IDENTIFICATION OF LINK CONGESTION DEPENDENCE PATTERNS FOR DYNAMIC ROUTE GUIDANCE

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ABSTRACT

This study explores the congestion dependence relationship among links using microsimulation, based on data from a real road network. The work is motivated by recent innovations to improve the reliability of Dynamic Route Guidance (DRG) systems. By adding a function to predict the congestion in the road network, the reliability of DRG systems can be significantly enhanced. The identification of link congestion dependence patterns is considered to be the first step towards this target. Previous work on link reliability and failure dependence relationships is reviewed and the results of simulation and analysis are presented here.

1. INTRODUCTION

As Dynamic Route Guidance systems are a rapidly growing market, more sophisticated systems are continuously being developed, including more advanced functions. In recent research work (Chen et al, 2005; 2006; Kaparias et al, 2006; 2007), a new Dynamic Route Guidance algorithm was developed, which, besides travel time, also takes travel time reliability into account. By defining reliability as the probability that a link will be uncongested, the algorithm uses a penalty procedure to where possible exclude from the route search links classified as unreliable, under the assumption that a link’s state is a binary variable, congested or uncongested.

Nevertheless, in previous work on Dynamic Route Guidance it is assumed that the travel times of the links in a network are statistically independent, i.e. that the occurrence of congestion on one link does not influence the occurrence of congestion on other links. This assumption may be appropriate for networks with a large number of alternative routes and sparse traffic, it is however inappropriate for an urban road network with dense traffic, as adjacent links are highly inter-dependent and the traffic situation on one link is very likely to affect the situation on other links.

The aim of this paper is to explore the congestion dependence relationships among links in a network using microsimulation. Based on data from a real road network for the City of Coventry in the UK, the congestion correlation between a target link and its adjacent links is investigated. The method of analysis used is to monitor the congestion status on the adjacent links after creating congestion on the target link. The objective is to analyse the propagation of congestion through the network and also to look at time lags in the propagation, i.e. how long it takes for the congestion on the target link to reach the adjacent links. The results can be seen as a first step towards predicting congestion in a network and thereby the prediction of congestion propagation for Dynamic Route Guidance (Figure 1).
The present paper is structured as follows: Section 2 presents the background of the research reported here, while Section 3 describes the methods used in this study. In Section 4, the results from this study will be presented. Finally, Section 5 draws conclusions.

2. BACKGROUND

This section gives a brief review of previous relevant research and describes the background of the work presented in this paper. The link reliability and failure dependence relationship, which form the basis of the work presented here, are reviewed.

2.1. THE CONCEPT OF LINK RELIABILITY

Reliability studies so far have mainly focused on network reliability, with very few studies concentrating on the reliability of single links. The reliability of a link can be defined as the probability of encountering congestion on that link, in other words, the probability that the link’s state will be ‘abnormal’, as defined by Bell and Iida (1997). If the link’s traversal time exceeds some preset threshold, then the state of that link is defined to be ‘abnormal’. If there is a high probability that the state of the link will be ‘abnormal’, then the link has a low reliability value. By using this definition of the reliability of a link, the reliability of a path can be calculated by simply multiplying the reliability values for the series of links constituting the path, provided the status of each link along the path is statistically independent.

The state of congestion of link $i$ is represented by the 0-1 state variable $x_i$,

$$x_i = \begin{cases} 
1 & \text{If link } i \text{ functions} \\
0 & \text{Otherwise}
\end{cases} \quad (1)$$

The link reliability value $r_i$ is the expected value of $x_i$, which is assumed to be a random binary variable.

$$r_i = \Pr (x_i = 1) \quad (2)$$
The above definitions are used in this study.

In the application of the reliability concept in the field of route guidance, some researchers use the link reliability approach to search for the shortest path deemed to be reliable. The idea is to use a travel time penalty for links having a reliability value lower than a preset threshold (Chen et al, 2005; 2006; Kaparias et al, 2006). The derivation of the link reliability value is simply from the distribution of travel time throughout the day. The variable of reliability takes values from 0 to 1, with 0 making the link unusable and 1 meaning that the travel time on that link is constant throughout the day. The value of \( r_i \) is thus the probability that link \( i \) will be found by the driver to be acceptably congested, and therefore not failed, at the time of use.

2.2. FAILURE DEPENDENCE RELATIONSHIP

The concept of link failure is derived from the definition of link reliability and represents the state of being unacceptably congested, which in the case of a road network means that the travel time on the link is longer than a preset threshold. Links in a real road network, however, do not usually fail independently. When a link fails or is degraded, the adjacent links or the links in the same area are also likely to be affected by the same degradation, although with a lag. In order to propose a more reliable path for the travellers, link failure dependence relationships should be taken into account in a robust route guidance algorithm.

Only a few studies on link failure dependence have been carried out so far. Chen et al (2005) introduce the idea of link failure dependence by defining three possible types of failure dependence between two links. Considering two links \( i \) and \( j \), if the performance of link \( i \) deteriorates, then link \( j \) is positively failure dependent on \( i \) if its performance also deteriorates. Alternatively, \( j \) is negatively failure dependent on \( i \) if a deterioration of the performance of \( i \) results in an improvement of the performance of \( j \), and if a deterioration of the performance of \( i \) leaves the performance of \( j \) unaffected, then \( i \) and \( j \) are failure independent. In order to quantify the degree of failure dependence, Chen et al (2005) introduce a failure dependence coefficient \( \mu_{ij} \), where \(-1 < \mu_{ij} < 1\).

The calculation of \( \mu_{ij} \) is carried out using a so-called ‘geometrical’ failure dependence approach, according to which it is assumed that links are failure dependent because of their location. For instance, if link \( j \) is located directly upstream to the incident link \( i \) or is an alternative to it, it is very likely that its performance will have a high positive correlation with the performance of link \( i \) and \( j \) will therefore be positively failure dependent on \( i \). Conversely, if \( j \) is located directly downstream of the incident link \( i \), it is very likely that it will be negatively failure dependent on \( i \), because it will benefit from lower travel times. Thus, depending on the location of the link in question, the failure dependence coefficient between them varies accordingly.

In this thesis, link failure dependence relationships will be further investigated using a VISSIM microsimulation model of the road network for Coventry in the UK. In the following section, details of the simulation model, design specifications and data generation from the model will be presented.
3. METHODOLOGY

Using a VISSIM microsimulation model for the analysis, a link is “artificially” set to be congested by becoming unusable and two sets of data are established, namely link travel time and link state. The former is just a database of the travel times on a number of relevant links in the network, resulting from a series of travel time measurements in the VISSIM microsimulator, while the latter is the conversion of the travel time values to link state binary values (0 for “congested”, 1 for “uncongested”), based on a certain link travel time threshold value characterising the link’s state, which will be introduced later in this section. With these two sets of data, it is first explored whether there is a correlation between the target link and other, mainly adjacent, links and if confirmed, the study proceeds to identify this correlation structure. The correlation analysis method will also be described in this section.

The methods discussed here are as follows:
1. Link travel time threshold;
2. Method of analysis;
3. Correlation analysis.

3.1. LINK TRAVEL TIME THRESHOLD

As was introduced in the literature review in the previous section, there are two states, which a link can have, normal and abnormal (Bell and Iida, 1997); if the link’s traversal time exceeds some preset threshold, its state is said to be abnormal. This concept is made clear in Figure 12, where the x-axis represents the link travel time and the y-axis shows the frequency of the travel time on the link in question. Provided there are enough travel time records for all links and assuming that travel times on links are subject to a certain distribution, a graph similar to the one shown in Figure 2 can be plotted. The threshold defining the normal-abnormal states can be set based on a certain percentage level.

For example, let the travel time on the link be $T$ and assume that it is subjected to a normal distribution, so that $(T - \mu)/\sigma \sim N (0, 1)$, where $\mu$ is mean link travel time and $\sigma$ is the standard deviation of travel time. The threshold is set to be a value $t$ at the level of 95%. Therefore the probability of the travel time for any link selected at random being less than the threshold $t$ (i.e. the reliability of the link) can be expressed as:

![Figure 2: Threshold concept](image-url)
\[ r = Pr\{T \leq t\} = \Psi((t - \mu)/\sigma) = 95\% \] (3)

By reference to the normal distribution table:

\[ t = 1.65\sigma + \mu \] (4)

In the above equation, once \( \mu \) (mean) and \( \sigma \) (standard deviation) are known, the threshold \( t \) can be easily calculated. \( \mu \) and \( \sigma \) can be computed from the complete set of records of link travel time.

A limitation of this approach is that it applies the same threshold to all links, irrespective of length or normal operating speed. While the notion of an unacceptably large travel time is intuitive, in recent work an alternative definition of reliability has been adopted, namely the ratio of link-specific mean travel time to the link-specific 95-percentile travel time.

As to the distribution of the link travel time, past studies indicate that link travel times in a generally busy network are usually normally distributed, whereas for sparser and quieter networks, their distribution may be skewed such that a log-normal distribution should be used (Asakura & Kashiwadani, 1991; Nicholson, Bell & Schmöcker, 2001). In this study, as the modelled simulation period is the peak, the normal distribution offers a reasonable representation of the travel time distribution. To further verify this assumption, the Kolmogorove-Smirnov test is performed for a number of typical links and the result shows that the assumption is justifiable.

The state of congestion of a link \( i \) is represented by the 0-1 state variable \( x_i \), such that \( x_i = 0 \) if the link has failed and \( x_i = 1 \) otherwise. The link reliability value \( r_i \) is the probability of link being uncongested, so the function is \( r_i = Pr(x_i = 1) \).

In this study, we use the value of threshold calculated from the base model, and compare against the travel time derived from the ‘target link failed’ model. If the travel time on the links exceeds this threshold \( t \), then the link is deemed to have failed.

### 3.2. Method of Analysis

Under the notion of link travel time threshold concept, the link travel time can be converted into binary data. An example of binary data coding is given in Figure 3, where the left hand side table is the travel time measurement at 300 seconds intervals. A threshold value is used to classify the condition on the link and the red highlighted cells show the cases where travel time exceeds the threshold. The converted binary data is shown on the right hand side of Figure 3.
The test network used is a VISSIM microsimulation model of the City of Coventry (West Midlands, England). Figure 3 demonstrates the analysis method, where the congested link is denoted by a red colour and the links of interest is highlighted by yellow and blue colour.

**Figure 3:** Link travel times converted to link state data

3.3. **CORRELATION ANALYSIS**

Correlation analysis is employed in the analysis of the link failure dependence relationships. The primary data includes the link travel times and link states (derived from the travel times), while autocorrelation and correlation analysis shed light on the relationships within and among links.
An important property of a time series is its autocorrelation coefficients, which measures the correlation between observations made at different times. The autocorrelation coefficient for each link gives an insight into the congestion phenomenon. By then comparing correlation coefficients between adjacent links one could draw important conclusions about congestion propagation. For example, if the autocorrelation coefficients of a link during the first few lags have high positive values and the preceding link also shows a significant positive value of autocorrelation, it is reasonable to suspect that there is a relationship between these two links, and that further correlation analysis and statistical modelling to investigate the relationship is worthwhile.

For travel time data analysis, the formula for the calculation of the autocorrelation coefficient is:

\[ r_k = \frac{\sum_{i=1}^{N-k} (x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \]  

where \( k \) is the lag.

Links are selected, for which the autocorrelation coefficients are calculated; these are mainly the links adjacent to and upstream of the failed link, as they are more likely to have a correlation between each other.

In the binary data, the autocorrelation is mainly observed in Excel by highlighting the failed links at each time interval. Finally, the results from the different types of data analysis are presented.

4. RESULTS

The micro simulation results of link failure for the City of Coventry network are obtained and congestion patterns are presented in a series of diagrams by using the method of travel time threshold we introduced in the last section. In order to further investigate the congestion dependence relationship, the correlation analysis is carried out and the results are also presented in this section.

4.1. SIMULATION RESULTS

The results confirm that there is clear congestion dependence between the congested link and the links to adjacent it, as within a certain time period of the occurrence of the congestion incident they too become congested. The links that seem to be more prone to be affected are the links located upstream of the congested link. Namely, the findings suggest that the state of a link located upstream of the congested link depends on its state during previous time intervals and on the state of the congested link. From the microsimulation model, the congestion pattern following congestion on a certain link can be identified (Figure 5).
4.2. CORRELATION ANALYSIS RESULTS

For the travel time data analysis, the links upstream of the failed link are chosen for the calculation of the autocorrelation coefficient (shown in Figure 6). It is expected that the travel time on the upstream links increases with time during the period that the failed link remains congested. The calculation of the autocorrelation coefficient should help to identify the relationship between the failed link and the upstream links with respect to the rate of increase in travel time of the latter. Table 1 presents the results of the autocorrelation analysis for a typical upstream link.
Table 1: Autocorrelation coefficient for link 25

From the above results, it is found that the first autocorrelation coefficient is significant in the first lag; however it fades away as the lag increases. The value of the autocorrelation coefficient of the first lag is approximately 3 times larger than it is in the second lag and the coefficient value becomes negative in the third lag. Since the coefficients are most important during the first few lags, only results for the first three lags are presented here.

This result indicates that there is a strong evidence of correlation in the change of travel time during the first and second time interval. However, it is not possible to conclude whether there is a correlation between the first, the third and later time intervals. This phenomenon can also be identified in the time series plot and its correlogram (Figures 6 & 7).

<table>
<thead>
<tr>
<th>Lag</th>
<th>Autocorrelation</th>
<th>Std. Error(a)</th>
<th>Value</th>
<th>df</th>
<th>Sig.(b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.587</td>
<td>.256</td>
<td>5.261</td>
<td>1</td>
<td>.022</td>
</tr>
<tr>
<td>2</td>
<td>.215</td>
<td>.244</td>
<td>6.040</td>
<td>2</td>
<td>.049</td>
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<tr>
<td>3</td>
<td>-.240</td>
<td>.231</td>
<td>7.112</td>
<td>3</td>
<td>.068</td>
</tr>
</tbody>
</table>

a The underlying process assumed is independence (white noise).
b Based on the asymptotic chi-square approximation.
c The shaded area indicates the value bigger than 2 x ±Std Error, meaning they are significant.

**Figure 6:** Time series plot
For binary data, the same upstream links are chosen to analyse the autocorrelation. Visual inspection is used in this analysis (Table 2), where red coloured cells indicate that the link has failed. By looking at each column, it can be observed that the state of each link is autocorrelated. A link having failed previously is very prone to fail again.

<table>
<thead>
<tr>
<th>Link No:</th>
<th>J1</th>
<th>J1</th>
<th>J1</th>
<th>J1</th>
<th>J2</th>
<th>J2</th>
<th>J3</th>
<th>J4</th>
</tr>
</thead>
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<tr>
<td>2100s</td>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
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<td>1</td>
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<tr>
<td>2400s</td>
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<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
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<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2700s</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
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<tr>
<td>3000s</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
</tr>
<tr>
<td>3300s</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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</tr>
<tr>
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<td>0</td>
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<tr>
<td>3900s</td>
<td>0</td>
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<td>4500s</td>
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<tr>
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<td>1</td>
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<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 2: Binary data for the upstream links

5. CONCLUSION

In this paper, the link congestion dependence relationship is explored. The congestion propagation patterns are identified and time lags between congestion dependent links are
observed. The results can be seen as a first step towards predicting congestion in a network and considering this prediction in Dynamic Route Guidance.

For a future task, fully understanding the relationship underlining the link congestion dependence can lead to the prediction of the congestion in the future and therefore enhance the reliability in Dynamic Route Guidance System.

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REFERENCES


