s_t} + \theta_2 Po_{s_{t+1}s_t} + \theta_3 El_{s_{t+1}s_t} + \theta_4 D_{s_{t+1}s_t}. \tag{4}$$

TT is the travel time from zone i to j. Po, El, and D are the population, the average elevation, and the distance from the sea of zone i, respectively, and affect utility when an evacuee chooses to stay ($i = j$). We estimate the parameters with the data on evacuation behavior in Ishinomaki City during the 2011 Great East Japan Earthquake. Table 1 shows the estimation result.

Table 1 – *Estimation result of sequential zone choice model*

Param.	Attributes	Estimates	t-value
θ_1	travel time (min.)	-1.185	-118.74^{**}
θ_2	population (/100)	0.068	47.46^{**}
θ_3	elevation (/100m)	0.616	22.78^{**}
θ_4	distance from sea (km)	0.155	33.12^{**}
β	discount factor	0.821	160.53^{**}
	number of samples		1568
	initial log-likelihood		-75946.00
	final log-likelihood		-50419.71
	likelihood ratio		0.34

** significant at 0.01

A quadratic function approximates the MFD for each zone, and its parameters are estimated using vehicle speed data in Ishinomaki City on the day of the 2011 Great East Japan Earthquake. For more details on the data, please refer to Hara & Kuwahara (2015). By assuming Greenshields' fundamental diagram, the average traffic volume every 15 minutes for each link is obtained. Then, the outflow-accumulation relationship for each zone is plotted on the MFD.

3.2 Network design with graph neural network surrogate model

Evacuation simulation with the dynamic NTM is run repeatedly under different combinations of link capacity. By varying the link capacity, the simulation results change with the change in the MFD and the boundary capacity of the zone. To determine the shape of the MFD with the link capacity, we regress the MFD parameters on the total link length and population in the zone.

Then, we construct the GNN surrogate model. The surrogate model inputs the node (zone) features (total link length weighted by the speed limit, population, elevation, and distance from the sea) and edge features (boundary capacity), outputs the number of successful evacuees. It is trained with 4000 samples output by the dynamic NTM, and the performance is evaluated with 1000 samples. The dynamic NTM and the GNN are performed on a personal computer with Apple M1 chip (8-core CPU, 8.0 GB RAM). The dynamic NTM took 7398[s] to simulate 1000 times. Train time, inference time for 1000 samples, and RMSE for the test data of the GNN are 52[s], 0.51[s], 22.81, respectively, which is a significant reduction in calculation time.

The number of successful evacuees (z_1) and the amount of capacity enhancement (z_2) are plotted in Figure 2. The black line shows the Pareto frontier, where the maximum number of successful evacuees is achieved under a particular amount of capacity enhancement. The Pareto frontier shows that the inclination increases when z_2 is around 6. This indicates that the effect of reducing road congestion on evacuation reaches a ceiling around $z_2 = 6$. Therefore, it is reasonable for policy-makers to adopt the Pareto solution of $z_2 = 6$, where two links that connect lower ground and higher ground are particularly expanded.

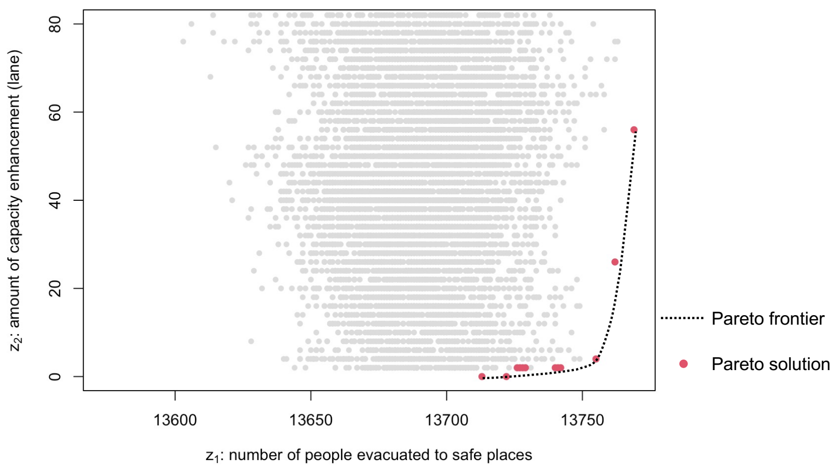

Figure 2 – *The Pareto frontier of capacity enhancement and the number of successful evacuees*

4 CONCLUSION

In this study, we proposed a framework for fast evaluation of a large number of evacuation planning scenarios while modeling the evacuation behavior theoretically. By incorporating the DRL model into the macroscopic traffic model, we developed the model that represents the dynamic decision-making of evacuation and reduces the computational cost. In addition, the GNN surrogate model achieves a speed-up of 14506 times for the inference time. Then, we evaluated evacuation plans regarding the efficiency of capacity enhancement for the number of successful evacuees using the Pareto frontier. The Pareto frontier can capture the trade-offs between costs and benefits, allowing us to determine the optimal content of investment. This framework will be helpful when developing evacuation plans, as the decision must be made under multiple objective functions and many policies. Future work will include further refinement of the MFD parameter estimation, checking the accuracy of the NTM and the GNN model, and analyzing other policy variables. In particular, it is necessary to check the characteristics of MFD under evacuation conditions with actual data and microsimulation models, as MFD requires a certain degree of homogeneity in the network.

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