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Resilience Analysis of Transport Networks by Combining Variable Message Signs With Agent-Based Day-to-Day Dynamic Learning

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ABSTRACT To date the resilience of transport networks has not been effectively modelled by taking into account the traffic dynamics along with individual drivers' learning process and irrational behaviours. This study proposes an agent-based day-to-day dynamic model with bounded rationality to capture traffic evolution and drivers' inertial behaviours when transport networks suffer from local capacity degradation, and variable message signs are incorporated into the proposed model to improve the resilience, which is indicated by the rapidity of recovering to a new approximation equilibrium after disruptions. We employ a small network as a numerical study to conduct resilience analysis, and variable message signs with different compliance rates are utilized to induce traffic flows for alternative routes when a given link of the network is subject to mild (25%), moderate (50%), severe (75%) capacity reduction. The results show that variable message signs can apparently improve the resilience of the network in most of cases, and a larger compliance rate of variable message signs does not necessarily lead to better rapidity of recovery for approximation equilibrium. This study may provide an insight into the resilience analysis and improvement of transport networks under different levels of disruptions, which fully takes into account the individual drivers' day-to-day learning process, behavioural inertial and the control mechanism of variable message signs with different compliance rates.

INDEX TERMS Resilience, transport networks, variable message signs, compliance rate, day-to-day dynamics.

I. INTRODUCTION

Reliable and resilient transportation networks are one of the backbones underpinning the prosperity of our society and economy [1], [2]. As an important lifeline infrastructure to secure the normal operations of cities, if transport networks suffer from internal or external disruptions and cannot recover to normal state timely, the huge amount of loss of life and economic loss will be incurred. However, transport networks are frequently exposed to a variety of disasters, such as Indonesian tsunami, Hurricane Katrina, the Haiti earthquake, floods in north-eastern Australia and Brazil and so on. These may cause great destruction of

transport infrastructure. Particularly, various natural disasters are significantly increasing due to global climate change. Meanwhile, worldwide terrorist attack are also increasingly rampant, for example the 9/11 attacks in 2001, the London bombings in 2005, the Paris attacks in 2015, and the Brussels bombings in 2016, and so on [3]. Regardless of the type of these disasters, however, they are all able to result in the huge damage to transport infrastructure. All examples above highlight the importance and urgency of understanding and analyzing resilience of transport networks. Therefore, resilience of transport networks have been a primary focus of planning and management of transportation.

However, there is no universal definition for resilience of networked systems due to the diversity of the network type and research purpose. To date, the studies regarding resilience

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have been conducted in many fields, such as ecological system [4], economic system [5] and urban infrastructure system [6]. In the field of materials, resilience is regarded as the ability of a material to return to its former shape after a deformation. Following this, the study in [6] argues that resilience should involve ‘bouncing forward’ and ‘moving on’, not just ‘bouncing back’ after an event. Reference [6] deems that resilience can be defined as “*the intrinsic capacity of a system, community or society predisposed to shock or stress to bounce forward and adapt in order to survive by changing its non-essential attributes and rebuilding itself.*” The work in [7], meanwhile, defines network resilience as the ability of a network to maintain an acceptable level of service when experiencing various faults and challenges to normal operations.

In the field of infrastructure, the research in [8], [9] describe the resilience of a system through four key characteristics, as follows:

- 1) *Robustness: the inherent strength of or resistance in a system to withstand external demands without degradation or loss of functionality;*
- 2) *Redundancy: system properties that allow for alternate options, choices, and substitutions under stress;*
- 3) *Resourcefulness: the capacity to mobilize needed resources and services in an emergency;*
- 4) *Rapidity: the speed with which disruption can be overcome and safety, services, and functionality stability restored.*

There are many different definitions for resilience, but they all connect with the core part of the concept, namely, recovery after physical disturbances. In reality, the ability of transport systems to quickly recover to normal state is very important, particularly when transport networks suffer from non-catastrophic disruptions, such as the closure of traffic lanes and short-time flooding. In addition, engineering resilience which has the same definition as *rapidity of recovery* is pointed out that it is easier to calculate and evaluate the resilience in dynamic traffic models compared to other definitions [10]. Previous work [11], [12] both evaluate the resilience of traffic networks by using the rapidity of recovery. Therefore, this study also follows this approach to explore the resilience of transport systems from the perspective of the rapidity, and our study relates rapidity to the speed at which transport systems recover to an approximation equilibrium after disruptions.

Currently, it seems that there are no commonly accepted indices or unified modelling approach for resilience, and the existing research has been carried out from two perspectives: topology-based model and mathematical programming based model. The study [13] regards road networks as one of technical networks in cities, and utilizes redundancy index based on shortest paths and the number of neighborhood nodes of a given node to assess the resilience of Orleans, France suffering from flooding. The work in [14] considers the resilience of a node as the weighted sum of the number of reliable passageways of all other nodes in the network, and the sum

of the resilience of all nodes is the resilience of the network. In order to assess the resilience of road networks suffering from environment hazards, the work in [15] utilizes topological indices such as giant connected component of the network and betweenness to evaluate the resilience. Similarly, the work in [16] develops other topological index based on giant connected components to access the best strategy which can improve the resilience of rural transport networks in Nepal. In addition, the work in [17] employs the spatial-temporal clusters of congestion in real traffic to define resilience, and the study in [18] also proposes a method based on topological indices such as average path length and betweenness to evaluate the resilience of transport networks. These topology-based methods are easier for understanding and computing, but less take into account the realistic factors such as travel demand, road capacity and traveler’s irrational behaviors. Research based on mathematical programming models tends to cover these characteristics. The work in [19] utilizes an indicator to quantify network’s resilience when experiencing recurring capacity disruptions. The indicator is based on the ratio between the minimum possible expected system travel time (ESTT) at the state without disruptions and the ESTT at the critical stage, and a minimax program is used to seek the critical state ESTT. Following this, the work in [20] utilizes the similar model to propose a general resilience index to measure the evolution of resilience as demand varies, which is based on the calculation of ESTT. In addition, the study in [21] investigates the resilience of a traffic network by employing the normalized area over the exhaustion curve, which is obtained from a dynamic restricted equilibrium model (DREM) combined with a cost function using a random parameter following a generalized beta distribution to represent the time-varying hazards of extreme weather. After this, the work in [22] investigates the travel time resilience of the network under different disaster scenarios by proposing a bi-level, three stage stochastic mathematical program with partial user equilibrium constraints. In order to enhance the resilience of urban road networks, the work in [23] proposes a flexible signal control to mitigate the travel delay and random risk caused by hazardous material transportation, and a mathematical program with equilibrium constraints (MPEC) is proposed to model the resilience under signal control.

Although the resilience research based on mathematical programming models considers realistic characteristics, these studies often ignore the traffic dynamics along with individual drivers’ day-to-day learning process and irrational behaviors. Given this background, this study proposes an agent-based day-to-day (ABDTD) dynamic model with bounded rationality to capture the traffic evolution of transport networks suffering from disruptions. *Day-to-Day* (DTD) dynamics are used in this study to describe and predict the daily evolution of traffic flows and drivers’ route adjustment processes. Such DTD assignment methods are regarded to be most appropriate for analyzing traffic equilibration processes due to their flexibility to accommodate a wide range of behavior rules, levels of aggregation, and various traffic models

to be integrated within the same modelling framework [24]. In this study, the resilience of transport networks are observed from the perspective of day-to-day traffic evolution and disruptions; variable message signs (VMS) and distinct route choice behaviors are also incorporated into the model in order to demonstrate how drivers adapt their behaviors to improve the resilience when suffering disruptions. As for the detailed discussions on day-to-day traffic dynamical learning systems, we refer readers to [25]–[31].

In this study, DTD dynamic learning process at agent level is considered. As a popular method to model the complex collective behaviors of a large number of autonomous agents, *Agent-based simulation* (ABS) is able to reveal relevant characteristics, such as heterogeneity of individual drivers, self-organization and randomness, by endowing rules to agents at a lower level [32]. In the transportation field, ABS has been used to study the driving and travelling behaviors, and here we refer readers to [33]–[36].

To capture the inertial behavior of individual drivers and imperfect information of transport networks, *bounded rationality* (BR) is introduced to combine with the proposed ABDTD model. The BR user behavior can be incorporated into the DTD dynamics [37], [38], and they either focus on route choice [39], [40] or departure time choice [41]. In this study, in order to improve the resilience of the transport networks, VMS with different compliance rates (CR) is also incorporated into the proposed model. There are many studies to assess the impacts of VMS on traffic performance. The work in [42] proposes a time-varying traffic assignment model with travel time information relayed by VMS so as to examine the effectiveness of VMS, and [43] employs three questionnaires to examine the impacts of VMS information. In addition, the work in [44] develops a simulation model via VISSIM to evaluate the effect of route guidance with and without VMS under common and serious congestion. Meanwhile, the inefficiency and ineffectiveness of VMS manually designed by traffic administrators is pointed out in [45]. All these studies show that VMS has great impacts on route choice and network performance, and may play a positive role in mitigating delays and congestion in most of cases. However, how the VMS impacts the travel behaviors of individual drivers, and network performance through compliance rates and DTD dynamic learning process so as to improve the resilience of transport networks, is not clear yet.

The aim of this study is to analyze the resilience of transport networks suffering from different levels of disruptions via the proposed agent-based day-to-day dynamic model with bounded rationality, which captures the drivers' inertial behaviors and day-to-day dynamic learning. Based on this, VMS is combined with the model to examine how exactly compliance rates to VMS impact the resilience of transport networks after disruptions.

The rest of this paper is organized as follows. Section II presents the methodology used in this study, which includes agent-based day-to-day dynamic model and variable message signs, and four sub-models: route perception updating model,

route choice model, network loading model and bounded rationality, are also introduced. In Section III, we present a numerical case study to quantify the impacts of different compliance rates to VMS on rapidity of recovery of the traffic network suffering from capacity degradation. Finally, conclusions and future work are presented in Section IV.

II. METHODOLOGY

This section mainly introduces the methodology used in this study. An agent-based day-to-day dynamic model and variable message signs are introduced respectively, then the complete model is presented.

A. AGENT-BASED DAY-TO-DAY DYNAMIC MODE

The details of agent-based day-to-day (ABDTD) dynamic model is presented here. ABDTD model describes how individual drivers adjust their behaviors based on the perception of each route in the network, which may evolve as traffics on the network vary over time. Unlike other works [46] related to this model, this ABDTD model incorporates the *bounded rationality* (BR) to capture the inertial feature of individual drivers during day-to-day learning process.

Assuming there is a directed transport network $G(N, A)$, where N is a set of nodes and A is a set of arcs. W is denoted as a set of origin-destination(OD) and $(i, j) \in W$ denotes an OD pair. Following this, R represents the set of routes for OD pair $(i, j) \in W$, while c_t^r denotes the travel cost over routes $r \in R$ on day t . In addition, we use T_{ij} to denote a fixed travel demand and h_t^r to denote the flow on route r on day t .

1) ROUTE PERCEPTION UPDATE

Equation (1) presents the route perception update model. Here x_t^{ir} and c_{t-1}^r are denoted as the perceived and actual travel cost on route r by driver $i \in I$ on day t and day $t - 1$, respectively, I is the set of all drivers using the transport network. There are approximately two types of route perception updating model [47], the first type is that the perceptions on the routes for drivers depend on the measured costs of a finite number of previous days, and the weight is utilized to represent the influence level of previous days' cost on the route cost. Since such weight increases the complexity of the model, the second type updating model, named as exponential smoothing filter, assumes that drivers' perceptions on routes are only associate with the perceived cost and actual cost of the previous one day [28]. Here we employ the latter one, as shown in (1).

$$x_t^{ir} = x_{t-1}^{ir} + \alpha Y_{t-1}^{ir} (c_{t-1}^r - x_{t-1}^{ir}) \quad (1)$$

where Y_{t-1}^{ir} is random route choice index, and takes 1 if i chooses route r on day $t - 1$; takes 0 otherwise. α is a parameter which measures the impact of the travel experience (on day $t - 1$) on the perception. In order to make sure that the perception on day t always is positive, α varies between 0 and 1. This sub-model depicts how individual drivers update the perceptions of routes based on the day-to-day learning process.

2) ROUTE CHOICE MODE

In this study, the logit model is utilized to model the random route choices of individual drivers under the influence of their perceptions on routes. Here the probability choosing route r for a driver i is given by:

$$P(Y_t^{ir} = 1) = \frac{\exp(-\beta x_t^{ir})}{\sum_{l \in R_{o,s}} \exp(-\beta x_t^{il})} \quad \beta > 0 \quad (2)$$

where $R_{o,s}$ is the set of routes connecting OD pair $(o, s) \in W$, β is named as the *dispersion parameter* in the context of stochastic user equilibrium [48], and can be used to measure the sensitivity of drivers on route costs. As described by this logit model, the probability for choosing a given route depends on the subjective perceptions of drivers rather than actual or objective route costs, due to many reasons including imperfect information, drivers' socio-economic characteristics and driving experience. This route choice model captures the irrationality of drivers involved in the route choice process, that is, drivers do not necessarily choose the routes with the minimum cost because of imperfect travel information and drivers' predictive behavior.

3) BOUNDED RATIONALITY

Most of Deterministic DTD models assume that drivers' behavior is completely rational, which means that drivers always tend to switch to the routes with the minimal cost. However, In reality, due to the imperfect information and behavioral inertia, drivers prefer to sticking to the original route if the difference between actual cost of current route and the minimal perception among all routes is below a threshold (tolerance); otherwise, they are reluctant to consider the route change. This phenomenon is termed as *Bounded Rationality* (BR), and has been extensively studied in the field of traffic assignment [37], [38], [40]. In this study, as a sub-model of route choice, BR is introduced to capture the nature of imperfect information and inertial behavior, and we employ the BR model presented in [36], as shown below:

$$\frac{c_{t-1}^r - \min_r x_t^{ir}}{c_{t-1}^r} \quad (3)$$

If the difference between the actual cost of route r on day $t - 1 (c_{t-1}^r)$ and the perceived minimal route cost among all routes on day $t (\min_r x_t^{ir})$ is below the tolerance of drivers, the drivers choose to ignore such difference and are stick to the same route on the previous day; otherwise, drivers decide to change routes based on the logit model (2). Mathematically, if $Y_{t-1}^{ir} = 1$, then

$$\text{If } c_{t-1}^r - \min_r x_t^{ir} < e : \\ Y_t^{ir} = 1$$

Else:

$$P(Y_t^{ir'} = 1) = \frac{\exp(-\beta x_t^{ir'})}{\sum_{l \in R_{o,s}} \exp(-\beta x_t^{il})} \quad (4)$$

4) NETWORK LOADING

A route r is represented as a set of links it traverses in a network, and the link flows u_t^a on link $a \in A$ on day t is related to route flows h_t^r ; and can be formulated as follows:

$$u_t^a = \sum_{r \in R} \delta_{a,r} \cdot h_t^r \quad \text{for all } a \in A, t \quad (5)$$

$\delta_{a,r}$ is a link-route incident matrix:

$$\delta_{a,r} = \begin{cases} 1 & \text{if } a \text{ belongs to } r \\ 0 & \text{if } a \text{ does not belong to } r \end{cases}$$

Route costs can be presented in the following way:

$$c_t^r = \sum_{a \in A} \delta_{a,r} C_a(u_t) \quad \forall r \in R \quad (6)$$

where $C_a(u_t)$ is a cost function depending on the link flow $u_t^a = (u : a \in A)$. Here we utilize Bureau of Public Roads [49] (BPR) link performance function as the link function:

$$C_a(u) = A \cdot \left[1 + B \cdot \left(\frac{u^a}{CP_a} \right)^p \right] \quad (7)$$

where u^a is the flow on link a , CP_a is the flow capacity of link a , and A, B, p are positive parameters.

Above process is known as *network loading* problem. Mathematically, the network loading can be expressed as:

$$c_t = (c_t^r)_{r \in R}, \quad u_t = (u_t^a)_{a \in E}, \\ c_t^r = \sum_{a \in E} \delta_{a,r} \cdot C_a(u_t) \quad \text{for all } r \in R \quad (8)$$

Network loading process reflects the relationship between route cost and link flow.

B. VARIABLE MESSAGE SIGN

Variable Message Signs (VMS) are widely used to provide real-time traffic information related to congestion, incidents, roadworks and speed limits [50] as well as to make route suggestions [51]. As an instrument for the temporal and spatial management of congestion, these facilities may suggest that drivers take alternative routes, indicate the duration and location of incidents, or show general traffic conditions. VMS is able to divert traffic when incidents occur, such as in the case of the local capacity reduction considered in this study.

In this study disruptions are modelled as local capacity degradation of road links or nodes. A VMS facility starts working after the disruption occurs. The capacity degradation of the link suffering from the disruption leads to a decrease in travelers using the corresponding routes, including the affected link. In the meantime, alternative routes are used more frequently than before the disruption. During the disruption, the VMS makes recommendations to travelers regarding alternative routes. In this context, for each O-D pair, drivers will adapt their route choices with an exogenously defined *compliance rate* (CR), and switch to the alternative routes by following a logit route choice model:

$$\text{switch rate}_r = \frac{\exp(-\beta * c_t^r(h_t^r))}{\sum_{r' \in RL} \exp(-\beta * c_t^{r'}(h_t^{r'}))} \quad (9)$$

where RL is the set of alternative routes that drivers may choose from if they comply with the VMS recommendations. Here, c_t^r refers to the route r cost on day t .

For a given O-D pair, the total amount of flow that needs to be switched can be expressed as:

$$\Delta H = \sum_{r \in RS} h_t^r \times CR \quad (10)$$

where RS is the set of routes affected by the disruptions for a given O-D pair. Then, the routes directly affected by the disruption update their flows as:

$$h_t^r \leftarrow h_t^r - h_t^r \times CR, \quad r \in RS \quad (11)$$

where \leftarrow represents assignment of values. Alternative routes update their flows according to:

$$h_t^{r'} \leftarrow h_t^{r'} + \Delta H \times \text{switch rate}_{r'} \quad r' \in RL \quad (12)$$

C. THE COMPLETE MODE

These components illustrated in the previous two subsections are integrated to form the complete agent-based day-to-day (ABDTD) model combining with VMS as follows. The pseudo code for this complete model is provided in **TABLE 1**.

The complete model consists of two parts. In the first part, we begin with day one and randomly generate drivers' route perceptions. Then according to (2), the route choice probabilities are determined, and the actual route choices are randomly generated accordingly. Based on the network loading procedure, the actual (experienced) route costs are obtained. Following this, all the travel agents update the perceptions of all the routes based on (1). Then (4) is utilized to determine whether or not the agent should stick to the previous route or select new routes for travelling. These procedures are repeated on a day-to-day basis until the convergence is reached. It is worth nothing that ABDTD model has inherent stochasticity due to logit-based route choice model at atomic level, so quantifying convergence of the model is very difficult. Here the method of approximation convergence (equilibrium) is utilized to quantify the convergence, which can be referred to [40] for details.

In the second part, we assume that capacity degradation of a given link occurs when the network achieves approximation convergence. Then VMS starts guiding traffics for alternative routes after the disruption takes place based on (9)-(12). Following this, the actual route cost is obtained according to the network loading procedure (8). If the approximation equilibrium is achieved again, the model stops; otherwise, after updated perceptions and the actual route choice are achieved according to (1) and (4), return to Step 2 of this part.

III. NUMERICAL STUDY

In this numerical example, the BPR function is used to describe the link travel cost (see (7)), and the numerical values for the parameters are summarized in **TABLE 2**. In addition, α in (1), β in (2) and e in (4) take 0.25, 1 and 0.5, respectively.

TABLE 1. Pseudo code for the agent-based day-to-day model combining with VMS.

Pseudo code. The agent-based day-to-day dynamic model combining with VMS

Part 1

- 1: Assign the free-flow costs of all paths as the initial path perceptions of agents. Then determine their route choice probabilities according to the logit model (2). Perform network loading to obtain each agent's actual travel costs. Set $t = 0$.
- 2: Set $t = t + 1$. Update each agent's perception about all the routes according to the learning process (1).
- 3: Determine the actual route choice using (4), based on the agent's updated perceptions and their experienced travel costs on day $t - 1$.
- 4: Perform the stochastic network loading (3) according to the route choice probabilities determined in Step 3, and obtain the travel costs. If approximation convergence is obtained, go to **Part 2**; otherwise, return to Step 2.

Part 2

- 1: A given link suffers from mild (25%), moderate (50%) and severe (75%) capacity reduction.
- 2: Traffic flows on the link are diverted to other routes according to (9)-(12).
- 3: Perform the stochastic network loading according to (3) to obtain travel costs. If approximation convergence is obtained, stop; otherwise, set $t = t + 1$, update each agent's perceptions about all the routes according to (1), determine the actual route choice with (4), and then return to Step 2.

The criteria for approximation convergence (equilibrium) is identical to that in [40].

This numerical study assumes that link 9 is subject to 25%, 50% and 75% capacity degradation, which may represent different levels of disruptions: mild, moderate and severe. There are six routes in the networks: $a \rightarrow b \rightarrow c \rightarrow f \rightarrow i$ (route 1), $a \rightarrow d \rightarrow e \rightarrow f \rightarrow i$ (route 2), $a \rightarrow b \rightarrow e \rightarrow f \rightarrow i$ (route 3), $a \rightarrow d \rightarrow g \rightarrow h \rightarrow i$ (route 4), $a \rightarrow d \rightarrow e \rightarrow h \rightarrow i$ (route 5) and $a \rightarrow b \rightarrow e \rightarrow h \rightarrow i$ (route 6). The network will experience two stages: pre-disruption and post-disruption. Before the disruption, the network system is expected to reach equilibrium, which represents the normal state of the network. After the disruptions occur, traffic flows are assumed to be under the influence of a variable message sign (VMS) at a relevant location in respect to the disruptions. In this study, the VMS simply displays information regarding the disruption ahead without supplying any additional information such as suggested alternative routes, real-time travel information, etc. It is used as a means to divert traffic away from the location of the disruptions.

For the small network, the disruptions on the link 9 directly affect route 5 and route 6, and the other 4 routes become potential alternative routes for drivers. As a result of the

TABLE 2. Link parameters of the small network.

Link ID	A	B	γ	CP_a
1	15	0.15	4	500
2	15	0.15	4	500
3	15	0.15	4	500
4	15	0.15	4	500
5	15	0.15	4	500
6	15	0.15	4	500
7	15	0.15	4	500
8	15	0.15	4	500
9	15	0.3	4	500
10	15	0.15	4	500
11	15	0.15	4	500
12	15	0.15	4	500

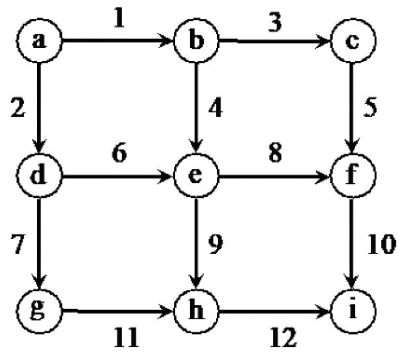


FIGURE 1. The small network.

VMS, the route flows of the all routes are updated according to (12). In this study, the compliance rate (CR) to VMS directly influences the performance of the network since a larger compliance rate implies more drivers' route choices are affected by the information provided by the VMS. The CR is varied (0.2, 0.1 and 0.05) to observe the sensitivity of the network performance to the compliance rates, which is usually very difficult to estimate in a real-world environment. The following re-assignment of route flows are instances of the more general modelling approach presented in part B of Section II.

$$\begin{aligned}
 h_t^5 &\leftarrow h_t^5 - h_t^5 \times CR \\
 h_t^6 &\leftarrow h_t^6 - h_t^6 \times CR \\
 \Delta H &= \sum_{r \in (5,6)} h_t^r \times CR \\
 h_t^i &\leftarrow h_t^i + \Delta H \times \text{switch rate}_i \\
 & \quad i \in (1, 2, 3, 4)
 \end{aligned} \tag{13}$$

where ' \leftarrow ' denotes assignment of values.

A. RESULTS ANALYSIS WITH VMS

This numerical study mainly utilizes VMS as a main tool for the mitigation of congestion caused by disruptions, so as to observe the rapidity of network recovery under different CR. In the numerical example, the drivers' perceptions on different routes are initially set to be equal to their free-flow time. We then follow the pseudo code presented in TABLE 1 to carry out the simulation.

Based on the simulations, the resulting route costs, route flows and network-wide total cost over time are presented in FIGURE 2, FIGURE 3 and FIGURE 4, one for each compliance rate of the VMS (e.g. 0.05, 0.1 and 0.2).

FIGURE 2 presents how the route costs, route flows and network-wide total costs evolve when a VMS with a CR=0.05 is used to manage the traffic after different levels of disruptions. In this case, drivers adjust their route perceptions and choices based on their daily travel experience. As can be

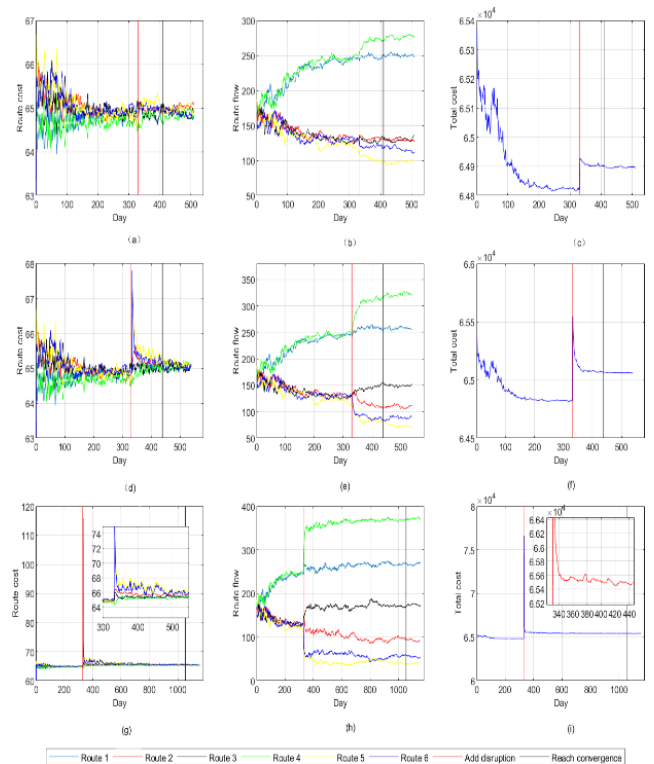


FIGURE 2. Route costs, route flow and total cost evolution under VMS control with CR = 0.05. First row (from (a) to (c)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 25%; second row: (from (d) to (f)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 50%; third row: (from (g) to (i)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 75%.

seen from FIGURE 2, the network starts with an arbitrary configuration of route flows and reaches an approximation equilibrium state. The red vertical line represents the time when the disruptions occur and initial approximation equilibrium is broken, and black vertical line marks the time of the attainment of a new approximation equilibrium. With this compliance rate, the route costs do not react significantly to the minor disruption (25% capacity reduction), and the network takes approximately 70 days to reach a new approximation equilibrium. For the moderate and severe disruptions, the route costs and route flow both significantly fluctuate

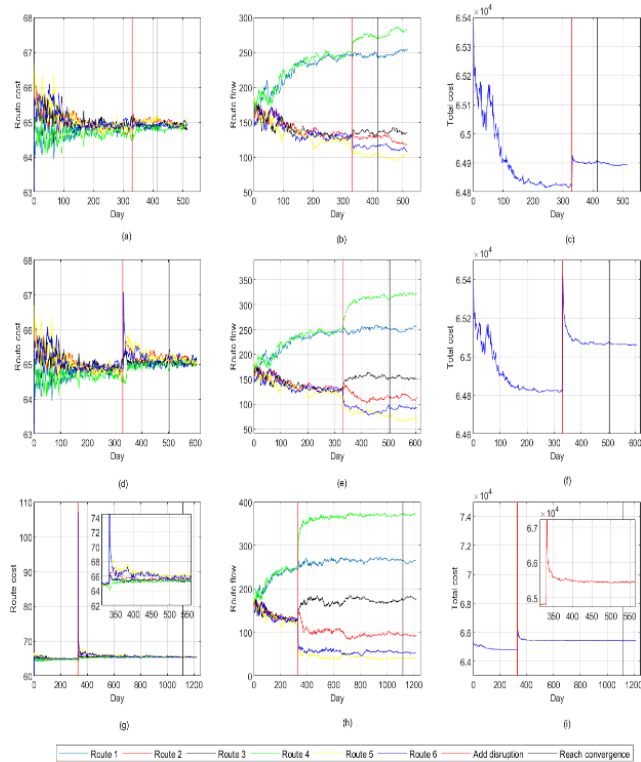


FIGURE 3. Route costs, route flow and total cost evolution under VMS control with CR = 0.1. First row (from (a) to (c)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 25%; second row: (from (d) to (f)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 50%; third row: (from (g) to (i)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 75%.

over time, and the network also takes longer to reach an equilibrium. The increase in the total cost is more significant when more severe disruption occurs, and the total cost at the new approximation equilibrium is further deviated from the original approximation equilibrium.

FIGURE 3 shows the evolution of route costs, route flows and network-wide total cost over time when a VMS with a CR=0.1 is employed to mitigate the congestion caused by different levels of disruptions. It seems that the network is less affected by the minor disruption (25%), and the network takes 85 days to reach a new equilibria under the influence of VMS, which is longer than that with CR=0.05. For 50% and 75% capacity reduction, the route costs abruptly increase then gradually reach stability, and the fluctuations on route flows are significant. Compared to the case where CR=0.05, the networks take longer days to reach equilibria in these scenarios. Through the observation and analysis from FIGURE 2 and FIGURE 3, it may be concluded that the greater compliance rate may not always lead to the better outcome.

As can be seen from FIGURE 4, the utilization of VMS with CR=0.2 gives rise to significant fluctuations of route flows, but facilitates the networks suffering from minor and severe disruptions to reach new approximation equilibria

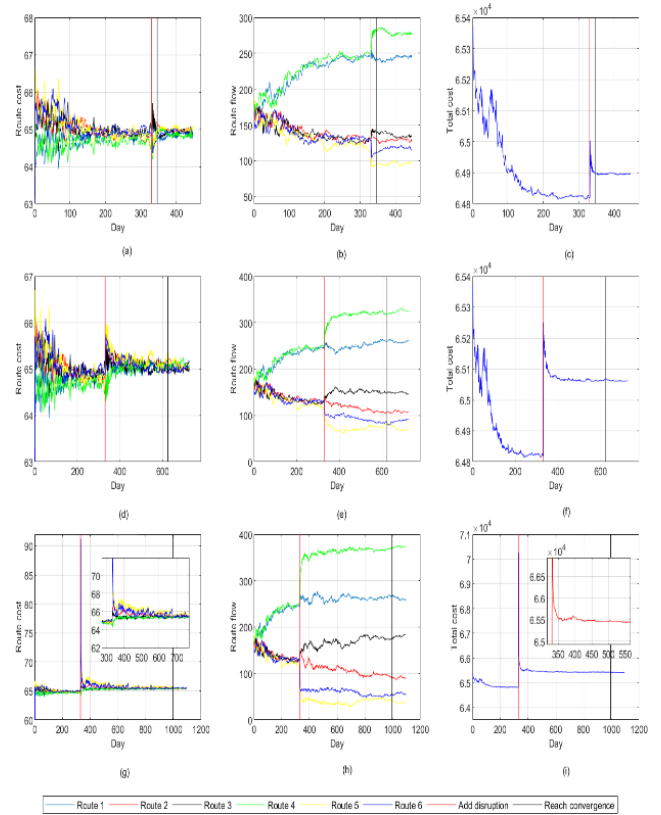


FIGURE 4. Route costs, route flow and total cost evolution under VMS control with CR = 0.2. First row (from (a) to (c)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 25%; second row: (from (d) to (f)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 50%; third row: (from (g) to (i)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 75%.

faster than the case where CR=0.05 and 0.1. The explanation for this is that drivers are more likely to follow the information provided by VMS, which suggests to use other alternative routes, and it quickly stabilizes traffic after the disruptions. Interestingly, however, it does not speed up the convergence of the network when suffering from moderate capacity degradation, since at this level CR overestimates the impacts caused by the disruptions. For severe disruption, on the other hand, this level of CR improves the rapidity compared to the case where CR = 0.1 and 0.05.

Through the observations from FIGURE 2, FIGURE 3 and FIGURE 4, we can see that the route costs, route flows and network-wide total costs evolve over time as the CR of VMS takes 0.05, 0.1 and 0.2, respectively. For minor and severe disruption, the case of VMS with CR=0.2 shows the fastest convergence, whereas the case where CR=0.1 presents the worst rapidity. This clearly demonstrates that the larger value of CR does not necessarily facilitate the network to reach convergence faster. It is even worse for moderate disruption; the larger CR hinders the convergence of the network to some extent. The quantitative results are presented in TABLE 3.

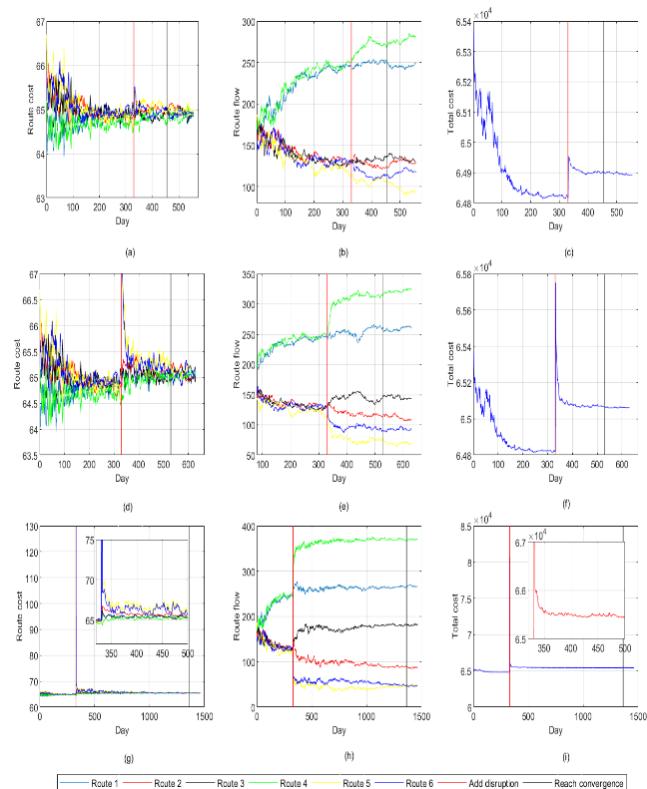


FIGURE 5. Route costs, route flow and total cost under mild, moderate and severe disruption without VMS (CR = 0). First row (from (a) to (c)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 25%; second row: (from (d) to (f)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 50%; third row: (from (g) to (i)): the evolution of route costs, route flow and total cost when the capacity of link 9 reduces by 75%.

B. RESULTS ANALYSIS WITHOUT VM

In order to clearly demonstrate the role of VMS in improving the rapidity of recovery when the network suffers from the disruptions, the simulation of ABDTD model without VMS is conducted as well. In fact, the case without VMS is equivalent to that with CR=0. In this case, the network gains new equilibrium only by day-to-day dynamic leaning of all drivers. The results of route costs, route flow and total cost under mild, moderate and severe disruptions are shown in **FIGURE 5**.

As can be seen, the first column of **FIGURE 5** shows that route costs evolve over time when the network suffers from different levels of disruptions without VMS control (CR=0). There is an insignificant increase in the route costs when mild disruption (25%) occurs, and it takes 125 days to reach a new convergence. When the network suffers from moderate disruption (50%), the route costs increase greatly and daily fluctuations for the route costs are more significant. The network reaches a new equilibrium 199 days after the disruption. Route costs drastically increase when the network is subject to severe disruption (75%), and, as expected, it takes more days to reach a new equilibrium, 1033 days. The second column of **FIGURE 5** shows the daily evolution of route flows after the disruptions. Due to the capacity degradation

TABLE 3. KPI of resilience for the small network under the VMS control.

CR	Rapidity	Capacity reduction		
		Mild (25%)	Moderate (50%)	Severe (75%)
0.05		79	108	723
0.1		85	175	786
0.2		16	294	666
0 (without VMS)		125	199	1033

of link 9, traffic flows on the two paths, route 5 ($a \rightarrow d \rightarrow e \rightarrow h \rightarrow i$) and route 6 ($a \rightarrow b \rightarrow e \rightarrow h \rightarrow i$), which are directly affected, decrease greatly, as expected, whereas the flows on route 4 ($a \rightarrow d \rightarrow g \rightarrow h \rightarrow i$) and route 1 ($a \rightarrow b \rightarrow c \rightarrow f \rightarrow i$) increase due to the low perceptions of drivers. It seems that the more serious the disruption is, the more significant the changes in route flows are. Route 4 and route 6 show the most significant increase and decrease in route flow, respectively. The third column of **FIGURE 5** depicts how the total cost of the network evolves over time before and after the disruption. Compared to the case of 25% capacity reduction, the total cost in the cases of moderate and severe disruptions increase apparently since disruptions take place, and then it goes down to reach new convergence. As expected, the total cost for 50% and 75% capacity degradation takes more time to recover to equilibrium, and the network does not retain its initial performance in terms of total travel cost.

C. RESILIENCE ANALYSIS

As presented in **Section I**, the rapidity of recovery can be regarded as *key performance indicator* (KPI) of resilience. Here, recovery means that the network reaches a new equilibrium that is not necessarily the same as the previous one if the disruption is not removed and/or the network capacity is not restored. Rapidity, therefore, can be quantified as the time between the day of the disruption and the time when new equilibrium state is reached.

VMS is widely used to provide information related to incidents and disruptions to drivers in order to change their route decisions. The brief discussions regarding how route costs, route flow and total cost of the network evolve under VMS with different compliance rates (CR) are presented in the previous section, and a quantitative evaluation and analysis of resilience under the VMS control is conducted here based on rapidity of recovery. The results are summarized in **TABLE 3**. In order to visually observe the resilience of the network under different CR, **FIGURE 6** is also presented.

As can be seen from **TABLE 3**, in the scenario of the network suffering from mild (25%) disruption, we can see that VMS with CR = 0.2 facilitates the network to achieve best rapidity of recovery (16 days), but the greater CR does not necessarily achieve better rapidity. For example, the network takes 79 days to recover to a new equilibrium with CR = 0.05,

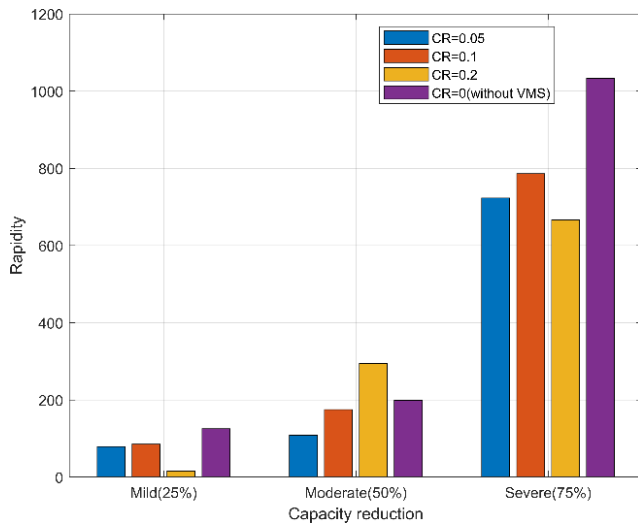


FIGURE 6. Comparisons of resilience for the small network under the VMS with different CR.

whereas takes longer (85 days) as CR increases to 0.1. For the scenario of 50% capacity reduction, the rapidity worsens as CR increases from 0.05 to 0.2. The possible explanation is that higher compliance rate probably leads to the overestimation of disruption impact on the network at this level. When the network suffers from severe disruptions (75%), the case with CR = 0.2 shows the best rapidity (666 days), followed by cases with CR = 0.05 (723 days) and CR = 0.1 (786 days). The impact of different CR on resilience can also be visually presented in **FIGURE 6**.

Compared to the scenarios with VMS, in general, the network without VMS achieves worst rapidity of recovery except the case where CR is 0.2 and capacity reduction 50%, which implies that VMS cannot always play a positive role in improving resilience of the network. These comparisons can be clearly shown in **FIGURE 6**.

To summarize, the larger CR does not necessarily always play a positive role in improving resilience time since the combination of VMS with higher CR may lead drivers to overestimate or underestimate the real impacts of the disruptions. Therefore, the magnitude of the CR must be related to many factors such as the degree of disturbances, the quality of extra information and the socio-economic background of the drivers and so on, and this means that efforts to make drivers follow the VMS must be balanced carefully.

IV. CONCLUSIONS AND FUTURE WORK

Resilience of transport networks has been a central concern for transportation management, but few studies are able to effectively model the resilience by considering drivers' learning process and irrational behaviors at agent level.

This study proposes an agent-based day-to-day (ABDTD) dynamic model with bounded rationality to analyze the resilience of the transport network suffering from different levels of disruptions, and VMS with different compliance

rates (CR) is incorporated into the ABDTD model to improve rapidity of recovery of the network. The complete model takes into account the behavioral inertial, travel demand, network topology and so on, and VMS is utilized to induce traffics to other alternative routes based on day-to-day dynamic learning process at agent level when the network is subject to the local disruptions. In the study, a numerical example of a small network is presented, and the results show that a larger CR of VMS does not necessarily play a positive role in improving the resilience of the network because a higher CR in respect to route guidance may cause traffic to overreact to network situations, impeding convergence of the network, and also demonstrates that in most of cases VMS can apparently improve the resilience of the network when suffering from disruptions.

In the future, this research may extend from several directions. Firstly, this study mainly focuses on the network's performance before, during, and after, the disruption without considering the recovery phase of infrastructure or network capacity. In reality, network capacity influenced by certain types of disruptions tends to be restored after a period of time. This causes additional disturbances to the traffic in ways that may not be easily represented due to the presence of potential network paradoxes. Therefore, network performance during recovery stage is an interesting field of inquiry as it encompasses a wide range of topics including network stability, resource allocation, and infrastructure management. In addition, this study sheds lights on the improvement of resilience of transport networks, the magnitude of the CR must be pertaining to many factors such as the nature and degree of disturbances, the quality of real-time information and the socio-economic characteristics of the drivers and so on, which implies that the values of CR should be balanced carefully correspondent to different levels of disruptions. It is critical to come up with an accurate estimation of the CR in order to understand the impact of VMS on the network performance. This may be an interesting optimization problem for future research. Furthermore, this proposed ABDTD model explores the resilience only by drivers' own perceptions and experience, our future research will incorporate the external information sources and other drivers' perceptions into the model in bid to capture the resilience from other ways. Many other types of dynamic assignment models and other control measures, such as adaptive signal controls and advance information technology system (AITS), can also be employed to explore the resilience of traffic networks in the future.

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