Spatial econometrics models of congestion prediction for in-vehicle route guidance

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ABSTRACT

Current research on in-vehicle information system, more specifically dynamic route guidance, is offering the prospect of improved individual trip efficiency by enabling drivers to avoid recurrent and propagated road congestion. One of the next major advances in developing route guidance systems will be the short-term prediction of congestion in road networks. This will inform the driver about the road network conditions one or two hours in advance and assist them to avoid anticipated congestion. This paper discusses the application of spatial econometric modelling in congestion prediction, by using historical Traffic Message Channel (TMC) data stored in the vehicle navigation unit. The nature of TMC data is in the form of a time series of geo-referenced congestion warning messages which is generally collected from vehicles acting as traffic probes. The prediction of future congestion could be based on the previous year of TMC data. Synthetic TMC data generated by microscopic traffic simulation for the network of Coventry are used in this study. The feasibility of using econometric modelling techniques to predict congestion is explored. Results are presented at the end. The study will add new content to applied spatial econometrics in the transport field.

1. INTRODUCTION

1.1. Background

Congestion data are required in many new dynamic route guidance systems. At present, car navigation systems from Garmin, Tomtom and other suppliers can be supplied with congestion warning messages via the Traffic Message Channel (TMC), provided the driver has subscribed for the service. These warnings can then be displayed on the in-vehicle map in the form of triangles (see Fig. 1) and can cause the route recommended to the driver to be modified. However, this data relates to congestion that has already happened and has been detected by traffic monitoring systems. The quality of guidance could be significantly improved if accurate short-term predictions of congestion were also available. Then the optimum route could be sought which would take encountered, rather than current, network conditions into account.
As current vehicle navigation systems are limited to detect incidences of congestion, there is no guarantee that the recommended route will turn out to be congestion-free or indeed avoid sites of undetected congestion. Since congestion often propagates in predictable ways and is recurrent, reasonably accurate short-term forecasts of congestion should be possible.

![In-vehicle display of a BMW](image)

**Fig. 1: In-vehicle display of a BMW**

### 1.2. Objectives

This paper seeks to:

1. Study the impact of congestion on neighbouring links as well as the propagation and dissipation of congestion.
2. Establish a congestion forecasting framework based on the speed data.
3. Investigate the potential for using a panel data model for congestion forecasting.

### 1.3. Structure

To achieve above objectives, the following tasks are carried out:

A VISSIM microscopic traffic simulation model of the city of Coventry has been built. A short-term blockage is used to simulate congestion propagation and dissipation in the Coventry network, yielding link speed data for subsequent analysis. The description of the model and database are presented in Section 3.

Panel data models have been fitted to the simulated data. The detailed descriptions of the model along with the results are included in the Section 4. Section 5 concludes the paper by summarising the findings and outlook the future research.

However, before any modelling tasks are carried out, we should first understand the problem. The next section studies the phenomena of congestion propagation and dissipation.
2. THE NATURE AND CAUSES OF THE PROBLEM

It is said in the introduction that congestion is often predictable, because of the way it propagates and dissipates as well as because of its frequently recurrent nature. In this section, we further explore congestion prediction and also explain why spatial econometrics is considered to be the best tool to solve this problem.

One interesting aspect of congestion is its propagation. It tends to propagate in a direction opposite to the flow of traffic. Its propagation has been studied in previous research (“Reliability and Link Failure Dependence Relationships in Dynamic Route Guidance” MSc dissertation by Jun Hu, 2006). The results shed light on the phenomenon of progressive link failure which characterises the propagation of congestion, where failure is characterised by a collapse in link speed. Fig. 2 illustrate the situation at the time of the initial link failure (circled on left) and 30 minutes later on the right (red indicates link failure). So if we study the pattern of congestion generation, propagation and dissipation, in other words the dependent relationship among these link speeds, we could predict when congestion is likely to arise on a certain link. However, this dependent relationship is complicated, since links speeds are usually spatial and temporal correlated with each other.

Inter-dependencies in link speeds depend on network topology. The incidence of congestion on a certain link depends on its location and distance from the initial congested link. The blockage of the initially congested link usually results in the congestion of the upstream links. The distance to that initial congested link and the extent of shared flow determine the degree of impact. On the other hand, downstream links usually appear to be less congested when the traffic is blocked upstream. In previous link reliability studies, Chen et al (2005) categorise this geometrical relationship into three types: positively dependent, negatively dependent and independent. This can be quantified by the so-called failure dependency coefficient, denoted by $\mu_{ij}$ for links $i$ and $j$. This is elsewhere used to find reliable routes for dynamic route guidance. Works refer to Kaparias paper on ‘an approach to time-dependence and reliability in dynamic route guidance.

Link speeds on the network are also autocorrelated. The speed on a link at a particular period $t$ is determined by the state of the link at previous periods, $t-1$, $t-2$, etc. For
example, if we know a link is congested in the previous period, there is a high probability that the link will be congested in next period.

Spatial econometrics is a subfield of econometrics that deals with the treatment of spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data (Anselin, 1988). Because of the nature of this problem, using spatial econometrics approach is proposed in this study. There have been some previous studies on predicting link journey time by using generalised statistical modelling (Hounsell et. al, 1997) and predicting the congestion based on machine learning approach (Horvitz et. al., 2005). But only few studies have tried to use spatial econometrics for this purpose.

3. CASE STUDY OF COVENTRY CITY MODEL

3.1. Description of the model

In order to generate useful database for this study, we used the Coventry city traffic simulation model. The model represents the existing traffic situation during a weekday afternoon peak hour (17:00 – 18:00) in 2004. A sudden road closure caused by an incident or vehicle breakdown is artificially created on the city ring road, in order to generate the congestion data for the analysis. The incidence link is denoted as the ‘failed link’ on the map. Then the following 8 links are selected for analysis. In Fig. 3 colour is used to identify the links analysed. The traffic flows in an anticlockwise direction on the selected links, so these links are all upstream links of the incidence link.

The road closed for a duration of 30 minutes and reopened at 17:30. The whole simulation period is from 16:30 to 18:30, which is 2 hours. Therefore, we could be able to look at the three stages (incident-free, congestion propagation and congestion dissipation).
3.2. Database

Analogue speed data is used in this study to investigate the propagation of congestion and therefore predict the congestion. The state of the link can be very well characterised by the speed on that link. The lower the speed, the more severe the state of congestion is on that link.

Speeds on the 8 selected links are collected. The average speed of vehicles travelled on the links is recorded for 3 minutes interval over 2 hours, giving us 40 observations for each link. That leads to a cross-sectional \((N=8)\) time series \((T=40)\) panel data set with a total of 320 \((N \times T)\) observations.

However, there are 3 observations of speed missing on link 25 during the highly congested period, as the simulation software could not estimate the travel time on that link since the speed was zero or nearly so. Other data missing is due to the nature structure of the data. For example, our independent variable \(V_{it-1}\), speed lag on the link \(i\) at time \(t-1\). The first value of this variable will naturally be missing. An example of the structure of the data is shown in Table 1.
### Table 1: Example of panel data set

<table>
<thead>
<tr>
<th>Link id</th>
<th>t</th>
<th>Speed</th>
<th>S (speed on previous link at time t)</th>
<th>speed_lag1</th>
<th>speed_lag2</th>
<th>S_lag1</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1</td>
<td>37.0</td>
<td>30.3</td>
<td>37.0</td>
<td>30.3</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2</td>
<td>37.3</td>
<td>30.3</td>
<td>37.0</td>
<td>30.3</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>3</td>
<td>35.9</td>
<td>28.9</td>
<td>37.3</td>
<td>37.0</td>
<td>30.3</td>
</tr>
<tr>
<td>10</td>
<td>4</td>
<td>35.0</td>
<td>28.5</td>
<td>35.9</td>
<td>37.3</td>
<td>28.9</td>
</tr>
<tr>
<td>10</td>
<td>5</td>
<td>36.5</td>
<td>30.3</td>
<td>35.0</td>
<td>35.9</td>
<td>28.5</td>
</tr>
<tr>
<td>10</td>
<td>6</td>
<td>34.7</td>
<td>31.3</td>
<td>36.5</td>
<td>35.0</td>
<td>30.3</td>
</tr>
<tr>
<td>10</td>
<td>7</td>
<td>35.9</td>
<td>29.4</td>
<td>34.7</td>
<td>36.5</td>
<td>31.3</td>
</tr>
<tr>
<td>10</td>
<td>8</td>
<td>32.7</td>
<td>25.1</td>
<td>35.9</td>
<td>34.7</td>
<td>29.4</td>
</tr>
<tr>
<td>10</td>
<td>9</td>
<td>36.5</td>
<td>24.4</td>
<td>32.7</td>
<td>35.9</td>
<td>25.1</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>35.9</td>
<td>26.8</td>
<td>36.5</td>
<td>32.7</td>
<td>24.4</td>
</tr>
</tbody>
</table>

### 3.3. Method of analysis

Here we use the simplified network diagram to illustrate the way that the analysis was carried out.

![Network Diagram](image)

**Figure 4: network diagram**

The arrow in the diagram indicates the direction of traffic flow. Suppose link \( j \) is the link in question, we wish to predict the average speed on link \( j \) at time \( t \). This is determined by many factors, most importantly: the speed on downstream link \( i \) in the previous time interval \( (S_{i,t-1}) \) as well as the speed on link \( j \) in the previous time intervals \( t-1 \) and \( t-2 \) (\( speed\_lag1 \), \( speed\_lag2 \)). We used a panel data model to establish this relationship. This is explained in the next chapter.

### 4. MODELLING SPEED DATA: PANEL DATA MODEL

#### 4.1. Introduction

Panel data are observations on a cross-section of units, links in our case, on the network that are observed over a period. The fundamental advantage of panel data models over cross-section models is that they take into account autocorrelation as well as correlation between links (Greene, 2003). Two types of panel data model are frequently encountered in the literature. One is the fixed effects model while the other is the random effects model. The main difference between these two models is whether or not the unobserved link effects are correlated with the regressors in the model. The basic forms of two models are as follows:

The fixed effects model is:

\[
y_{it} = x_{it}'\beta + \alpha_i + \varepsilon_{it}
\]
where $\alpha_i$ is a link-specific constant term and does not vary over time. The corresponding random effects model is:

$$y_{it} = x_{it}'\beta + u_i + \varepsilon_{it}$$

where $u_i$ is a link-specific random element. Vector $x$ represents the regressors and vector $\beta$ represents the parameters.

The regressand and regressors of the model are listed below:

<table>
<thead>
<tr>
<th>$V_{it}$</th>
<th>= speed on link $i$ at time $t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{i,t-1}$</td>
<td>= speed on the most immediate downstream link at $t-1$</td>
</tr>
<tr>
<td>$V_{i,t-1}$</td>
<td>= speed on the link $i$ at time $t-1$</td>
</tr>
<tr>
<td>$V_{i,t-2}$</td>
<td>= speed on the link $i$ at time $t-2$</td>
</tr>
</tbody>
</table>

The model captures both spatial and temporal autocorrelation. However, because the panel data in our case has a small number of cross-sectional unit $N$ and large $T$, if we use the dynamic panel data model, its estimator, called Arellano and Bond estimator will not be efficient for our problem (Greene, 2003). It is thought that the general panel data model is more appropriate to fit into the dataset with small $N$ and large $T$.

In our case, both the random and fixed effects models will be fitted and then we use the Hausman test for random effects model to decide which model is more appropriate.

### 4.2. Panel data model

Both the fixed and random effects models are fitted to the data. The results are compared and Hausman test is carried out for the random effects model. Table 2 shows that the chi-square test statistic is 24.42. From Chi-square table, we find $Prob(\chi^2 > 24.42) = 0.0000$ with three degrees of freedom, showing that the difference is statistically significant. Therefore the null hypothesis that the individual effects are uncorrelated with the other regressors in the model should be rejected. So we would conclude that of the two alternatives we have considered, the fixed effects model is the better choice according to the Hausman test result.

<table>
<thead>
<tr>
<th>Table 2: Hausman test for random effects model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Hausman test</td>
</tr>
<tr>
<td>FE</td>
</tr>
<tr>
<td>S_{lag1}</td>
</tr>
<tr>
<td>Speed_{lag1}</td>
</tr>
<tr>
<td>Speed_{lag2}</td>
</tr>
</tbody>
</table>

Test: Ho: difference in coefficients not systematic

$chi^2 (3) = \frac{(b-B)'(V_b-V_B)'(b-B)}{b-B} = 24.42$

$prob > chi^2 = 0.0000$
This fixed effect model is therefore defined as:

\[
V_{it} = \alpha_i + \beta S_{jt-1} + \gamma V_{it-1} + \gamma V_{it-2} + \epsilon_{it}
\]

\( i = 1, \ldots, N; j = 1, \ldots, N; t = 1, \ldots, T \)

(1)

Where as defined earlier \( V_{it} \) is the speed for an observation unit (link) \( i \) in a given period \( t \) (3-minute intervals), \( \alpha_i \) is a link-specific constant term in the model, which does not change over time, and \( \epsilon_{it} \) is the usual residual.

In case of random effect model, the form can be defined as:

\[
V_{it} = \alpha_i + \beta S_{jt-1} + \gamma V_{it-1} + \gamma V_{it-2} + \nu_i + \epsilon_{it}
\]

(2)

Where \( \nu_i \) is a link-specific random element.

4.3. Model estimation results

The fixed effects model is estimated by the OLS regression, the results of the estimation is shown in the Table 3:

<table>
<thead>
<tr>
<th>Model: Fixed effects</th>
<th>Coef.</th>
<th>t-value</th>
<th>p-value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower limit</td>
<td>Upper limit</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_lag1</td>
<td>0.26</td>
<td>5.31</td>
<td>0.00</td>
<td>0.16 0.35</td>
</tr>
<tr>
<td>speed_lag1</td>
<td>0.88</td>
<td>13.94</td>
<td>0.00</td>
<td>0.75 1.00</td>
</tr>
<tr>
<td>speed_lag2</td>
<td>-0.16</td>
<td>-2.93</td>
<td>0.00</td>
<td>-0.27 -0.05</td>
</tr>
<tr>
<td>Constant</td>
<td>0.94</td>
<td>1.72</td>
<td>0.09</td>
<td>-0.14 2.03</td>
</tr>
</tbody>
</table>

From the estimation result, the p-value indicates that all coefficients are statistical significant from zero. The coefficient of variable \( S_{jt} \) from estimation is 0.26 with a positive sign, indicating that the speed on link \( i \) is positively correlated with speed on the downstream link. This indicates that increasing speed by one unit on the downstream link will result in an increment of 0.26m/h speed on the current link \( i \) in the same period. In the congestion situation, when the previous link starts congested, the speed will be gradually reducing, consequently the speed on the following link will also be reduced. The intuition is consistent with the estimated coefficient sign.

Comparing the coefficients of \( S_{lag1} \) and \( speed_{lag1} \), it appears the coefficient of \( speed_{lag1} \) is much higher than \( S_{lag2} \) and has the opposite sign. This indicates that the influence of \( speed_{lag1} \) is much higher than \( S_{lag1} \) and that speeds tend to oscillate when perturbed.

In order to inspect the goodness of fit of the model, we make a comparative plot between of the observed & fitted speeds on links 10 and 304.
The estimated speeds are consistent with the observed speeds. The estimated values follow the trend of actual speed changes. However, the estimated values tend to underestimate the actual speed values, especially in periods before and after incident. A possible explanation for this is because the model only has a few explanatory variables, it cannot capture all effects on the dependent variable. It may also be the case that the model form is misspecified with respect to the variables currently included. Hence, other models are being considered.
4.4. Other models

Other possible forms of model have also been explored in this study. Potential explanatory variable $S_{jt}$, the speed on the previous link at time $t$, is included in these models. The form of model B is as follows:

$$V_i = \alpha_i + \beta S_{it} + \gamma V_{it-1} + \gamma' V_{it-2} + \epsilon_i$$  

(3)

$i = I, \ldots, N; j = I, \ldots, N; t = I, \ldots, T$

The model presumes the speed on link $i$ depends on the speed on the downstream link simultaneously (that is $S_{jt}$) instead of speed of previous link at time $t-1$ (that is $S_{jt-1}$).

The model C will be:

$$V_i = \alpha_i + \beta S_{it} + \beta' S_{it-1} + \gamma V_{it-1} + \gamma' V_{it-2} + \epsilon_i$$  

(4)

$i = I, \ldots, N; j = I, \ldots, N; t = I, \ldots, T$

This model assumes both the $S_{jt-1}$ and $S_{jt}$ affect the speed on link $i$ at time $t$.

The results of the two model estimations are as follows:

<table>
<thead>
<tr>
<th>Model: Fixed Effects</th>
<th>Model B</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>t-value</td>
</tr>
<tr>
<td>$S$</td>
<td>0.27</td>
<td>7.65</td>
</tr>
<tr>
<td>$S_{lag1}$</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>speed_{lag1}</td>
<td>0.85</td>
<td>14.52</td>
</tr>
<tr>
<td>speed_{lag2}</td>
<td>-0.12</td>
<td>-2.23</td>
</tr>
<tr>
<td>Constant</td>
<td>0.40</td>
<td>0.75</td>
</tr>
<tr>
<td>Observations</td>
<td>289</td>
<td></td>
</tr>
<tr>
<td>Overall R-square</td>
<td>0.87</td>
<td></td>
</tr>
</tbody>
</table>

From the results in Table 4, the coefficients in model B are statistically significant as suggested by the $p$-values, except the constant. The value of the coefficients emphasize the importance of each explanatory variables on the speed on link $i$ at time $t$. The coefficient of speed_{lag1} is the highest among others. It indicates the speed on link $i$ at time $t$ is largely dependent on the speed in the most previous time interval $t-1$ on the link $i$. The finding is consistent with our basic model A.
Model C includes one more variable than models A and B. The estimation results show that the coefficient of \( s_{lag1} \) and constant term are statistically insignificantly different from zero. Again the coefficient of \( speed_{lag1} \) is the highest among others.

4.5. Comments on models

All these three models show that the speed \( V_i \) is largely dependent on the speed in the previous time interval on the same link. This is shown by the value of the coefficient for \( speed_{lag1} \). Model A’s \( speed_{lag1} \) coefficient is 0.88, models B and C are 0.85 and 0.82 respectively, which are reassuring consistent with each other.

In terms of the prediction, only model A could be used to predict the speed on a link at future time period, because the model only requires information from past time periods, \( s_{j,t-1}, V_{i,t-1} \) and \( V_{i,t-2} \). Both models B and C involve the variable \( s_j \). That means we need to know the speed on the downstream link for the prediction period. However, models B and C are still valuable as a comparison for model A and provide an insight into the problem.

5. CONCLUSION

The aim of this study was to set up econometric models to predict the congestion propagation and dissemination on the road network for eventual use in car navigation systems. Before the modelling was carried out, the nature and causes of the problem are illustrated using a VISSIM model for Coventry. The spatial and temporal nature of link congestion pointed to a spatial econometric approach. Speed data for eight links was simulated. Simple linear panel data models were fitted, with a view to gaining a model that could be used for forecasting. The results showed that the fitted value of speed from model is fairly consistent with actual speed. However, only a limited number of explanatory variables are considered in the model, so we could not explain all the variation of speed on the selected links.

For the future work, other forms of model possibly involving more explanatory variables will be investigated. Currently, the regression model has a simple linear form with spatial and autocorrelation. The support for alternative non-linear regression models will be explored. Special treatment for autocorrelation among variables should be further considered in the model, the suggested technique being co-integration. Finally, we will build a model to forecast congestion along a route based on real TMC data.
References: