Evaluating and Predicting Road Network Resilience Using Traffic Speed and Log Data

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ABSTRACT

Resilience plays a crucial role in management of large-scale road network. This research studies the relationship between resilience changing of roads under the influence of the incident and explores the resilience changing of road sections. The road incident is matched through the incident log data based on the speeds of the vehicle on the road segments provided by the Amap data platform. The remaining resilience (RR) of the road is calculated according to definition the resilience of road sections. Besides, the topological model of incident influence spread is proposed to analyze the spread influence of incidents occurring in roads. A case study with the accident data on roads near Beijing Olympic Park during October to December,2019, is analyzed the relationship of resilience between different road sections. The result shows that there is a certain linear relationship in the remaining resilience between the affected road sections after incident.

INTRODUCTION

More serious consequences always come with nonrecurring congestions. Nonrecurring congestions are always caused by traffic incidents/accidents, road construction, weather, or other special events such as sports events and concerts(Afrin and Yodo,2020). Among these disturbances, traffic incidents arise widely attention in research areas because of the heterogeneity and randomness of traffic incidents. Additionally, various incidents could cause devastating impacts and even loss of lives. When an incident occurs, severe congestion and inadequate accessibility may immerge concomitantly, and even causing cascading failure of transportation networks. Thus, to cope these disturbances efficiently, many countries have established their emergency agencies and taken lots of measures for improving the capability in disaster mitigation and emergency responses(Wang *et al.*, 2019). Identifying the impact of incidents on road network is the basis for improving appropriate emergency strategies. In this paper, we mainly focus on the impact of traffic incidents on the resilience of road network.

Resilience is the ability to withstand and recover from disruptions. Resilience was introduces firstly in the context of ecological systems and expanded to other fields such as earthquakes(Bruneau *et al.*, 2003) and transportation(W. H. Ip and Wang, 2009). Now most scholars believe that transportation resilience includes three abilities: the ability to withstand disruptions, the ability to recover from disruptions and the ability to absorb disruptions. Mojtahedi et al.(Mojtahedi *et al.*, 2016) predicted the recovery rate and cumulative probability of transport infrastructure and resilience under different conditions with a regression model. Research on resilience now focuses on evaluating and improving it. Zhou et al. divided the resilience metrics into three categories: topological metrics, attributes-based metrics, and performance-based metrics(Zhou *et al.*, 2019). And the performance-based metrics are thought the best evaluating index because it doesn't need to consider the traffic flow in the road network and its straightforwardness. Travel time is one of attributes to assessing resilience and a The research suggests that travel time can always be used in both severe and slight perturbations(Gu *et al.*, 2020). Additionally, the integration of travel time before shock over it after shock is one of three popular indicators(Zhou *et al.*, 2019) used to assess resilience(Omer *et al.*, 2013). This index accounts for changing trends of resilience. Similarly, the speed also could be used to achieve the same goal.

The data-driven approaches have attracted more attention from researchers and have been applied in traffic flow/speed prediction(Ma *et al.*, 2015; Jin *et al.*, 2018), traffic status recognition(Wang *et al.*, 2018), and so on. An amount of traffic data has been accumulated from various sensors and transferred to a platform, like Baidu and Amap. The spatiotemporal patterns of resilience can be discovered from these historical data. Tang et al.(Tang *et al.*, 2020) proposed a deep learning framework to estimate and predict the transportation resilience under extreme weather events. In this paper, they measured the spatiotemporal patterns of transportation resilience with five indexes: Loss of Resilience (LoR), Response Time (RST), Response Rate (RSR), Recovery Time (RCT), and Recovery Rate (RCR). What is interesting about the results is that the characteristics of urban transportation resilience under extreme weather are similar to those of general precipitation events. At the same time, there is a fascinating finding that different from more efficient cities, many urban road systems operated inefficiently under normal conditions are resilient to disruption(Ganin *et al.*, 2017). It suggested that some efficient areas may be more fragile, such as the Ring Road in cities. Additionally, the traffic control systems implemented in Intelligent Transportation Systems (ITS) can open new vulnerabilities(Ganin *et al.*, 2019). Assessments and predictions are thus more significant when we need to know the resilience trends after an attack.

Researchers have conducted several studies in assessing road network resilience from a data perspective(Tang *et al.*, 2020; Adams *et al.*, 2012; Stamos *et al.*, 2015; Mojtahedi *et al.*, 2016; Wang *et al.*, 2020), but few researches focus on road resilience prediction(Mojtahedi *et al.*, 2016). Therefore, this paper aims to propose an efficient resilience prediction model for assessing the influence of traffic incidents.

In this paper, we use the speed variety to measure the remaining resilience, and study the road sections that may be affected according to the accident, and establish a road network topology that affects the propagation of resilience. Then calculate the remaining resilience of road sections, explore the relationship of remaining resilience between road sections, and use this relationship to predict the resilience of unknown road sections.

METHODOLOGY

This method is mainly applied to study and analyze the resilience relationship of different road sections under the influence of the accident. The chapter can be divided into three steps to construct the method. Firstly, pre-processing the vehicle speed on the road, and eliminating the influence of speed changes by normalizing the variance of the speed. Secondly, determining the road section affected by the accident through the variance of the speed in the previous step. Finally, determining the remaining resilience of the road section and calculating the remaining resilience, and finding out the relationship between the remaining resilience of the road section, then predicting the remaining resilience of the unknown road section based on this relationship.

Road vehicle speed data pre-processing

The vehicle speed will not change significantly under free traffic scenarios. For the entire road sections, to find out the locations affected by the incidents in a more refined manner, we need to divide the road section into smaller units according to the structure of the road network. And then number every smaller section with a specific id. Moreover, both the speed and time of vehicle driving on the road section can be obtained. By comparing changed speed on each numbered smaller road section, not only the events sites can be located concretely, but also the floating changes can be investigated through the spread of speed changes on different road sections. In this way, the resilience of the road sections can be determined under the occurred events.

The transformation in vehicle speed in a road section will cause resilience changes. To ensure the stability and reliability of speed changes, the variance of speed in each road section can be used to reflect the degree of disruption of the vehicle speed caused by recurring and nonrecurring factors.

The road speed limit and the car's actual speed differ between arterial road and branch road which are needed to be calculated separately. Because the variance of each section of the arterial road and the branch road is quite different, numerous errors would have occurred between them. Thus, the first thing is to normalize the speed among them before calculating the variance.

Determine the road section affected by the incident

In this section, a threshold α is set. When the variance of vehicle speed meets the conditions that the value variance>α on the road section, it can reflect the road section resilience has changed due to event. α is a comprehensive reference factor of speed variance obtained by integrating the influence of historical events on the road section. The speed changes on the passing road section can reflect whether it is affected by the event and the road resilience has changed. For the sequence statistics of the main road and branch road speeds, a specific speed value of the same percentage is taken as the speed change under the influence of resilience. We could find the road sections affected by the event and conduct the resilience spread analysis on the selected road sections.

The congestion wave will spread upstream if a disruption arises. When it transfers to a section, it will be divided into different direction waves. For example, the congestion wave has been divided into downward wave and leftward wave in Figure 1. Regarding resilience propagation in the road section, a suitable physical model is constructed according to the network structure. The spread of free flow is related to the direction of the road section and the construction of the road network.

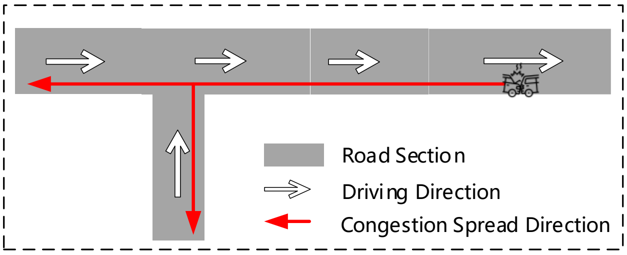

Figure 1 Topology of Resilience Spread in the Road Section

Build the residual resilience calculation model

The resilience triangle is one of the essential evaluation methods of road resilience evaluation. The relationship between speed and time is used to study road resilience at different stages of speed changing with time under the influence of events. This research extends the resilience triangle and changes based on traffic incidents, such as traffic accidents and congestion caused by peak periods.

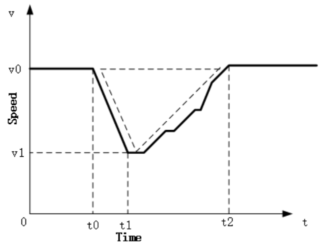

Figure 2 Resilience Triangle

In Figure 2, five indicators are used to measure the resilience of road sections, including Remaining Resilience (RR), Response Time (RST), Recovery Rime (RCT), Response Rate (RSR), and Recovery Rate (RCR). The Remaining Resilience refers to the remaining resilience of the road section after being affected by the events, which corresponds to the area under the speed curve during the period. The current speed and the free flow speed are used in this research. RST is the period from the beginning time of the event to the time that leads to the worst performance of the system. RCT refers to the period from the worst performance to the performance recovery of the system. The RSR refers to the change in the system that the account is reduced to the lowest point of the resilience triangle. RCR reflects the recovery speed of system services. Based on the definition of the above indicators for each indicator in this study. It is essential to find events that can affect the resilience of road sections in data sets. The above data can calculate the defined resilience indicator such as RR, RST, RSR, RCT, and RCR.

The event's start time is $\mathrm{t_0}$, peak time is $\mathrm{t_1}$, and the end time is $\mathrm{t_2}$. And the next thing is to find the critical points of speed during the speed change process of the road section, including the speed $\mathrm{v_0}$ before the event, the lowest point of speed $\mathrm{v_1}$, and the speed of the recovery point $\mathrm{v_2}$.

The RR is measured by the speed changes overtime in each road section of the whole road network. Under the condition of different road section lengths, the strength of the road section should also be related to the size of the road section to a certain extent. There is also a specific correlation in the road resilience, the upper limit speed or free-flow speed of the road section. Therefore, the Eq.1. can be defined to reflect the resilience in this study:

$$\mathrm{RR}_i = \frac{\int_{t_0}^{t} \frac{v_{it}}{v_{ff_i}} dt}{t - t_0} \tag{1}$$

RR_i is the RR of i-th road section, t_0 is the time before the event occurs, t represents the current time, v_{it} refers to the average vehicle speed of the current road section, and v_{ff_i} is the speed of free flow in i-th road section.

The effect of congestion spread in the network can be further studied. Because the space of the event's impact on the continuous road section is gradually weakened, the resilience variety of the road section will also be affected by the distance and frequency of spread under the event's influence. In the construction of road resilience calculation under the influence of affect spread of event, the return function is introduced here to show the relationship between the impact of the event and the number of space. As shown in the following Eq.2.

$$\boldsymbol{RR_i} = [RR_{i-1} \;\; RR_{i-2} \cdots RR_{i-n}] \cdot \boldsymbol{\beta_j} \tag{2}$$

where $\boldsymbol{RR_i}$ is the resilience of i-th road section, $\boldsymbol{\gamma}$ refers to the weakening factor of the impact of the event, $\boldsymbol{\beta_j}$ is spread steering factor, which in the following conditions, $\boldsymbol{\beta_j}$=$[\beta_1, \beta_2 \cdots \beta_n]^T$, for which

$$\beta_j = \begin{cases} s_1 & right \\ s_2 & straight \\ s_1 & left \end{cases} \tag{3}$$

$$s_i(i = 1,2,3)$$

β_j is the influence factor for the spread direction of the event's influence.

Prediction of remaining resilience of unknown road sections

In the previous sections, the road sections affected by the incident can be determined, and the direction of the accident impact flow can be analyzed according to the structure of the road net. Therefore, the direction and strength of the incident impact transmission can be judged according to the spatial relationship between the affected road sections. The model can help us to judge the remaining resilience relationship among the affected road sections. However, sometimes the impact of incidents is very extensive, and the affected road sections are also large. It is required to calculate the relationship between each road section. It is important to infer the residual resilience of the unknown road section based on the resilience relationship between the known road sections. At the same time, the estimation and prediction of the RR of the unknown road section can also play an early warning role, and make advance deployment for the road section and nearby vehicles.

CASE STUDY

Data description and processing

The Olympic Park in Chaoyang, Beijing is selected as a research area. The Amap, a well-known map company in China, provides the surrounding area data of the Olympic Park. For primary information data such as road conditions, the road is divided into small sections with different lengths and IDs, and the size of each divided road section is obtained from the known data. The length varies from 24 meters to 1169 meters. The speed of vehicles on each road section is collected every minute at an interval—corresponding to recorded travel time and other traffic information. Figure 3 is the area that provides data support.

Figure 3 Research Area Supported by Data

In addition, the incident data on the road section was also used in this study. The incidents affect the regular traffic of the road section, including road construction, traffic congestion, and traffic accidents. The road section incidents in this study area from October to December 2019 were collected through the Amap platform. The event data includes the start time, end time, location number of the road section that occurred of the events, event type, etc. These data can reasonably explain and verify the speed changes in the road section.

There are several basic steps to process the data in this area. Firstly, according to the actual situation in Beijing, select the speed data of the traffic section of the site for one day, and normalize the speed of the main road and branch road, then calculate the speed variance of each section, and carry out the road section numbering according to the conflict of the speed of the road section.

Sorting and selecting the more continuous road sections within a specific range and the more considerable variance as the research area, and individually number the road sections to be studied. Corresponding to the road section of the research area and when the speed fluctuates wildly, find the event that may occur on the day, and proceed to the event. The vehicle speed in the road section, the vehicle speed in each road section, and the corresponding time and other data, combined with Eq.1, to calculate the road section resilience. In Eq.1, the v_{ff} is free-flow speed, which is calculated as the 85th percentile of off-peak rates, where off-peak is defined as Monday through Friday, 9 am to 4 pm, and 7 pm to 10 pm, as well as Saturday and Sunday 6 am to 10 pm. For UCR, the free-flow speeds are calculated for each TMC path and are based on the previous 12 months of data[1]. Calculate the resilience value per minute in different road sections. From this calculation basis, we can study the resilience change regulation of the influence of later events in the road section.

Experiment details

Researching the road traffic and road conditions around the Beijing Olympic Park on December 6, 2019, and then collect the vehicle speed and traveler time of all road sections in the area on that day, and calculate the volatility of the rate of each road section. To calculate the variance of each road section and find the resilience change of the road section according to the size of the conflict.

In addition, according to the event data that occurred on each road during the day provided by Amap data, the event was matched with the road section with large road speed fluctuations. The event with a more significant impact on the day was identified and marked. The section where the incident occurred was section 0 (North Fifth Ring Road, west to east, traffic accident). From the accident log of the road section on that day, the traffic accident was 06:47, and the end time was 07:55. However, according to the speed changes in the accident section and its associated

[1] https://ops.fhwa.dot.gov/perf_measurement/ucr/documentation.htm

areas, it is known that the accident caused the road. The impact lasted longer. According to the analysis of each road section's vehicle speed recovery time, the effect of the incident on the studied road section was about 6 hours. Based on the above analysis, the research period is determined to be 6 o'clock to 12 o'clock of the day. Based on this, according to the possible changes of the impact range of the event along with the road section, the road sections that may be affected are sequentially marked along the direction in which the event propagates. In this case, 17 road sections that may be affected by the incident were selected. The road section researched as Figure 4 shown.

Figure 4 Road Section Researched

Result and analysis

Resilience of road sections

According to the content of data processing and experimental details, Calculate the resilience indicators RR_i in different sections of the road separately according to Eq.1.The change in the resilience of sections 0-16 from 6 am to 12 am is shown in Figure 5.

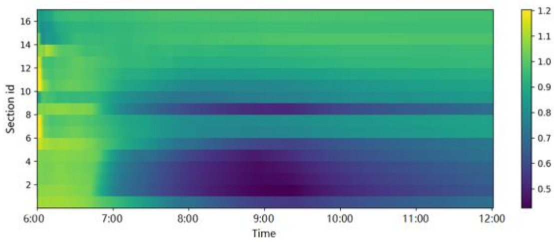

Figure 5 The Resilience Changes in Different Time and Road

From Figure 5, it can be seen that under the influence of the incident, the resilience changes in different road sections show similar trends. They all decrease first and then slowly recover. However, there is a specific time difference in the toughness reduction of varying road sections. According to the spread of the event's impact, the regulation of resilience between the research sections is determined.

Incident impact spread model

According to the resilience relationship between the road sections, event spread affects the resilience of the road section.

Firstly, according to the topological model of the road section resilience under the influence of the incident, a model of the spread of the incident influence in the road sections 0-16 in the study area is built, as shown in Figure 6.

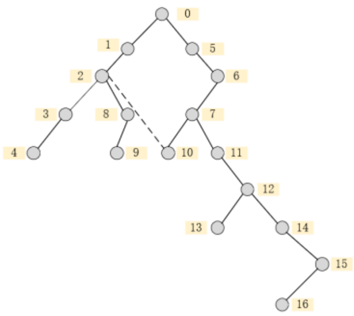

Figure 6 Topological Structure of Road Section

Section 0 is the accident occurred section, and the remaining sections are the direction of the accident spread. Based on the diversion and distance of the event in different sections and the impact of the event changes with the pursuit of the road section, the hobby is taken according to the actual road conditions and the effect of the road diversion. The steering influence factor of the road section is β_i=0.5, and the resilience relationship under the influence of different road section events is explored, respectively.

In the case, a certain number of road sections close to the event source are mainly studied to ensure the significance of the resilience changes of the studied road sections. Besides, when many road sections need to be studied, the α needs to be judged to determine the resilience changes of the road sections affected by the event.

Select R1= [0,1,2,3,4] to explore the regulation of the event impact on the resilience changes of the road section, and analyze the resilience of the most upstream road section 4 with the strength of other road sections to determine the value of γ, which is helpful to make resilience predictions on unknown road sections, relevant measures can be made in advance.

The resilience of sections 4 and sections 0, 1, 2, and 3 in the road of R1 are fitted to the sample. It can be found that RR_4 has a specific linear relationship with RR_0 RR_1, RR_2andRR_3. The curve of the fitting process is shown in Figure 7.

In Figure 7, the blue points are the distribution of RR_0 RR_1, RR_2 and RR_3. The black dotted line is the straight line after linear fitting in a two-dimensional plane. The horizontal axis is a time series in units of one minute and the vertical axis is the value after the resilience of all variables is expanded by 100 times, which can reduce the error.

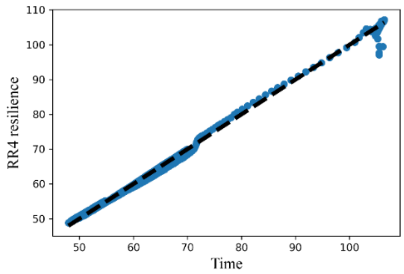

Figure 7 Sample Fitting Curve Graph

To make the data better serve the model, the unary linear regression method is used to train the model. Firstly, the event's impact needs to be diverted according to the topological structure of Figure 6.$RR_0{}^* = \frac{1}{2} \times RR_0$, $RR_2{}^* = \frac{1}{2} \times (RR_2 + RR_{10})$. According to the one-variable linear regression analysis of the updated resilience index of each road section at this time, the following results are obtained:

$$\boldsymbol{RR_4 = 0.2139RR_0{}^* - 0.5085RR_1 - 0.1538RR_2{}^* + 1.5190RR_3 + 5.4083}$$

Through cross-validation, the MSE and RMSE of the model are obtained as 0.00022 and 0.015 and this shows that the fitted value is very good. In the above formula, to improve the accuracy of the result calculation, the resilience of the tricky road sections is expanded by a certain multiple, and the linear relationship remains unchanged.

Road section resilience prediction

Applying the linear model constructed above to verify the resilience under the influence of event spread on the road section with R2 = [0,1,2,8,9], and use the model to demonstrate the road section 9 and the results are shown in the Figure 8:

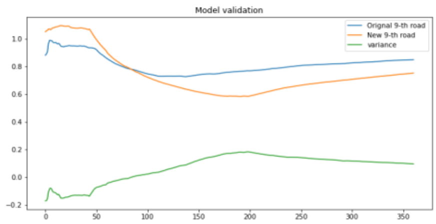

Figure 8 Comparison of the Road R2 and R1

Since the roads of R1 and R2 are similar in structure, there is a strong relationship between the spread regulation of the event's influence on R1 and R2. Therefore, it is reasonable that the section resilience linear model is applied to the road section of R2. The following needs to analyze the applicability and error of the model. In Figure 8, the curve in the green part represents the difference between the actual value of Section 9 and the predicted value of the model. The curve in the figure shows that with the increase of sample data, the predicted error first increases and then decreases. The error curve starts to grow at about 50 minutes, which is 6:50 in the morning. Soon after the accident, as the impact of the accident spreads, The resilience curves of the two show similar changes. Therefore, the weakest time point of resilience can be predicted based on the model.

CONCLUSION

The impact of the incident on the resilience of the road section during the spread process of the road section and the spread regulation between the resilience of the road sections is studied. The Olympic Park Area is researched, selection of road sections and the matching of related events are carried out through the model, and the choice of area and time is carried out. Under the influence of incidents on the selected 17 road sections, the resilience change regulation of each road section is explored.

Through the construction of events affecting the topology of the road network, an appropriate number of road sections are selected to explore the resilience relationship. In this study, two roads are chosen, one is used for a model built, and the other is used for model verification. First, through the resilience data of the road and the resilience relationship between the streets, the data is fitted and analyzed to determine the construction of a linear model, as shown in the following expression: $RR_4 = 0.2139RR_0{}^* - 0.5085RR_1 - 0.1538RR_2{}^* + 1.5190RR_3 + 5.4083$. Verify the selected road, and compare and analyze the results predicted by the above procedure with the original data. It is found that the two have the same changing regulation, and the two error is always within a specific acceptable range, so the model can be considered reasonable. In addition, the weakest time of road section resilience can be predicted based on the model so that the vehicle can be forecasted and early warning on the traffic section.

ACKNOWLEDGEMENTS

This paper is supported by National Key R&D Program of China (2021YFB1600100). The authors also thank Joint Laboratory for Future Transport and Urban Computing of Amap for data support.

REFERENCES

Adams, T.M., Bekkem, K.R. and Toledo-Durán, E.J. (2012), “Freight Resilience Measures”, Journal of Transportation Engineering, Vol. 138 No. 11, pp. 1403–1409.

Afrin, T. and Yodo, N. (2020), “A Survey of Road Traffic Congestion Measures towards a Sustainable and Resilient Transportation System”, Sustainability, Vol. 12 No. 11, p. 4660.

Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O’Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A. and Winterfeldt, D. von (2003), “A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities”, Earthquake Spectra, Vol. 19 No. 4, pp. 733–752.

Ganin, A.A., Kitsak, M., Marchese, D., Keisler, J.M., Seager, T. and Linkov, I. (2017), “Resilience and efficiency in transportation networks”, Science advances, Vol. 3 No. 12, e1701079.

Ganin, A.A., Mersky, A.C., Jin, A.S., Kitsak, M., Keisler, J.M. and Linkov, I. (2019), “Resilience in Intelligent Transportation Systems (ITS)”, Transportation Research Part C: Emerging Technologies, Vol. 100, pp. 318–329.

Gu, Y., Fu, X., Liu, Z., Xu, X. and Chen, A. (2020), “Performance of transportation network under perturbations: Reliability, vulnerability, and resilience”, Transportation Research Part E: Logistics and Transportation Review, Vol. 133, p. 101809.

Jin, Y., Tan, E., Li, L., Wang, G., Wang, J. and Wang, P. (2018), “Hybrid Traffic Forecasting Model With Fusion of Multiple Spatial Toll Collection Data and Remote Microwave Sensor Data”, IEEE Access, Vol. 6, pp. 79211–79221.

Ma, X., Tao, Z., Wang, Y., Yu, H. and Wang, Y. (2015), “Long short-term memory neural network for traffic speed prediction using remote microwave sensor data”, Transportation Research Part C: Emerging Technologies, Vol. 54, pp. 187–197.

Mojtahedi, M., Newton, S. and Meding, J. von (2016), “Predicting the resilience of transport infrastructure to a natural disaster using Cox’s proportional hazards regression model”, Natural Hazards, Vol. 85 No. 2, pp. 1119–1133.

Omer, M., Mostashari, A. and Nilchiani, R. (2013), “Assessing resilience in a regional road-based transportation network”, International Journal of Industrial and Systems Engineering, Vol. 13 No. 4, p. 389.

Stamos, I., Mitsakis, E., Salanova, J.M. and Aifadopoulou, G. (2015), “Impact assessment of extreme weather events on transport networks: A data-driven approach”, Transportation Research Part D: Transport and Environment, Vol. 34, pp. 168–178.

Tang, J., Heinimann, H., Han, K., Luo, H. and Zhong, B. (2020), “Evaluating resilience in urban transportation systems for sustainability: A systems-based Bayesian network model”, Transportation Research Part C: Emerging Technologies, Vol. 121, p. 102840.

W. H. Ip and Wang, D. (Eds.) (2009), Resilience Evaluation Approach of Transportation Networks, IEEE.

Wang, L., Xue, X. and Zhou, X. (2020), “A New Approach for Measuring the Resilience of Transport Infrastructure Networks”, Complexity, Vol. 2020, pp. 1–16.

Wang, P., Hao, W., Sun, Z., Wang, S., Tan, E., Li, L. and Jin, Y. (2018), “Regional Detection of Traffic Congestion Using in a Large-Scale Surveillance System via Deep Residual TrafficNet”, IEEE Access, Vol. 6, pp. 68910–68919.

Wang, P., Tan, E., Jin, Y., Wang, J. and Wang, L. (Eds.) (2019), A Deep Reinforcement Learning Evolution of Emergency State during Traffic Network, IEEE, Piscataway, NJ.

Zhou, Y., Wang, J. and Yang, H. (2019), “Resilience of Transportation Systems: Concepts and Comprehensive Review”, IEEE Transactions on Intelligent Transportation Systems, Vol. 20 No. 12, pp. 4262–4276.