Response to Reviewers' Comments/Questions
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We thank the two reviewers for their constructive comments aimed at improving the quality of this paper. Following the suggestions from the reviewers, we have revised the manuscript (referred to as R1 in the following). The reviewers' comments and our responses are addressed below.

Reviewer: 1

Comments to the Author
In this paper, an explicit approach for modeling the time-varying traffic patterns in an urban region after an earthquake is proposed. The reviewer recommends the authors address the following comments and revise the manuscript for resubmission.

Response: Thank you for taking the time to review our paper titled "An explicit approach for modeling the performance of transportation networks immediately after an earthquake". We appreciate your feedback and the valuable insights you have provided. We are committed to improving the quality and rigor of our research, and your comments will undoubtedly help us in achieving that goal.

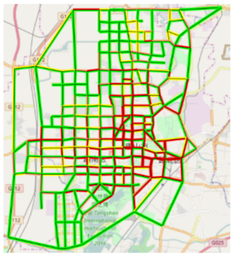
We have carefully considered your comments and recommendations and will address each of them in the revised manuscript. Your suggestions for improvement are highly valuable, and we believe they will contribute significantly to the overall quality of our work.

1. Please describe the validity of the proposed methodology in the manuscript. The reviewer wonders if the post-earthquake traffic model estimated by this methodology is accurate.

Response: This is a great question. The accuracy of the model could be evaluated in two parts: 1) whether it is able to capture reality and 2) whether the methodology is convincing.

For the first part 1) whether it is able to capture reality, the traffic reality is separated into two parts: 1) pre-earthquake traffic condition, which describes the spatial distribution of commuting vehicles, with their origin and destination information from the agent level. Gathering this information is important in traffic planning and we are employing the UE method, which is classic and widely used in this community, to generate this information. We compared the average speed estimated by our UE model with the traffic reports. "During the morning rush hour, the average speed of all vehicles is 32.5km/h in Figure 3, which is consistent with that in the 2020 AutoNavi traffic report (32.34 km/h) (AutoNavi, 2021). Furthermore, the average free-flow traffic speed before the earthquake is 47.5 km/h, which is consistent with the recorded 48.5 km/h in AutoNavi, 2021."
There are no official sources for global traffic patterns, but we could compare our simulation with real-time traffic observations here. The right figure shows a sample of congested roads in the morning peak of Tangshan (08/28/2023; to be noticed there is a time gap between our

simulation and this observation and there is the randomness of daily traffic; the orange state in the Bing map is similar to the red state in our simulation), and the left figure shows our pre-earthquake condition. These two results show a consistency in the congested regions and directions.



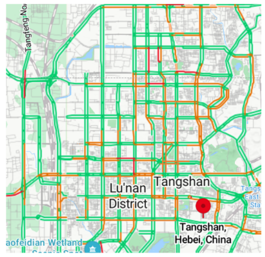


Fig.3 Static congestion state before earthquake   Fig.R1. Bing map real-time traffic for Tangshan at 8 am 8/28/2023

For the post-earthquake part, here we are following the physical settings of the paper “Feng, Kairui, Quanwang Li, and Bruce R. Ellingwood. "Post-earthquake modeling of transportation networks using an agent-based model." Structure and Infrastructure Engineering 16, no. 11 (2020): 1578-1592.” , which points out the abrupt changes in destination, irrational behavior of drivers in the chaotic aftermath of a severe earthquake, unavailability of traffic information and impairment in traffic capacity due to bridge damage and building debris by a case study. The validation of our model presents significant challenges. One of the primary issues is that there has not been a major earthquake in Tangshan since 1976, which limits our ability to test the model against real-world data. Additionally, even when we have access to perfect traffic observations following an event, it represents just one possible scenario, and this alone is insufficient for robust post-earthquake traffic modeling validation. To address these limitations, we are actively developing a fast simulation tool based on the Agent-Based Model (ABM) described in Feng et al. 2020. This model has already demonstrated its reliability in estimating parameters for multiple traffic behaviors in post-earthquake scenarios. It's worth noting that Feng et al. 2020’s approach is computationally intensive and cannot cover a wide range of scenarios. Thus, our goal is to generate a large sample of simulations using the fast-simulation tool described in this paper. By doing so, we aim to assist local governments in identifying common challenges and trends through this extensive dataset, which could capture a wide range of real cases that may happen in the future. This, in turn, will support more robust transportation design decisions and help evaluate the importance of enhancing structural elements, including various bridge sectors. Here we added a paragraph to explain this, and also, as an answer to your major comments 6.

For the second point, 2) whether the methodology is convincing. Though the analytic model is point-to-point simplified from the ABM, there may still be a gap between the predictions. Here we added a section that validates the fast analytical model in this paper with the ABM. The added text reads:
“A simplified model may provide accurate overall performance information, but usually not for detailed road-level information that is most useful for medical emergency requirements. In this section, the post-earthquake traffic conditions predicted under this model are compared with a former sophisticated agent-based model. As mentioned before, this model could finish modeling 50,000 structural damage cases by its computational efficiency. However, performing one agent-

based model on one damage case will take over 9 hours for the study area. Note that, the code here for both methods has been optimized and certain parallel computation and vectorization skills are employed. Under this case, the traffic state following these 50,000 damage cases can not be fully investigated by ABM in a reasonable time period. Here the first 1,000 damage cases are selected and the predicted post-earthquake traffic conditions following these cases under the analytic model and the ABM are compared (ABM is performed on a 128-core cluster, which is 16 times the core number used to perform the analytic method, and it takes ~1 months to complete the 1000 cases).

A comparison of the average speed of the whole traffic system is shown in Fig. 5 for time instants of 10, 30, 60, and 90 minutes after the earthquake. The average speeds are 21.7(20.7-22.9), 28.8(25.3-33.6), 33.1(28.3-39.9), and 37.7(30.2-43.1) km/h for each time instant under the analytic model. The corresponding average speeds under ABM are 22.9(21.3-23.8), 31.2(26.7-36.0), 35.9(30.1-42.2) and 40.7(37.6-44.6) km/h. The average speed distribution for both models generally matches well. The uncertainty interval of ABM is larger than the analytic method for 10,30 and 60 minutes after the earthquake. This is because analytic methods average over individual decisions to speed up the simulation. However, the uncertainty interval of ABM is smaller than the analytic method for 90 minutes after the earthquake. This is because in many cases, the traffic conditions are predicted to be clear under ABM and the average speed distribution becomes bounded. To be noticed, both model captures the multi-modal distribution of average traffic speed. Statistically, the analytic model, so simplified from ABM, could capture complex traffic behaviors as ABM.

To show that the analytic model could capture road-level details, we compare the distribution of traffic time between two hospitals under both the analytic model and ABM (Fig. 11). The average traffic time costs are not largely different between these two models for all the time instants (less than one minute). Also, these two models capture the same models. This confirms the road-level modeling ability of the analytic model proposed in this paper.”

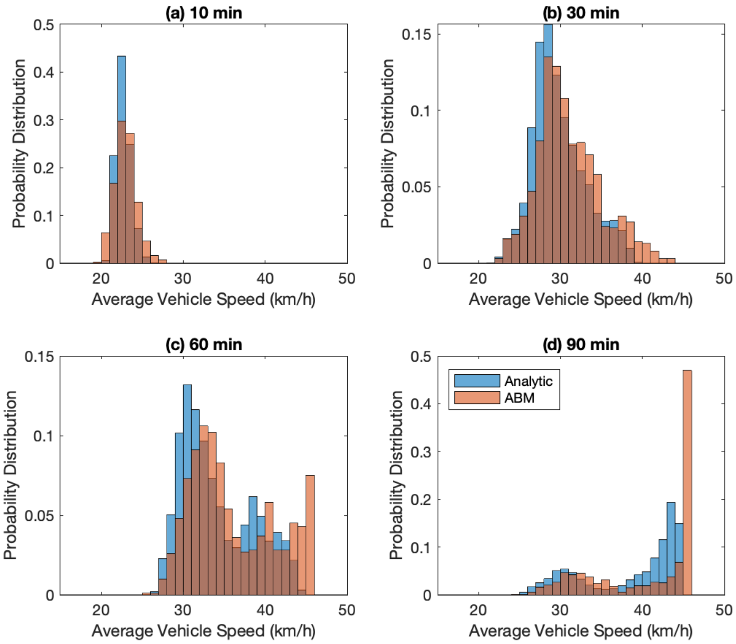


Fig. 10. The distribution of the average speed of the whole traffic system under the analytic model and ABM.

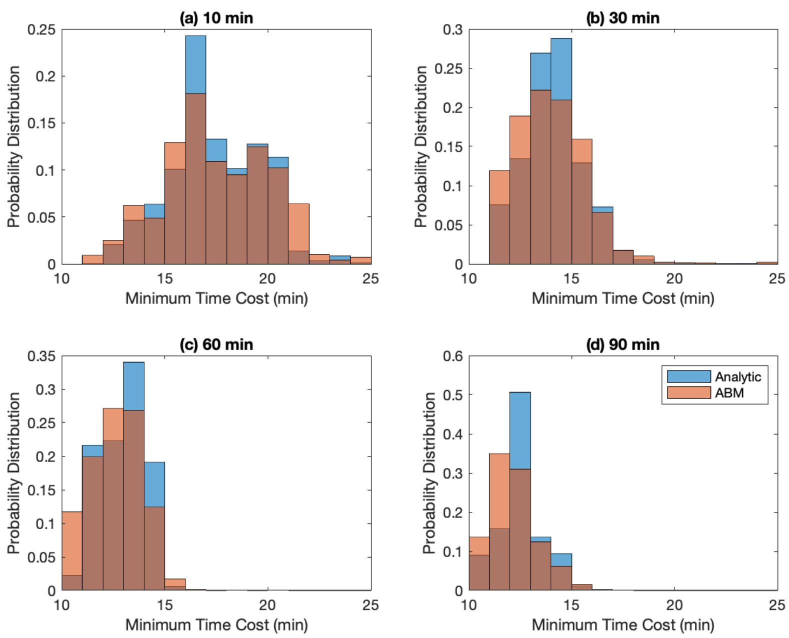


Fig. 11. Distribution of traffic time between two hospitals under analytic model and ABM.

2. Eq (12): Can you explain how to determine the value of θ?

Response: We've edited the main text as (P6, line 140-144)"The value of θ is 0.1 in the existing literature on dynamic traffic modeling under normal conditions (Lam et al., 1999; Nguyen, Pallottino, & Gendreau, 1998). Considering the fact that traffic conditions become more unpredictable after the earthquake, the value of θ is set to be 0.05 following the earthquake in our analysis following Feng et al. (2020)."

3. p.10 Lines 30~44: How can various parameters required for the application of the proposed methodology, such as the parameters for the gravity model and length of each car, and the traffic condition in the analyzed region be determined before an earthquake considering the application to the actual road network?

Response: We are generally still following Feng et al. 2020 for the pre-earthquake traffic modeling. We edit the main text (P11, Line 260-266)"First, the OD travel demands, which are generated with parameters provided in Chinese criteria (CJJ-37), and the user-equilibrium model are used to determine the pre-earthquake traffic congestion, as shown in Figure 3." The comparisons between observed morning peak traffic conditions and simulated have been made in the reply to Q1.

Since the proposed methodology can contribute to the identification of effective disaster prevention measures when applied before an earthquake, it is important to discuss whether the information required for using the proposed methodology can be collected.

Response: It is a good question. If we do it from the very beginning, here's a general outline of the process: a) Data Collection: Collect data on trip origins and destinations. This data can come from various sources, including travel surveys, GPS data, mobile apps, or traffic sensors. b) Compile information on the number of trips between different origin-destination pairs. c)Choose a Gravity Model Form: Common gravity model forms include the traditional gravity model, the modified gravity model, and the production-constrained gravity model, among others. And d)Estimate Parameters: Use statistical techniques, such as regression analysis, to estimate the parameters of the gravity model.

However, as this field is well developed, urban planners might not do these from the very beginning. Given the population information and POI (where are residential buildings and where are office/merchandise/school), the ODs could be generated with parameters defined in criteria, while different places might have different parameters. For countries with more detailed data, e.g. USA, urban planners may even directly have work-to-job data from the census, which means no model is required (https://lehd.ces.census.gov/applications/help/j2j_explorer.html#!what_is_j2j_explorer). We further explained this in the main text (P11, Line 260-266) "It's worth noting that when applying this model to different locations, while the underlying UE model may exhibit similarities, the OD demands may not necessarily need to be estimated by the gravity model with local parameters. For instance, in some countries, OD demands are routinely collected through work-to-job census data.".

4. p.6 Lines 46~51: Isn't the destination of each trip usually determined before the earthquake occurs?

Response: Yes, for the pre-earthquake modeling, where for each vehicle the origin and destination are predetermined.

Although the destinations of some of the trips would change due to the earthquake, the reviewer wonders if the destinations of all trips are probabilistically determined.

Response: The understanding of the reviewer is correct. The destination of some of the trips would change due to the earthquake. Following Feng et al. 2020, where it says "Past earthquake surveys have shown that once an earthquake occurs, most individuals who are on the road change their original destinations, heading for or returning to home immediately, picking up their spouses or children, etc (Liu, Zu, & Li, 2008; Ahn, Sun, Tsukaguchi, & Ogawa, 2014). Social disruptions following disasters depend on the nature of the affected urban area and may cause abrupt changes in traffic patterns. Since a detailed study of social vulnerability is beyond the scope of this study, however, in the sequel it is assumed that 30% of drivers maintain their original destinations, 40% return to their homes, 20% drive to school to pick up their children and 10% drive to hospitals to meet their injured relatives."

In this paper, the distance between each car and its destination is set based on a normal distribution.

Response: Thank the reviewer for asking this good question, which helps us to increase the clarity of our paper. Technically, we did not set the "distance between each car and its destination" to be a normal distribution. After the destination is determined for each vehicle post-earthquake, we statistically calculate the distribution for the "distance between each car and its destination" on each road, which could be described by a normal distribution (or not, so this is the largest assumption). On the other hand, we use another equation to capture the probability of each vehicle coming out from this road to each of the upcoming roads (eq. 13).

Then we could neglect vehicle level information and use dynamic equations set for each road, which is that when vehicles go out of one road sector, then those with a remaining distance lower than the length of this road sector (but larger than 0) will be absorbed by this sector (they stop somewhere around this road), and the remaining will go out of this road and go into another road sector. On the other hand, the distance distribution for the vehicles and their destinations going out of this road will be the original destination minus the length of this road. For a road sector that takes vehicles from other road sectors, the remaining distance for vehicles and their destinations on this road sector is a weighted average of the remaining distance distribution for the upstream road sectors, which is still a normal distribution. This design makes the very fast analytic simulation possible. But in reality, it is a strong assumption to assume a normal distribution for the "distance between each car and its destination" on each road sector (the only physics side difference between this model and Feng et al. 2020's agent-based model which traces the destination dynamically for each vehicle). The comparison of this fast analytic model and Feng et al. 2020's model is shown in Fig. 11 and 12. We add the text, (P7,156-159)"To initialize the post-earthquake traffic simulation, the normal distributions for each road are statistically calculated from the agent level information for each vehicle following Feng et al. (2020). This assumption may lead to bias between this model and the ABM in Feng et al. (2020), thus, a cross-model comparison is conducted in Section 4."

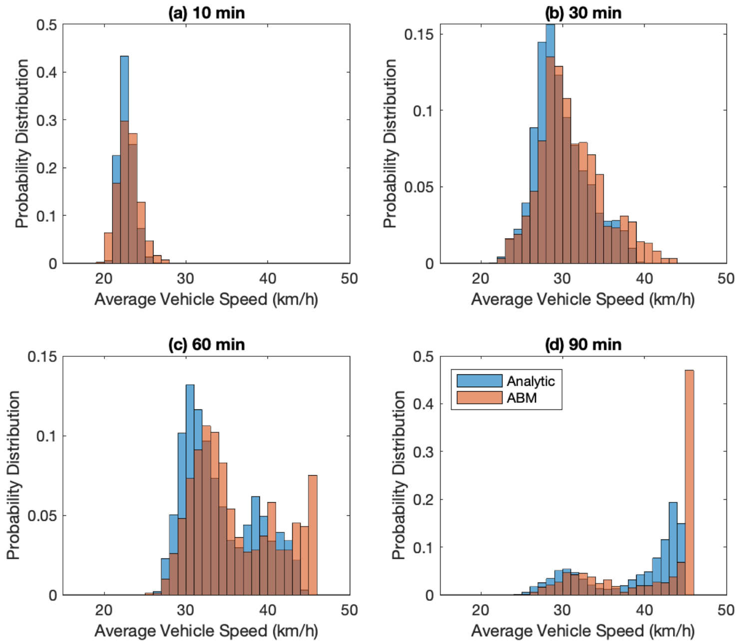


Fig. 10. The distribution of the average speed of the whole traffic system under the analytic model and ABM.

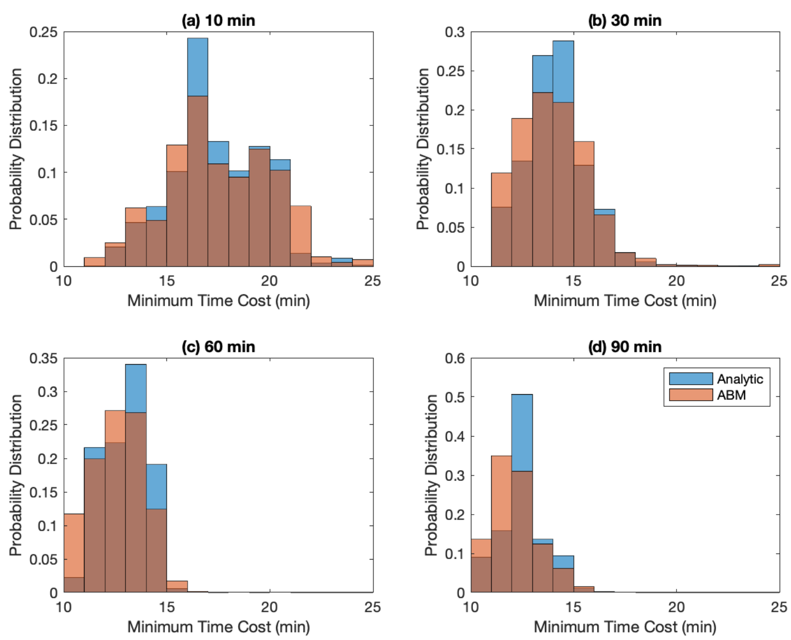


Fig. 11. Distribution of traffic time between two hospitals under analytic model and ABM.

5. p10 lines 20~29: Can you describe in the manuscript how the relationship between PGA and the failure probability of buildings is considered?

Response: We clarified earlier when we talked about PGA for bridge damages as "Within this paper, all simulations have been conducted under the assumption that Tangshan city experienced an earthquake with a magnitude of 8 around 8 a.m. during the morning rush hour.". We edited the main text as (P10,240-246)"Given our specific focus on a short-term post-earthquake traffic simulation and we are using a predetermined earthquake scenario, we employed a straightforward function to approximate the likelihood of debris impacting roadways. However, for a more comprehensive assessment of debris-related risks across various earthquake scenarios, it becomes imperative to utilize a fragility curve associated with Peak Ground Acceleration (PGA). An illustrative example of such a curve can be found in the analysis of Japanese tsunami evacuations conducted by Castro, Poulos, Herrera,and de la Llera (2019), which underscores the necessity of employing PGA-related fragility curves in such evaluations.".

6. Can you add a discussion in the manuscript about which parameters and structures, such as bridges and buildings, have a significant impact on traffic conditions and the recovery process after an earthquake? The value of this paper is greatly enhanced by presenting the dominant parameters (or structures) that affect post-earthquake traffic conditions because it would help to show what measures can improve post-earthquake traffic functionality.

Response: We thank the reviewer for the very good idea. We added an experiment in the main text in Table. 1. We find that (in the newly added section 4)"In our analysis, we have chosen to assess the influence of different parameter settings on emergency hospital responses by examining the post-earthquake delivery areas of two hospitals. As illustrated in Table 1, our findings reveal that in scenarios where there is no simulated bridge damage, indicating that the bridges have been fortified to withstand earthquakes of M8, there is a substantial increase in the delivery radius. Furthermore, the uncertainty interval narrows significantly under these conditions. This observation underscores the significant value of bridge enhancement in mitigating the risks associated with post-earthquake emergency traffic, as it leads to expanded and more reliable post-disaster emergency response capabilities." And also, we include these parts in the discussion "This study also investigates the influence of critical parameters on post-earthquake simulations and transportation system performance. Strengthening bridges emerges as a pivotal factor, in expanding emergency response capabilities."

Table 1. delivery radius of two hospitals post-earthquake under different model settings

Cases	Hospital 1 delivery radius (km)				Hospital 2 delivery radius (km)			
	10 min	30 min	60 min	90 min	10 min	30 min	60 min	90 min
Original Case	3.8 (1.7,5.5)	5.2 (3.3,6.2)	5.7 (4.4,6.6)	5.8 (4.6,6.7)	4.8 (3.8,6.2)	5.4 (4.2,6.5)	5.7 (4.6,6.7)	5.8 (4.8,6.8)
No Bridge Damage	4.9 (4.2,5.5)	5.8 (5.4,6.3)	6.4 (6.2,6.7)	6.6 (6.5,6.7)	5.7 (5.2,6.2)	6.1 (5.6,6.6)	6.5 (6.2,6.7)	6.7 (6.6,6.8)
Panic Driver Rate (-20%)	4.0 (1.8,5.6)	5.5 (4.0,6.3)	5.8 (4.6,6.6)	5.9 (4.6,6.7)	5.1 (4.2,6.2)	5.6 (4.3,6.6)	5.8 (4.9,6.8)	5.9 (5.1,6.8)
Panic Driver Rate (+10%)	3.7 (1.6,5.5)	5.0 (2.8,5.9)	5.5 (4.2,6.5)	5.8 (4.5,6.7)	4.6 (3.5,5.9)	5.2 (4.0,6.3)	5.6 (4.5,6.7)	5.8 (4.8,6.8)
Time limit to return to rational (+10 mins)	3.8 (1.7,5.5)	4.5 (2.6,5.6)	5.4 (4.0,6.5)	5.5 (4.4,6.7)	4.8 (3.8,6.2)	5.2 (3.5,6.3)	5.5 (4.3,6.7)	5.7 (4.5,6.8)
Time limit to return to rational (-10 mins)	4.4 (2.8,6.0)	5.8 (4.6,6.4)	6.0 (4.8,6.6)	6.3 (5.2,6.7)	5.4 (4.5,6.3)	6.1 (5.3,6.7)	5.9 (5.0,6.7)	6.1 (5.2,6.8)

Reviewer: 2

Comments to the Author
The paper is well written and on initial review, it seems to have good scientific and technical contributions to this field of study. However, several major comments need to be addressed. The application to a practical example makes this study very.

Response: We greatly appreciate your positive feedback on our paper titled "An explicit approach for modeling the performance of transportation networks immediately after an earthquake". Your initial impressions are encouraging, and we are pleased to hear that you find the scientific and technical contributions valuable to the field of study.

These comments are given below:

Page 1 "economy" should be "economic"

Response: Thanks for carefully reading. Edited.

Page 2:
Lines 32 to 39 needs to be explained better.

Response: We added a paragraph in methodology to explain ABM and the relationship with ABM and this paper as (P4, Line 83-95)"In a traditional ABM, e.g. Feng et al. 2020, agents are modeled as making decisions individually. For each agent, the model needs to calculate the probabilities of rational behaviour, destination choice, and route choice. Then, the simulated decision of that agent is a realization of the calculated probability distribution. This action repeats for each agent and each time step, which leads to significant computational costs. In the proposed analytical model, we first calculate the vehicle number on each road for a specific time point. We then assume all the vehicles on this road share the same probability distribution of rationality, destination choice, and route choice. Then the vehicles on this road would move to the next road section (or reach their destination) given the expectation of these probability distributions. To simplify the calculation, we allow the vehicle number on each road to be non-integer rather than random numbers. Further, by assuming all the vehicles on the same road section share the same routing distribution (for the given time point), we save the computational power of calculating routing distributions by applying the complete shortest route algorithm only once at each time step. In the ABM version, however, each agent needs to perform one complete shortest route algorithm based on the available traffic information for each time step.".

Page 3
Line 50: What does " loaded" mean?

Response: In the context of traffic assignment, "load" typically refers to the amount of traffic or the volume of vehicles using a particular road or transportation network segment. Here we refine the text as "No vehicle could load (move) into downstream road section through the blocked intersections.".

Line 55 "of the post-earthquake one" – What does this mean?

Response: refined as (P3, Lin 76-77) "traffic condition, which includes the total number of vehicles and the location of each vehicle."

Page 4:
How does it account for partial bridge closure as indicated in Hazus for different damage states

Response: We appreciate the reviewer's feedback. We agree that partial closure of bridges is important for post-earthquake bridge restoration in a week-to-month timescale. To be noticed, in this simulation, we are trying to model the immediate capacity for post-earthquake bridges.

Here we explained in the main text (P9,212-218)"In long-term (days to months) post-earthquake traffic recovery, the bridges will have a partial closure state. In this research, we operate under the assumption that immediately after an earthquake, government and emergency management agencies may not have the resources or time to execute formal bridge closures. Instead, the decision to use or avoid a bridge falls to the residents, who will base their choices on visual assessments of the bridge's condition, taking into account factors such as visible cracks and deformation. As a result, we anticipate that severely damaged bridges will not be utilized by drivers in the immediate aftermath of the earthquake."

Page 5:
T = 0 need not be the time when driver "feel" the earthquake. What is the threshold intensity, or how can it be incorporated?

Response: The reviewer raised a very good question. Here we implicitly define the T=0 as the time vehicles start to move post-earthquake. In reality, there may not be that kind of time point for the whole city. We further explained in the paper that (P10,254-257)"In reality, the commencement of movement for each vehicle can exhibit variations, and there may not be a uniform, explicit starting point for conducting traffic simulations across an entire city. In future study, it is crucial to gather additional data and information to accurately capture the diverse starting times for individual drivers in response to varying local PGA levels and their observations of structural damage.".

Page 6:
Lines 3-9: It assumes that drivers have a full knowledge of routes?

Response: It is a very good question. The model does not assume drivers have full knowledge of routes, though the equation seems to require full knowledge of possible routes. Technically, the model just decides the probability of the choice of the next intersection for each driver with a specific O-D pair. The most generalized version of this model (just as described in this paper) uses all the possible routes, for convenience, to approximate the decision that may be made by the driver, though the possibility for the driver to choose a specific route would be 0. In practice, many other models limit the routes enumerated in this model (usually limiting the maximum length of each potential route) and also get similar results.

Line 32 : Meaning of "be absorbed" is unclear

Response: Refined as "For a car that is in rational behavior, when it arrives at an intersection, it will either select another road or arrive at its destination."

Page 7:
Line 42: critical value depends on the size of the interception. How is that modeled?

Response: We explain in the main text (P8, Lin 176-181) “The size of interception may also impact the blockage of the intersection. If the downstream road sector is blocked, a larger intersection will still have an empty line if only one vehicle enters the intersection, but it can not take two vehicles. In most cases, one vehicle that enters the intersection will fully block the intersection. In the analytic model, we are averaging over vehicles, so a discrete number of vehicles can not be modeled, which may lead to a bias of simulated traffic condition.”

Generally, the blockage of the downstream road sector is more important as illustrated in this figure from Feng et al. 2020. When the downstream road sector is blocked, the vehicles can only stay in the intersection. The width of one lane in Tangshan is 3.5 ~ 3.75m, where a vehicle is usually longer than 4.5 meters, which will almost for sure to block a two-lane intersection. However, there might still be a place if the intersection has 3 lanes.

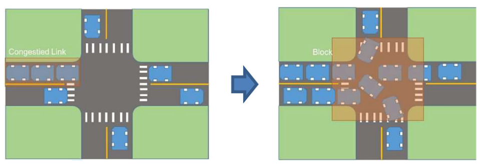


Figure 1. Blockage of an intersection due to congestion of a link.

Page 8:
Relevance of Padgett and Descroches for the case-study city?

Response: we further explained, “The bridges in Tangshan are Multispan Bridges that cross rivers, which is similar to the bridges discussed in Padgett and DesCroches 2009.”

Page 9: Please explain how the Gaussian copula is used

Response: we further explained, “The coupla approach takes into account the correlation between the failure states of each bridge based on their distance from each other.”

Line 37: Justification behind the 70% assumption ? Several assumptions in this section needs to be clearly justified

Response: This is a very good question. As discussed in Feng et al. 2020, many factors in this paper should be further evaluated by social science studies. In this paper, we could not simply justify the parameters to a single number, but we did a sensitivity test in section 5 instead.

These parameters are discussed “

Furthermore, we conducted a sensitivity analysis on two key parameters: the panic rate (default value set at 70%) and the maximum time allotted for drivers to regain composure and return to rational decision-making (default value set at 20 minutes).

Our observations confirm a trend: as the panic rate increases, the emergency traffic conditions tend to deteriorate, contributing to more challenging traffic scenarios. Conversely, a decrease in the panic rate leads to improved traffic conditions in emergency situations. What's particularly intriguing is that within a relatively wide range (ranging from 50% to 80% panic rate), the traffic conditions exhibit minimal variation. This observation implies that the findings presented in this paper are robust and likely applicable across a wide range of scenarios. It suggests that, as long as the panic rate is set within a reasonable range, the overall outcomes and conclusions of this study are less sensitive to variations in this particular parameter. This result enhances the generalizability and practicality of the findings, making them valuable for a broader spectrum of real-world emergency traffic management scenarios.

Regarding the maximum time limit (from 10 to 30 minutes) for drivers to return to rational behavior, our analysis indicates that a quicker return to rational decision-making leads to improved traffic conditions in general. However, we also observed that this parameter becomes more sensitive when the 30-minute traffic condition post-earthquake is considered.

This sensitivity to the maximum time limit highlights the need for further research to quantify and justify the optimal value for this parameter, especially in scenarios where longer recovery times may be necessary.

Additionally, our findings underscore the importance of proactive social initiatives, such as risk communication and disaster preparedness efforts targeted at local residents in Tangshan. Enhancing these aspects of disaster response can significantly benefit emergency traffic management, potentially reducing panic and improving overall traffic conditions during critical post-earthquake situations."

And it is also added into the conclusion "Sensitivity analyses reveal that panic rates and driver recovery times play key roles in shaping traffic conditions, with a noteworthy stability range for panic rates. Furthermore, this research underscores the importance of proactive social initiatives for earthquake, such as risk communication and disaster preparedness ultimately enhancing overall traffic conditions."

Page 15: What is the uncertainty around the time of 10 minutes?

Response: We refine that to (P16,Line 342-343) "It is found that 10 minutes after the earthquake, the time cost on average would increase to 18 minutes (with 5-95% intervals 13 minutes to 21 minutes)."

Overall, the 'agent based modeling needs to be explained a bit more in details.

Response: We extended the methodology part as "In a traditional ABM, e.g. Feng et al. 2020, agents are modeled as making decisions individually. For each agent, the model needs to calculate the probabilities of rational behaviour, destination choice, and route choice. Then, the simulated decision of that agent is a realization of the calculated probability distribution. This action repeats for each agent and each time step, which leads to significant computational costs. In the proposed analytical model, we first calculate the vehicle number on each road for a specific time point. We then assume all the vehicles on this road share the same probability distribution of rationality, destination choice, and route choice. Then the vehicles on this road would move to the next road section (or reach their destination) given the expectation of these probability distributions. To simplify the calculation, we allow the vehicle number on each road to be non-integer rather than random numbers. Further, by assuming all the vehicles on the same road section share the same routing distribution (for the given time point), we save the computational power of calculating routing distributions by applying the complete shortest route algorithm only once at each time step. In the ABM version, however, each agent needs to perform one complete shortest route algorithm based on the available traffic information for each time step.".