A Composite Resilience Index for Road Transport Networks

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Abstract

This paper is concerned with the development of a composite index for the resilience of road transport networks under disruptive events. The index employs three resilience characteristics, namely redundancy, vulnerability and mobility. Two different approaches, i.e. equal weighting and principal component analysis, are adopted to conduct the aggregation. In addition, the impact of the availability of real-time travel information for travellers on the three resilience characteristics and the composite resilience index is described.

The application of the index on a synthetic road transport network of Delft city (Netherlands) shows that it responds well to traffic load changes and supply variations. The composite resilience index could be of use in various ways including supporting decision makers in understanding the dynamic nature of resilience under different disruptive events, highlighting weaknesses in the network and in assisting future planning to mitigate the impacts of disruptive events.

Introduction

The transport sector plays a leading role in enhancing economic growth and societal welfare in addition to its influence on various types of human activities. However road transport networks can be exposed to a wide range of disruptive events that vary in their type, scale and consequences. Disruptive events are responsible for around 25% of the congestion experienced on motorways in England (Highways Agency, 2009) and are the largest single cause of journey unreliability (Hooper et al., 2014). In the USA, the estimated loss due to disruptive events is 1.3 billion vehicle-hours of delay every year, at a cost of almost US$10 billion (FEMA, 2008).

An assessment of the resilience of a road transport network could cover several issues, some of which could be related to the configuration of the road transport network and available capacity (Lhomme et al., 2013). This may include the number of routes between origin-destination (OD) pairs and the road capacity under different scenarios (Ip and Wang, 2009). It may increase understanding of how management policies and/or technologies could improve the overall performance of the road network under disruptive events, or improve daily operation of the network. It could be used, for example, to assess the effect of pre-trip travel information or en-route travel information on driver decisions during disruptive events. Furthermore, Rogers et al. (2012) suggested that new ways of engineering, managing and delivering resilient local infrastructure need to be developed.

Several quantification approaches can be identified in the resilience literature. The first approach is based on identifying resilience characteristics (Bruneau et al., 2003; Murray-Tuite, 2006). These include redundancy, diversity, resourcefulness, efficiency, autonomous components, robustness, collaboration, adaptability, mobility, safety, vulnerability and the ability to recover quickly. The dependence of each of these characteristics on others and the complex relationship between them represents a barrier to designing a resilience index (Murray-Tuite, 2006). However, to the best of the authors' knowledge, to date there is no resilience index utilizing all the above characteristics.

This paper, therefore, presents a composite resilience index based on three resilience characteristics, namely redundancy, vulnerability and mobility, using equal weighting and principal component analysis. However, the proposed methodology could be extended to include further resilience characteristics. A synthetic Delft city road transport network is used to test the ability of the indices to show variations in the level of resilience under different scenarios.

Resilience Characteristics

In this paper, the resilience of road transport network refers to the ability of the road transport network to function to acceptable levels under disruptive events. A number of characteristics are used to quantify the resilience of road transport networks in line with the approach used by McManus (2008), Murray-Tuite (2006) and Bruneau et al. (2003), as presented in Table 1.

Three of the characteristics in Table 1, namely redundancy, vulnerability and mobility are employed here. They have been chosen to reflect different aspects of road transport network resilience, as discussed in the following section. In reality, all these characteristics interact with each other and it may be difficult to investigate one in isolation.

In the following sections, the interdependence of the three resilience characteristics and the importance of each characteristic is explored, followed by the development of a composite resilience index. A case study to illustrate the use of the index is also presented.

Indicators for the Characteristics of Resilience

Indicators are used to quantify changes in (and the effectiveness of) the system elements. They should have the ability to reflect the impact of a certain policy or technology on the targeted system. In previous investigations, the authors developed indicators to assess the three resilience characteristics using various attributes and methodologies briefly described below, while the full details are available in EL Rashidy and Grant-Muller (2014, 2015 and 2016). These indicators of the characteristics of resilience are used as the basis for the composite resilience index developed in this paper.

Redundancy Indicator

Redundancy has a significant impact on the resilience of road transport networks as it represents the spare capacity of road transport networks under different scenarios. The approach proposed by El Rashidy and Grant-Muller (2016) to quantify the redundancy characteristic will be adopted in the composite resilience index. A brief explanation of this approach is covered below, see (El Rashidy and Grant-Muller, 2016) for full details. In this method, a junction redundancy indicator is first developed by taking into account both traffic flow variations and network topology using the concept of entropy. Various network parameters based on different logical combinations of link flow, relative link spare capacity and relative link speed were examined to identify the best system parameters that could be used to develop a junction redundancy index, reflecting junction topology and traffic flow conditions. Such an approach facilitates the identification of critical junctions within the network that have low redundancy indices. A network redundancy indicator, NRI, was, then, obtained from an aggregation of all network junction redundancy indices, based on the junction flow compared with the total flow for all junctions. The range of NRI is between 0 and 1; where 0 indicates no redundancy in the network and 1 reflects the highest redundancy level of the network.

Vulnerability Indicator

The aim of including a vulnerability assessment in the resilience composite index is to investigate the influence of disruptive events on the road transport network links. Barker et al. (2013) used vulnerability as the only resilience indicator during disruptive events, emphasising its importance. However, disruptive events have a wide spectrum in many dimensions, causing different scale impacts at various parts of road transport networks.

El Rashidy and Grant-Muller (2014) proposed a vulnerability indicator for road transport network based on a number of link attributes, such as link flow, free flow speed, capacity and number of lanes as stated in Table 2. The set of link attributes were selected to capture as many features as possible of the impact of link closures on the network vulnerability and were as orthogonal as possible. In order to combine various link attributes into a single link vulnerability indicator, both fuzzy logic and exhaustive search optimisation techniques were adopted. A network vulnerability indicator, NVI, was also calculated based on the ratio of the link flow to the total flow for all links. NVI ranges between 0 and 1; where 0 indicates no vulnerability in the network and 1 reflects the highest vulnerability of the network.

Mobility Indicator

Mobility is defined as the ability of road transport networks to provide connections to jobs, education, health service, shopping, etc., at an acceptable level of service (Hyder, 2010). As such, the variation in the level of mobility could be a direct indicator to measure the response of the road transport network to changes in conditions, e.g. deterioration of road capacity due to adverse weather conditions or an increase in demand.

The technique proposed by El Rashidy and Grant-Muller (2015) for the quantification of the mobility characteristic is applied here to develop the composite resilience index. In this approach, two mobility attributes were proposed to account for the physical connectivity and road transport network level of service. The physical connectivity attribute is used to evaluate the ability of road transport network to offer a route to connect OD, whereas the traffic condition attribute was considered as a measure of the road transport network level of service, based on traffic conditions. The relative importance of the two mobility attributes was established through a fuzzy inference reasoning procedure in order to estimate an origin-destination mobility indicator. A network mobility indicator, NMI, was also estimated based on the level of demand between each origin-destination pair. The range of NMI is between 0 and 1; where 0 indicates no mobility in the network and 1 reflects the highest mobility of the network.

Interdependence of the Resilience Characteristics

Figure 1 illustrates the relationship between road transport network resilience, the three characteristics and their attributes using the bottom-up level of the attributes for each characteristic. For example link flow changes affect the redundancy characteristic by increasing or decreasing the spare capacity on the link and several attributes of vulnerability characteristic, as shown in Figure 1. Variations in traffic flow can result in a change to the travel speed on a link, affecting the level of mobility by increasing or decreasing the traffic condition attribute. However changes in mobility could also vary under the same level of traffic flow due to the network configuration, measured by the physical condition attribute. Similarly, a decrease in network capacity due to the closure of one or more links (e.g. due to an accident, floods or adverse weather conditions) could also influence the three characteristics, as shown in the case study later. Table 2 summarises the attributes used to quantify the three resilience characteristics, the level of measurement and importance of each characteristic. The level at which the redundancy and vulnerability indicators are calculated (i.e. junction level and link level respectively) suggests that both characteristics reflect resilience from the perspective of planners, decision makers and stakeholders. However as mobility is calculated at OD level it could be considered to be a reflection of resilience from the travellers point of view (see Table 2). Given that the proposed indicators are calculated at different levels, each indicator has finally been aggregated to the network level.

The three characteristics represent three interconnected capabilities of road transport networks, as presented in Table 2. Redundancy can be considered as the ability of the network to adapt to a change in demand or supply, e.g. the availability of several routes to a junction under different scenarios. A high level of network redundancy could result in links being less vulnerable given there is the possibility for traffic to be distributed more widely over the network links, rather than congestion being concentrated on certain routes. The vulnerability characteristic indicates the ability of the network to recover as it captures the interaction between the distribution of traffic and the capacity of the road transport network. Mobility is also essential to fulfil the resilience concept as it assesses the main function of the road transport network.

The three characteristics could be influenced by some common factors, as will be shown using the principal component analysis. However the magnitude of the impact of these common factors on the characteristics can vary from one characteristic to another, as demonstrated in the case study. Moreover, the type of impact (i.e. positive or negative), may change from one period of time to another for the same characteristic, reflecting the complex relationships inherent in the road transport network under different conditions. As an example, the reassignment of traffic due to an accident could, in some cases, lead to a decrease in the level of vulnerability compared with the 'no accident' scenario. This set of dependencies and levels of measurement provides the rationale for a composite resilience index.

A Composite Resilience Index for Road Transport Networks

Despite the importance of measuring the level of each characteristic separately, it could be useful to estimate the overall level of resilience using a composite resilience index. Smith (2002) outlined the advantage and disadvantages of a composite index in general. The advantages focus on its role as a communication tool that offers an overall rounded assessment of performance and in giving an indication of the behaviour of the system under consideration. It can be used to summarize multi-dimensional issues and include more information, allowing a comparison between different scenarios or places (Saisana and Tarantola, 2002). Despite the advantages of a composite index, a number of disadvantages also have to be taken into account. For example the use of a composite index only may lead to simplistic policy conclusions and may not be adequate to identify the changes required for improvements (Saisana and Tarantola, 2002). Consequently, it might be useful to consider both aggregate and disaggregate levels, (i.e. indicators for individual resilience characteristics in addition to a composite resilience index) in the assessment. In order to produce an aggregate index it is necessary to consider the method of aggregation and in particular the potential use of weights.

In the following section, a number of aggregation methods are briefly reviewed. Subsequently, two methods (namely equal weighting and principal component analysis) are implemented to develop the composite resilience index.

Aggregation Approaches

Aggregation often involves the use of weights on individual components rather than simple addition. According to Saisana and Tarantola (2002), weighting techniques can be classified into three main categories, statistical methods (e.g. principal component analysis), methods based on experts' opinions (e.g. analytical hierarchy processes) or equal weighting amongst variables. In the resilience literature, several weighting approaches have been adopted to obtain a composite index. Briguglio et al. (2009) used a simple average (i.e. equal weighting) to obtain a composite economic resilience index, whilst Stolker (2008) used analytical hierarchical process to estimate the overall operational resilience of an organization. In McManus (2008), the estimated values of the resilience characteristics are multiplied together to obtain the relative overall resilience for an organization. Hyder (2010) added the number of "Low" scores for ten characteristics to estimate a vulnerability index for each link as a method to estimate the resilience of road transport networks.

The equal weighting method is widely used in many disciplines (Estoque and Murayama, 2014; Briguglio et al., 2009) due to its simplicity and transparency. However, the equal weighting method suffers from potential double counting effects in the final index. In addition, it does not necessarily reflect the relative priorities of different indicators (Saisana and Tarantola, 2002).

Statistical methods such as principal component analysis have been widely used in many applications, including the development of a transport sustainability index (e.g. Reisi et al, 2014). It has many advantages as it does not involve any manipulation of weights through subjective process, unlike methods based around experts' opinions and overcomes the double counting effect inherent to the equal weighting method. However, the method is sensitive to the dataset used, as the weights may change according to the dataset from which the indicators have been derived.

A wide range of further methods can be used to develop a composite index using many indicators, such as regression, conjoint analysis, benefit of the doubt and data envelopment analysis (see Saisana and Tarantola, 2002). However, the choice of an appropriate weighting method could be a challenge as no agreement on the ideal aggregation method has been reached so far. To construct a composite resilience index based on the three proposed characteristics in this research, two methods of weighting are adopted i.e. equal weighting, and principal component analysis. The equal weighing method was chosen due to its simplicity and transparency, which could facilitate its use in practice. Principal component analysis has also been implemented as it allows the elimination of interdependence among the indicators for the characteristics.

Equal Weighting Method

In line with the approach taken by Briguglio et al. (2009), the equal weighting method (EWM) is used here to combine redundancy, vulnerability and mobility indicators into a composite resilience index (CRI_{eq}). The method is based on allocating equal weights to all the indicators considered, as given by Eq. (1) below:

$$CRI_{eq} = \frac{((1-NVI)+NRI+NMI)}{3} \qquad (1)$$

where NVI, NRI and NMI are the vulnerability, redundancy and mobility indicators for the road transport network respectively. As vulnerability is inversely proportional to resilience, the value $(1-NVI)$ is used.

However the use of the EWM could result in double counting with implications for the value of the composite index (as previously discussed). In order to avoid this weakness, principal component analysis is also implemented as a second approach and a comparison is, then, made with use of the EWM.

Principal Component Analysis

The main aim of the principal component analysis (PCA) approach is to convert a set of data of possibly correlated variables into a set of values of linearly uncorrelated variables, called principal components (Tabachnick & Fidell, 2007). The principal components calculated are still able to capture all the information present in the original variables. However, the first principal component accounts for the largest possible variance whilst the last component accounts for the least variance. It should also be noted that each principal component is orthogonal to the preceding one (Tabachnick & Fidell, 2007).

The applicability of PCA is based on the correlation (positive or negative) among the original variables. The first step in PCA is therefore to measure the sample adequacy using the Kaiser-Meyer-Olkin[1] measure (Reisi et al., 2014), with high values between 0.6 and 1.0 required in order to apply PCA. The second step is concerned with the extraction of a number of principal components to fully represent the original variables:

$$PC_j = \sum_{i=1}^{n} a_{ij} X_i \tag{2}$$

where PC_j is the principal component j, X_i represents the original variables (e.g. NVI, NRI and NMI) and a_{ij} is the weight for the *jth* principal component and the *ith* indicator X_i. As vulnerability is inversely proportional to resilience in this context, the corresponding variable is assumed to be 1 minus the vulnerability index (as explained for the EWM). The mobility and redundancy indicator values are input directly. The number of principal components could be as many as the number of original variables, n. The weights a_{ij} are calculated from the eigenvectors of the covariance matrix of the original data. a_{ij} is given by Eq. (3) below (Reisi et al, 2014):

$$a_{ij} = \frac{\varepsilon_{ij}^2}{\lambda_j} \tag{3}$$

where ε_{ij} represents the factor loadings and λ_j is the corresponding eigenvalue of the covariance matrix for the data. The above weights are normalised with respect to the sum of weights in order to scale them between 0 and 1. The method developed by Nicoletti et al. (2000) is then adopted to calculate a composite index of road transport network resilience from the principal components obtained using the original data for

[1] The Kaiser-Meyer-Olkin measure is a ratio of the sum of squared correlations to the sum of squared correlations plus the sum of squared partial correlations (Tabachnick & Fidell, 2007).

the three characteristics. The aggregated PC_j (based on its eigenvalues) can then be used to calculate the composite resilience index, CRI_{pc} as presented in Eq. (4) below:

$$CRI_{pc} = \sum_{j=1}^{m} \frac{\lambda_j}{\sum_{j=1}^{m} \lambda_j} PC_j \qquad (4)$$

Further discussion on PCA is given in Tabachnick & Fidell (2007).

Case Study

In this section of the paper, the variation of the proposed composite resilience index will be explored for a road transport network under different demand-variation scenarios. It will also allow a comparison between the proposed composite resilience index using the two aggregation techniques, namely equal weighting and principal component as explained above.

As a traffic data set related to road transport networks under disruptive events is not currently available, road transport network modelling has been adopted as an alternative technique. It also introduces an effective way to understand traffic flow characteristics and dependence relationships among various parameters. Furthermore, it has been generally used by decision makers and planners to evaluate the effectiveness of various strategies and plans.

A synthetic road transport network of Delft city is used below to investigate the impact of real-time travel information on the variation in the three resilience characteristics and estimation of the resilience composite index. The synthetic Delft road network model is supplied for use with OmniTRANS software (Ver. 6.1.2) and deviates from the real network for the city of Delft. The Delft case study was chosen due to the availability of the data needed to illustrate the methodology but it is not possible to make direct validation of the link traffic data provided as the network is synthetic. There is also a limitation of the road transport network modelling approach in general, as only a limited number of attributes/parameters can be changed in the simulation, decreasing a potentially significant number of combinations with case-based reasoning. Consequently, some relevant combinations could be ignored. It is to be noted that the main objective of this research is to develop a generic methodology for the estimation of road transport network resilience. Thus, intensive calibration studies (as part of the modelling of a road transport network) are beyond the scope of this paper but are possible as part of future development.

The Delft road transport network consists of 25 zones; two of which are under development (24 & 25), and 1142 links; 483 links are two-way whilst 176 are one-way including connectors and different road types. In the OmniTRANS software (Version 6.1.2) a four step modelling software for road transport networks was used for the case study. Although OmniTran software allows the user to control the four steps of road transport network modelling, namely trip generation, trip distribution, mode choice and trip assignment stages, the trip assignment is the only stage altered in this research as traffic demand is assumed to be deterministic during the morning peak. The OmniTRANS software is able to take into account the impact of road transport network conditions on travellers' behaviour by implementing a route choice model within the dynamic traffic assignment (DTA) framework. The DTA framework has a number of blocks such as route generation, route choice behaviour, a dynamic network loading model (including a propagation model and junction model), in addition to traffic management controls. Full details are available in other sources, for example Dijkhuis (2012). To simulate the influence of real-time travel information, a number of route choice stages are included where travellers choose their routes during the simulation period, assuming dynamic user equilibrium (DUE) is achieved at every route choice stage. This simply means that at every route choice stage, travellers can reduce their travel cost by switching routes, assuming that they have real-time travel information enabling them to make a better route selection. The percentage of travellers who may consider changing their route should be identified in the simulation as it could influence the impact of operating the information system. However, it has been assumed that all travellers consider real-time travel information in selecting their routes in the current simulation.

Scenarios Implemented

Six scenarios were used to investigate the variation in NRI, NVI, NMI and CRI during the morning peak (i.e. 7:00am to 9:00am). The scenarios were divided into two groups according to the availability of real-time travel information. For each group of scenarios, three demand increases were used with the same departure rates. Table 3 presents the scenarios according to travel time updating conditions and percentage increase in demand, whilst Figure 2 shows departure rates used. It is to be noted that the departure rates selected in Fig. 2 are synthetic due to the limitation of OmniTRANS as higher variations in departure rates produced unreliable results. The three scenarios (i.e. S1_a, S1_e and S1_h) have the same travel time updating schedule of every 900 seconds, whilst traffic demand increases from 0% to 50%. The remaining 3 scenarios (S2_a, S2_e and S2_h) have similar demand increases to the first group, but no real-time travel information is provided.

For each of the 9 scenario reports (a 15 minute aggregated report for the time period between 7:00 to 9:00am) are produced from the OmniTRANS, including link travel time, speed and load, in addition to the number of lanes, direction, length, free flow speed, capacity, and upstream and downstream junctions. An OmniTRANS task was written to obtain the full set of routes for each OD pair, with the fraction of the demand used for each route for each time period under different scenarios (22760 routes for every scenario). The data obtained from OmniTRANS were then implemented in MATLAB code to calculate the network redundancy indicator NRI, vulnerability indicator NVI and mobility indicator NMI using the methodologies detailed in EL Rashidy and Grant-Muller (2014, 2015 and 2016).

Results and Discussion

The use of real-time travel information (updating every 900 seconds) generally leads to an improvement in NRI as shown in Figure 3. This is as intuitively expected and in line with the M42 (Junction 3a) motorway case study results presented in EL Rashidy and Grant-Muller (2016). However, the level of improvement varies according to different departure rates in each scenario as explained below:

- Between 7:00am and 7:15am, NRI has responded inversely to the increase in demand but with no notable changes arising from the use of real-time travel information (e.g. NRIs for scenarios S1_a and S2_a have almost the same value, ≈ 0.87 at 7:15am). This could be attributed to the fact that the traffic has been allocated based on the dynamic user-equilibrium technique in all scenarios, which could offset the advantage of real-time travel information in less-congested network conditions, as concluded by Mahmassani and Jayakrishnan (1991).

- However at 7:30am where the loading of the network increases, the use of real-time travel information has a positive impact in all three scenarios due to a better route choice by all travellers owing to level of information received, leading to less congestion on particular routes.
- The positve impact continues in the following time period (starting at 7:45am) for both normal demand and a 20% increase in demand (S1_a and S1_e compared with S2_a and S2_e, respectively). However there is no significant impact under the 50% demand increase scenario (e.g. $NRI = 0.80$ for S1_h compared with $NRI = 0.79$ for S2_h at 7:45am). This could be related to the ability of the road network to offer alternative uncongested routes to accommodate the network loading under scenarios S1_a and S1_e. In contrast, the use of real-time travel information may not offer improvements in S1_h due to the congested conditions that can result from residual traffic, as suggested by other literature (Yang and Jayakrishnan, 2013).
- Conditions in the subsequent time periods (i.e 8:00 - 8:30am) confirm the previous justification, given the road transport network has lower loading in S1_a and S1_e where the impact of real-time travel information is minimum (i.e. minor change under normal conditions and a 20% demand). Moreover, congestion could be relieved under a low departure rate and reduced residual traffic, leading to a significant improvement in the case of S1_h.

This reflects the complex relationship between increase in demand and the level of real-time travel information, as real-time travel information does not necessarily increase NRI for each scenario and under different network loadings.

The vulnerability indicator, NVI, shows variations under different departure rates when calculated for the six scenarios, as depicted in Figure 4. For example, using real-time travel information leads to a reduction in NVI at 7:30am and 8:15am under the normal demand scenario, and at 7:45am and 8:45am for a 20% increase in demand. It also leads to a decrease in NVI under a 50% demand increase scenario at 8:00am and 8:15am, as shown in Figure 4.

The variation in NVI may be related to that of NRI. For example, when the use of real-time travel information has a positive impact on NRI, it could be assumed that travellers have a better route choice, resulting in less vulnerable links in some cases, such as at 7:30am and 7:45am for the S1_a and S1_e scenarios, respectively.

However, the use of real-time travel information could also lead to a negative impact on NVI (i.e. increase in NVI) in some cases. For example, NVI value for S1_a scenario is higher than that of NVI for S2_a scenario at 7:45am, as depicted by Figure 4.

For the mobility indicator, NMI, the importance of real-time travel information updates increases with the increase in demand, as shown in Figure 5. NMI has a similar trend to NRI but with different values. However, at 7:45am for S1_a, NMI does not show any improvement with the use of real-time travel information in contrast to NRI, indicating the impact of the increase in NVI.

Before calculating the composite resilience index, the Kaiser-Meyer-Olkin (KMO) measure was estimated for the three characteristic indicators to examine sampling adequacy and the applicability of PCA. For the 6 scenarios, the values of KMO was found to be between 0.63 (S1_a) and 0.76 (S1_e), indicating the suitability of this approach. The values of loading factors, eigenvalues and eigenvectors were calculated using the PRINCOMP function available in MATLAB. a_{ij} and CRI_{pc} were then calculated based on Eqs. 3 and 4. The weighting of each characteristics varies for each scenario, as depicted from Table 4. For example, for PC1 (accounting for a maximal amount of total variance in the characteristics indicators), the vulnerability indicator has the highest values for scenarios S1_a, S1_e and S2_a, whereas, for scenario S2_e, both vulnerability and mobility indicators have nearly the same weight (0.43 and 0.41). In contrast, the mobility has the highest influence on PC1 for scenarios S1_h and S2_h. Overall, the redundancy characteristic has the lowest influence on PC1 compared with the other two characteristics as the network considered is a road transport network of a city where alternative routes are normally available. It should be noted these findings are valid for the synthetic road transport network of Delft city under the different scenarios considered.

Figure 6 presents the composite resilience index CRI_{pc} calculated using PCA under different scenarios. In general, the variation in CRI_{pc} due to demand increase reflects the ability of CRI_{pc} to respond to variations in departure rates and demand increase as listed below:

- At 7:00am, all scenarios have equal CRI_{pc} values, reflecting the network ability to recover with the increase in demand where the departure rate is low, with no or minimum residual effect.
- CRI_{pc} has the lowest values for a 50% increase in demand in both with and without real-time travel information scenarios (S1_h and S2_h), compared with its value under normal demand and other demand increases.
- Interestingly, for the period between 7:15am and 7:30am, CRI_{pc} increases in response to decreasing departure rates under normal demand. It has almost the same value with a 20% increase in demand, with a slight reduction in value for a 50% increase in demand, reflecting the ability of the road transport network to bounce back to its performance prior to the increase in departure rate. This ability seems to be inversely proportional to the increase in demand e.g. CRI_{pc} for the S1_a scenario increases more rapidly than that for the S1_h scenario, responding to a departure rate decrease.

The influence of real-time travel information is seen to vary from one scenario to another under different departure rates (see Figure 6), reflecting the complexity of the effect of information on the road transport network performance and in line with the literature (e.g. Mahmassani and Jayakrishnan, 1991). The use of real-time travel information could have a slightly positive impact on CRI_{pc}, for example at 7:30am under S1_a CRI_{pc} = 0.57, compared with 0.54 in S2_a scenario and from 8:00am to 9:00am for S1_h compared with the S2_h scenario. Under normal demand conditions for S1_a and S2_a scenarios, CRI_{pc} has improved due to the use of real-time travel information at some intervals, (e.g. 7:30am), whereas there is no change for other intervals (e.g. 8:30am) as depicted from Figure 6. This is similar to the variation in NRI for scenarios S1_a and S2_a between 7:00am and 7:15am as outlined above. However, the use of real-time travel information might also cause adverse effects, for example CRI_{pc} has a lower value in the case of real-time travel information than its value without travel information in the case of a 50% demand increase (S1_h and S2_h) at 7:45am. This could be due to the fact that all travellers receive the same information concerning the best routes without considering the rerouting effect (Yang and Jayakrishnan, 2013), resulting in a more congested network. This could be demonstrated using a vulnerability analysis, as the highest NVI for all scenarios occurs at this point (i.e. at 7:45am for S1_h), showing the concentration of traffic on certain routes. Together, these findings indicate that CRI_{PC} behaves in an intuitively expected manner and according to previous related research.

Figure 7 shows the composite resilience index (CRI_{eq}) using equal weights for different scenarios. The variation in CRI_{eq} exhibits a similar trend to that of CRI_{pc}, under different demand increases. This reflects the ability of CRI_{eq} to respond to variations in departure rate and demand increases. However, the values of CRI_{eq} are always higher than these of CRI_{pc}, as shown in Figure 8, potentially highlighting the impact of double counting using EWM. Furthermore, the correlation between the two indices, CRI_{pc} and CRI_{eq}, was found to be strong with the coefficient of determination $R^2 > 0.96$ for all scenarios.

Conclusions

This paper has introduced a composite resilience index based on three resilience characteristics, namely redundancy, vulnerability and mobility. The interdependence of the resilience characteristics has been explored using the influence of low level attributes such as link flow, capacity and speed on the characteristics. Furthermore, the role of each characteristic in assessing different abilities of the road transport network has been outlined. Two weighting methods have been used, namely equal weighting and principal component analysis, to obtain a composite resilience index for a road transport network based on the three characteristics. The composite indices developed are able to reflect the impact of demand increase and availability of real-time travel information.

Simplicity and transparency could be the main advantages of EWM, leading to a recommendation for this approach when a quick assessment of road transport network resilience is required. However, the values of CRI_{eq} are always higher than CRI_{pc} values highlighting the probable influence of double counting. Consequently, an overall recommendation is the use of PCA to calculate the composite resilience index to avoid double counting. However, the sensitivity of PCA to the data set should be taken into account when applying the method, as the weight allocated to each characteristic may change if further data is added.

Despite these caveats, the composite resilience indices developed are able to capture some of the complex relationships between the resilience characteristics of road transport networks and real-time travel information. The behavior of both indices for the scenarios investigated has shown to be in line with the related literature. It is recommended that various resilience characteristics be used in the planning and policy stages, but the composite index could offer an overall assessment of road transport network performance when comparing the impact of the implementation of new technology. Furthermore, it could also be used for a 'goal achievement' purpose or in a 'distance to target' context.

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