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A Neural Network Approach to Motorway OD Matrix Estimation from Loop Counts

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Abstract： A method has been developed to estimate Origin Destination（OD）matrices using a neural network（NN）model and loop traffic data collected from a UK motorway site（M42）as the primary input. The estimated ODs were validated against matched vehicle number plate data derived from the ANPR（Automatic Number Plate Recognition）cameras which were installed at all the slip roads between junctions 3a and 7 of the motorway. Key research questions were：whether it is realistic to use the full loop data，whether particular features of the data influenced modelling success，whether data transformation could improve modelling performance through variance stabilization and whether individual ODs should be estimated separately or simultaneously. The method has been shown to work well and the best results were obtained using a square root transformation of the training data and individual models for each OD.

Key words： intelligent transportation；neural networks；time series；ANPR data；loop traffic data；origin destination matrix

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基于线圈数据的高速公路 OD 矩阵预测神经网络法

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摘要： 以英国 M42 高速公路线圈交通数据为输入，建立预测模型，提出神经网络 OD 矩阵预测方法. 将预测结果与该公路 3a 号至 7 号交叉口间各支路上自动车牌识别装置测得的车辆数据进行对比，验证其有效性. 解决了以下关键问题：利用线圈数据实现 OD 矩阵预测的可操作性，该类数据的特殊性是否影响模型构建，通过变异数稳定数据转换能否改善模型性能，能否同时进行单个 OD 预测. 得到基于训练数据平方根代换的最佳计算结果和单个 OD 预测模型.

关键词： 智能交通；神经网络；时间序列；自动车牌识别（ANPR）数据；线圈交通数据；OD 矩阵

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0 Introduction

Origin-Destination (OD) matrices are a key source of information within both urban and interurban environments, being used as part of the traffic planning and monitoring process, for forecasting purposes and to reflect behavioural changes by drivers over time. OD matrices are used regularly in developed and developing countries by government transport officials, public and private investors, planners and those involved in the management of road network. Despite this, the process of generating a matrix can hold considerable difficulties and be both costly and time consuming. As a result, the method proposed here addresses a problem that is of considerable significance in the transport community of operators. The capability to construct an OD matrix from link flow data (which is relatively easily collected over a continuous period) in certain conditions and with some limits allows the possibility for a less costly method with the potential to give estimated ODs in close to real time.

1.1 Theoretical framework

The problem of reconstructing or tuning an OD matrix from link flows is generally the inverse of the assignment operation of an OD matrix in "classic" transport models. A mathematical model of the assignment can be derived from the classic model of a transportation system in equilibrium[1]. This describes the behaviour of traffic demand d and its continuous relationship with link flows $\boldsymbol{f}$ as a function of the vector of link costs c as follows:

$$\boldsymbol{f} = \boldsymbol{A} \cdot P(c(\boldsymbol{f})) \cdot d(c(\boldsymbol{f})) \tag{1}$$

where $\boldsymbol{A}$ is the link-path incidence matrix (with elements a_{ij} equal to 1, if link i lies on path j, and 0 otherwise), P is the path choice probability matrix. Obviously some constraints must be added in order to fulfil constraints such as a non-negative link flow. Simplifying notations, the assignment problem can be written as: $\boldsymbol{f} = G(\boldsymbol{d})$, where G is a continuous function which can be calculated by either an exact formulation (i.e., using a deterministic approach) or through algorithms, i.e., a stochastic approach. Generally function G is not linear. In fact, linearity can be assumed only when there is no congestion, which is an unusual case for road traffic both in urban and motorway environments during peak hours.

Reconstructing (or tuning) an OD matrix from the link flows can be thought of the inverse of the assignment function, written as: $\boldsymbol{d} = G^{-1}(\boldsymbol{f})$. In many cases, G^{-1} is not linear (due to congestion effect) and also a unique solution cannot normally be obtained as in practice the number of observed traffic counts is much less than the number of OD matrices (i.e., traffic demand d). Generally G^{-1} is calculated by recursively applying the assignment procedure until it produces flows sufficiently equal to the observed ones. The acceptable margin of difference between the assigned flows and the observed ones is generally determined by the context in which the matrix is being generated.

Many OD estimation methods have been proposed, reflecting an overwhelmed interest in OD estimation and its usefulness for the control and management of both urban and motorway environments. Approaches to motorway OD estimation aim to address the rapidly changing nature of traffic and the effects of traffic management strategies (i.e., speed control or ramp metering). Camus et al[2] proposed a 'time slice' approach using the currently available traffic counts to predict the OD matrix up to 60 minutes ahead. A similar dynamic forecasting approach was proposed and tested with motorway OD data in Amsterdam and the effect of incidents on the OD estimation was considered[3]. These studies made a significant contribution to the traffic demand modelling but demonstrated the formidable challenges of dealing with the complex nature of traffic and implementing the methods in practice. Neural network based methods are arguably less knowledge demanding given that vast quantities of traffic data are now available to train a neural network model. Kikuchi and Tanaka[4] applied NN (neural networks) to a highway network continuously monitored at the inflow and outflow ramps. The neural network was designed in such a way that its weights represent the ramp-to-ramp volume expressed as a proportion of the inflow (origin) to each outflow (destination).

1.2 Outline of the proposed method

The proposed research was to investigate the use of NN-based models for motorway OD estimation, with a great focus on the analysis of the stationarity and co-linearity of link flows and the effects of their missing values on the model performance. The method used is based on high volume of flow data produced by the motorway incident detection and automatic signalling system (MIDAS) and vehicle data from an automatic number plate recognition system (ANPR) installed on the UK motorway M42. The MIDAS system is widely used in the UK and abroad to collect information about the type (in terms of length), speed, and occupancy of each vehicle passing over the loops placed at a typical interval of 500 m in each lane of the motorway. The vehicle data is then aggregated into one minute to produce lane-based traffic counts, average speed, occupancy, and flows by vehicle length. The ANPR data collected in this study was used to train and validate the NN models which are believed to be able to replicate the G^{-1} function used in OD estimation. The performance of a NN-based model lies on the careful design of the training dataset which normally consists of a number of input variables (i.e., explanatory variables) and the desired outputs (i.e., response variables). In this study, the inputs are the MIDAS traffic data collected from the loops between junctions 3 and 7 of the M42 motorway, and the outputs are the number of vehicles matched by the ANPR system between two junctions. Although the NN model may perform better using the matched trips at previous time intervals (i.e., at $t-1$, $t-2$, $\cdots$), the ANPR data was not used as input as the exercise aims to develop an OD estimation model using widely available loop data.

The paper is structured as follows. In Section 2 the study site used to demonstrate the method is described, including information on the arrangement of MIDAS detectors along the route. In this section the statistical properties of the ANPR and MIDAS data for this site are reported together with a summary of the relationship between the two data types. In Section 3 the OD estimation method is presented whilst the results from the application to the study site are discussed in Section 4. Finally, conclusions and recommendations for further research are given.

2 The study site and preliminary data analysis

The study site is defined by the M42 motorway Northbound from Junction 3a (where the M40 motorway joins the M42) to Junction 7, which joins the M6 and M6 toll road to the North East of Birmingham (Fig.1). The site contains 93 MIDAS detectors in each driving direction, installed typically 500 m apart on the three-lane mainstream section. Detectors were also installed on the ramps to monitor the traffic! coming off and joining the motorway. To form OD matrices for this study site, centroids were initially identified, i.e. nodes where traffic can entes and exit from the study site. These are taken to correspond to each entry/exit junction ramp plus the merging of the two motorways to the south of the study site (the M40 and M42 at Junction 3a), which is studied as two distinct entry junctions. For this research, Junction 7 is considered as an exit only junction and no distinction is made between vehicles either exiting the ramp or crossing the junction in the direction of the North. This! leads to a 6 × 6 upper triangular OD matrix, with 14 non-zero cells. It should be noted that the traffic demand within the site is not uniform and demand from Junctions 3a-M42, 3a-M40, and 6 are dominant entry points, whilst Junction 7 is the major destination point.

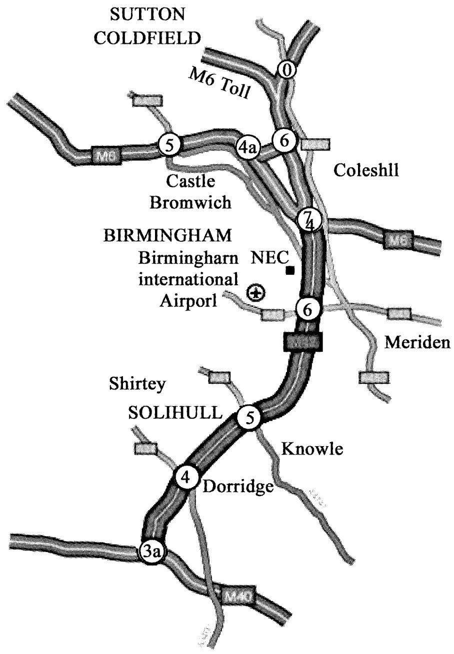


Fig.1　Map of M42 from section 3a to 7,
Source: Mott Macdonald Ltd

ANPR data are collected through a video system which has been installed at all entry and exit points in the study area. This system archives the images of vehicle plate numbers and times for each vehicle entering or leaving a junction and these can then be matched between junction pairs, indicating the number of vehicles moving between junctions, plus other traffic information such as the journey time. The proportion of recognised number plates by this recording system could range from 60% to 90% depending on a number of factors such as weather conditions, vehicle speed, vehicle dimension, camera errors, and capture rates. For these reasons it is very unlikely that a full OD matrix can be obtained using ANPR data alone, which is part of the rationale for developing the method based on MIDAS data and carefully selected ANPR data for training in this research.

A large quantity of data was potentially available for the site and there is an important issue of both how much data is required and what quality it should be for the method to perform satisfactorily. Preliminary analysis considered a number of issues including ANPR data selection and the aggregation level, the characteristics of the ANPR data especially the correlation between its variance and mean, the construction of OD matrices and the consistency between the ANPR data and the corresponding MIDAS data. These issues were discussed in detail by Mussone et al[5]. Sections A to C below summarise key points of the analysis which are directly relevant to the model development and the discussions of the results reported.

2.1 ANPR count matrices

For each day, ANPR count matrices were constructed using a 1 – hour time segment for each of the 14 pairs of ODs possible from Junction 3a to Junction 7 (noting that effectively, two Junction 3a origins exist). The maximum possible number of samples for each OD pair is 240 (10 days × 24 hours). For some days data were incomplete and as a result some OD pairs have less than the maximum 240 samples available. In Table 1, summary statistics for the ANPR counts for the northbound traffic on the M42 study site are reported. Values are probably underestimated but what we are interested in is the value ratio between OD pairs. From this it is possible to see that the mean count (calculated over each hourly period and each day) shows considerable variability between junction pairs, with the highest values corresponding to a destination of Junction 7. This represents traffic with a more northerly destination and which is likely to involve longer journeys. The standard deviation of the ANPR count is similarly variable and appears to be associated with the size of the mean (the higher the mean count the higher the standard deviation). This is illustrated through the values of the coefficient of variation, which are generally consistent at around 0.3 to 0.4. Exceptions to this are OD pairs 3, 7, and 13, which involve journeys from the two JN3a origins to JN7 (i.e. the whole route) and JN 5 – 7, involving traffic from the NEC exhibition junction heading Northbound.

Table 1 Summary statistics for OD data

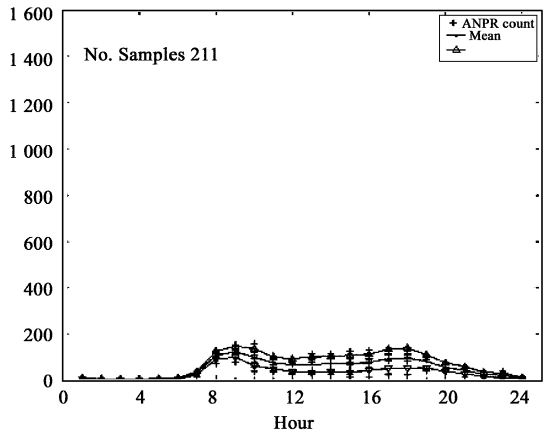
OD code*	OD pair	No. Samples	No. Samples/240 (%)	Mean ANPR count	Standard deviation of ANPR count	Coef. of variation
1	3a(40) – 4	202	84%	90.7	30.5	0.34
2	3a(40) – 5	211	88%	51.8	19.3	0.37
3	3a(40) – 6	215	90%	94.3	38.3	0.41
4	3a(40) – 7	214	89%	465.5	158.9	0.34
5	3a(42) – 4	202	84%	86.2	28.7	0.33
6	3a(42) – 5	209	87%	103.8	33.6	0.32
7	3a(42) – 6	218	91%	221.0	92.2	0.42
8	3a(42) – 7	222	93%	583.7	210.1	0.36
9	4 – 5	183	76%	57.8	15.5	0.27
10	4 – 6	189	79%	82.7	31.0	0.37
11	4 – 7	189	79%	134.6	48.0	0.36
12	5 – 6	157	65%	44.1	16.4	0.37
13	5 – 7	160	67%	140.9	60.6	0.43
14	6 – 7	229	95%	458.8	150.6	0.33

* Used as an OD pair identifier in subsequent analysis.

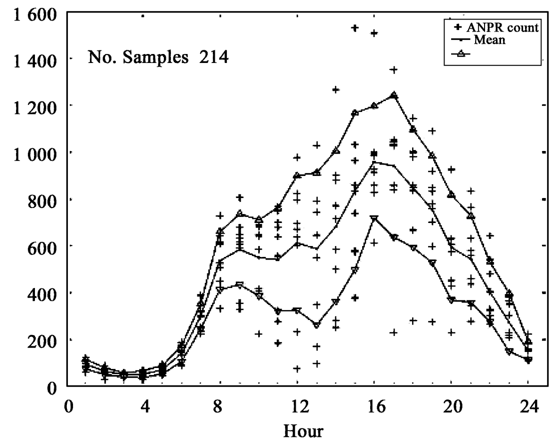
Plotting the ANPR count for each OD pair on an hourly basis throughout the day highlighted some similarities between particular pairs. As a result, it was possible to form classes for similar OD pairs based on a subjective visual assessment of the plots, as reported in Table 2. In Fig.2, plots of data for four representative OD pairs (one for each class) are shown to illustrate the typical patterns identified. Together with the mean count, the limits obtained by adding and subtracting one standard deviation to the mean are also indicated.

Table 2　OD pairs with similar ANPR count profiles

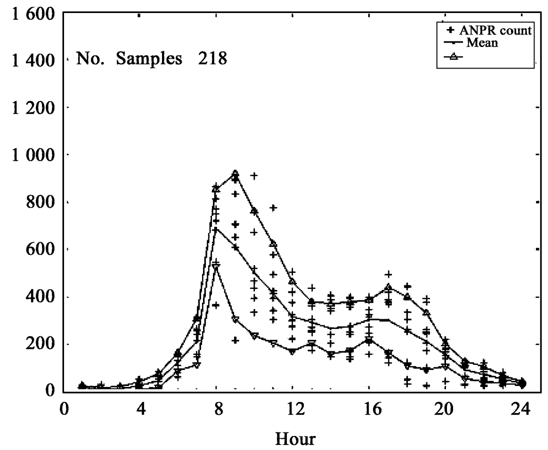
	OD pairs in class				
1	3a(40) - 5	3a(42) - 4	3a(42) - 5	4 - 5	5 - 6
2	3a(40) - 7	3a(42) - 7	6 - 7		
3	3a(40) - 6	3a(42) - 6	4 - 6		
4	3a(40) - 4	4 - 7	5 - 7		



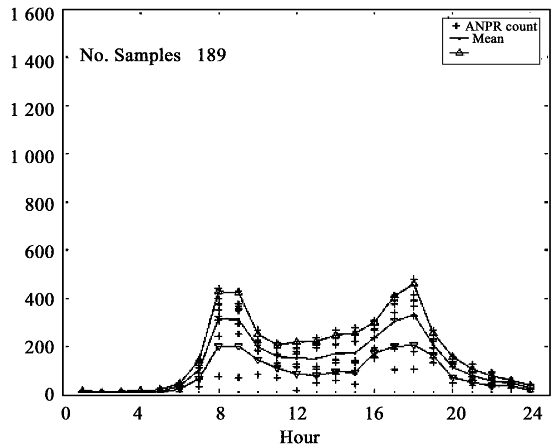
(a) Jn 3a(40)-Jn 5 ANPR count profile (class 1)



(b) Jn 3a(40)-Jn 7 ANPR count profile (class 2)



(c) Jn 3a(42)-Jn 6 ANPR count profile (class 3)



(d) Jn 4-Jn 7 ANPR count profile (class 4)

Fig.2　ANPR count profiles in each road section

As expected with the general pattern of traffic demand, the mean ANPR count changes according to the hour and in general two peaks can be identified, corresponding to the morning (approximately 09:00) and evening (approximately 18:00). For some OD pairs the morning peak is higher, whilst for others the evening peak is higher, reflecting different structures to the demand at particular locations of the network throughout the day. The OD patterns for each of the four classes can be summarised as follows. The first class includes OD pairs with low demand throughout the day. The second class includes OD pairs that involve Junction 7 as a destination and have high demand with a pronounced peak in the evening. The third class contains OD pairs with Junction 6 as a destination and has high demand with a pronounced peak in the morning. Finally, the fourth class includes those OD pairs with clear morning and evening peaks to demand. Junctions 6 and 7 outflows therefore form a particular contribution to the pattern of demand on the M42 northbound, which has a sensible practical interpretation as Junction 6 provides a connection to Birmingham airport whilst Junction 7 feeds through to the M6 motorway and northerly destinations. The identification of the four profile classes had significance for the subsequent analysis in that it suggested that different models may be appropriate for particular OD pairs.

2.2 The Variance—Mean correlation in ANPR count data

The proposed method involved the use of neural networks to produce estimates of the OD matrices. The general Neural Networks approach holds an assumption of stationary in the data (as does the classical least squares method) to produce good results. When the data process is non-stationary, the NN learning approach does not hold well and a transformation of the input data is required in order to obtain the best results. A study was therefore undertaken of the relationship between the mean and variance of the ANPR input data in order to investigate if a transformation would improve the NN learning process and the results obtained. It is worth noting that if a data set obtained from sources other than ANPR for training were used, it would still be desirable to investigate stationarity properties in order to obtain the best results. When the variance increases with the mean, this is an indication of non-stationarity and it may then be useful to apply variance stabilization transformations[6-7]. The square root, logarithmic and inverse square root transformation for example, can be applied in the case of a linear, quadratic or cubic variance-mean relationship respectively.

In Table 3 and Figs.3 and 4, the correlation coefficient (indicated with RHO) and RMSE are given for each of the three transformations by OD pair. In each case a linear, quadratic or cubic model was produced of the relationship between the mean and variance and then the RHO or RMSE value calculated for the observed and predicted values from the model. The RMSE is given by

$$\sqrt{\sum_{i}(x_i - y_i)^2/n} \tag{2}$$

where x_i is the predicted value, y_i the observed value at time $t = i$, and n is the number of samples. As can be seen from Table 3 and Figs.3 and 4, the best performance is obtained using a linear relationship and only in a few cases (pairs 4-5, 4-7 and 5-7, and to a lesser extent 3a(40)-6) does the quadratic or cubic relationship appear to be a better transformation according to both the RMSE and RHO statistics. It is interesting to note from a practical perspective that these OD pairs are not characterized by high traffic demand values. In subsequent analysis, only the square root (SQRT) (for a linear relationship) and logarithmic (log) (for a quadratic relationship) were applied as there were few instances where a cubic transformation offered any additional benefit.

Table 3 RHO and RMSE for OD variance-mean relationship

	Correlation coefficient (RHO)			RMSE (divided by 1000)		
OD pair	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
3a(40)-4	0.825	0.796	0.728	1.111	1.188	1.346
3a(40)-5	0.753	0.654	0.522	0.399	0.459	0.518
3a(40)-6	0.746	0.753	0.691	3.615	3.570	3.920
3a(40)-7	0.813	0.782	0.711	21.745	23.290	26.265
3a(42)-4	0.723	0.637	0.518	1.1680	1.303	1.447
3a(42)-5	0.601	0.447	0.292	1.6582	1.856	1.984
3a(42)-6	0.800	0.780	0.699	13.837	14.427	16.468
3a(42)-7	0.6207	0.531	0.418	62.075	67.091	71.930
4-5	0.706	0.776	0.802	0.393	0.349	0.331
4-6	0.926	0.838	0.737	0.701	1.015	1.257
4-7	0.906	0.951	0.949	1.981	1.445	1.477
5-6	0.785	0.754	0.689	0.317	0.336	0.371
5-7	0.810	0.889	0.909	5.520	4.315	3.929
6-7	0.815	0.750	0.669	14.836	16.937	19.031

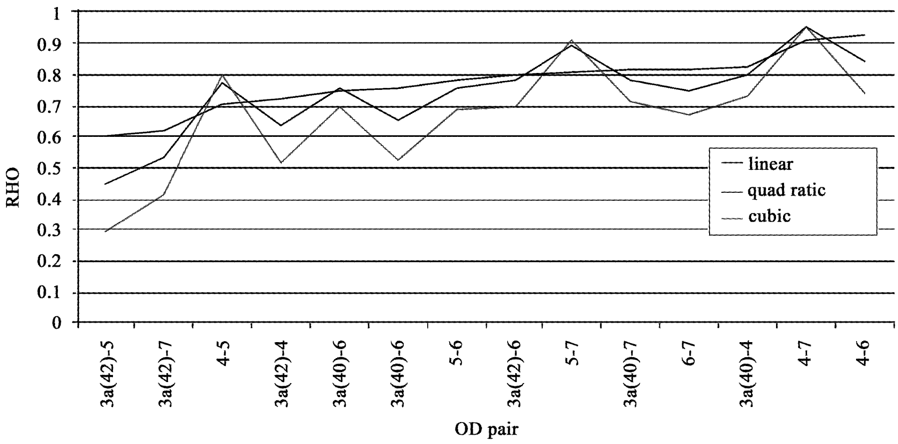


Fig.3　Correlation coefficient, RHO, for the variance-mean relationship of each OD pair

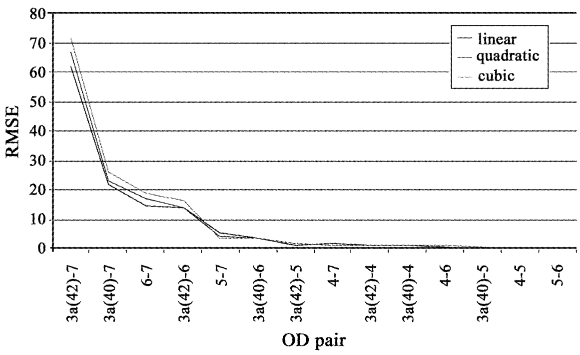


Fig.4　Root mean squared error (RMSE)/1000 for OD variance-mean relationship

3　OD estimation using MIDAS data

The general structure of the NN model used with the M42 data has one input layer (with a linear transfer function), one hidden layer (with a hyperbolic tangent sigmoid transfer function which has the form of $f(x) = \frac{2}{1+e^{-2x}} - 1$ and it is mapped in the interval $(-1, +1)$ and one output layer (with a linear transfer function). This structure is the result of many trials aimed at performing the best performance.

The type of NN model applied was a classical multilayer feed forward neural network with the Beale-Powell conjugate gradient back-propagation training algorithm to improve training performance with respect to the simple back-propagation[8]. The algorithm adjusts the weights in the steepest descent direction where the performance function decreases most rapidly. Although the function decreases most rapidly, this does not necessarily mean the fastest convergence to a solution. In the conjugate gradient algorithm, a search is performed along conjugate directions, which generally produces a faster convergence. The input vector consisted of the flow detected on links (MIDAS data) and the output vector was given by the OD pairs constructed from ANPR counts. The dataset was divided into three subsets (two fourth for the training and one fourth for the test and one fourth for the validation set). The test set is used to stop learning and the validation one to calculate the model error.

A large number of trials were carried out using different combinations of input and output vector dimensions, in order to explore and identify the best learning strategy with respect to overall performance. Note that the input and output vectors may have different dimensions according to the different strategies possible in utilising the data. An issue was whether to retain the MIDAS data for each lane or whether to aggregate across lanes and for a number of reasons, the individual lane data were retained. Single lane data are usually more effective in describing flow dynamics than data that have been totalled across lanes[9]. Furthermore, loops in one or possibly two of the three lanes at a particular detection point may not working, but if the requirement is for all three lanes to have data to produce an aggregated total, then the total amount of information available for use will be compromised. In general a great care on continuity of flow data was devoted when extracting the dataset.

Considering the possibilities for using different combinations of the data available, different sampling strategies were devised based on selection of particular lanes and links from the whole set (Table 4). The strategies were proposed to explore where the greatest information content in the data is and to provide a reflection of real conditions when potentially not all detectors are in working order. Obviously more strategies with a less regular step can be tested in order to better simulate real conditions but probably without adding further information. It must be stressed that flow on a link or even on a single lane of a link is functionally related to OD values and this provides the rationale behind the sampling strategy proposed by Table 4.

Table 4 Strategies for link data sampling

Strategy code	Sampling Strategy	Description
1	All links	All links
2	1:8	Every eighth link
3	1:15	Every fifteenth link
4	1:30	Every thirtieth link
5	Lane 3	Fast lane for all links
6	Lane 2	Middle lane for all links
7	Lane 1	Slow lane for all links
8	Ramp	All ramps

In the case of "All links" strategy, the input vector has a dimension of 103 and this requires an adequate number of training samples to achieve a better degree of statistical significance in the fit. Because some of the other strategies also had a high input vector dimension (relative to the number of samples), it was decided to apply PCA (principal component analysis) when more than 10 inputs (or links) were used for the model.

4 Modelling results

In addition to the RHO and RMSE statistics the GEH value is calculated as a means of comparing results, following the approach of Taylor et al[10]. The GEH value allows a relative independence of scale using the following formula:

$$\mathrm{GEH} = \sqrt{\frac{(x - y)^2}{(x + y)/2}} \tag{3}$$

where x and y are the predicted and observed data, respectively. Generally, a GEH value of 5 or less is considered acceptable and a target for model validation is that 85% of cases should have GEH < 5.

In Figs.5 and 6, the model performance according to RMSE and RMSE differences are presented. The latter gives the difference between the RMSE obtained when using the original training data and RMSE obtained when using the transformed training data. Positive values in Fig.6 indicate an improved performance achieved by the use of the transformation to achieve stationarity. On the horizontal axis is the OD pair code (from 1 to 14) and the sampling strategy code (from 1 to 8) are given in the format (OD code-strategy code) (see Table 2 for OD pair code).

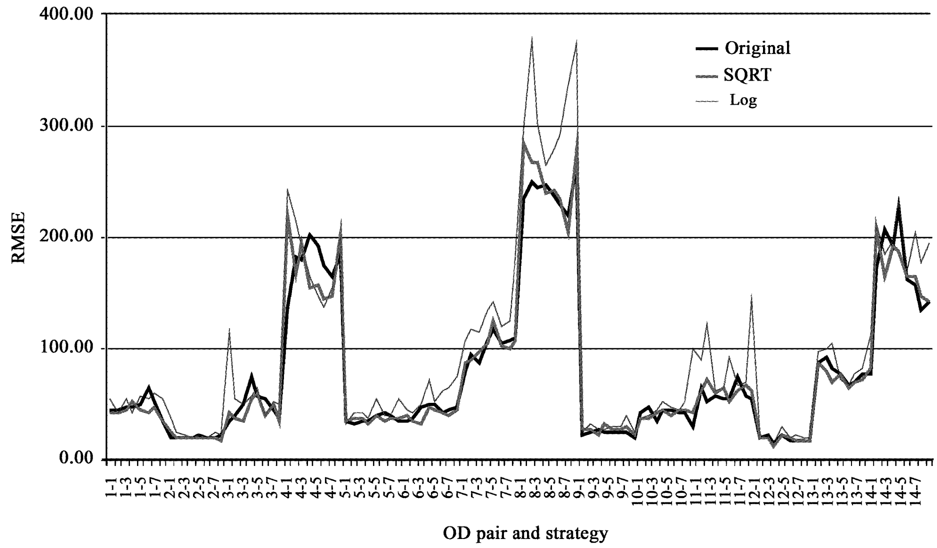


Fig.5 RMSE by transformation approach

The RMSE results from modelling individual OD pairs as the target output are given in Fig.5, indicating differences obtained using either a SQRT or Log transformation with the training data against RMSE values when the original data were used. This is clarified in Fig. 6 as calculated differences in RMSE. With the exception of some OD pairs originating at JN 3a(40), JN 3a(42) and JN 4, a transformation generally resulted in performance benefits. It is apparent that the SQRT transformation produces better results for almost all OD pairs and sampling strategies than the Log transformation. This was particularly the case for OD pair 8 (JN 3a(42) to JN 7) where a Log transform substantially worsened the performance. Similar findings were produced for the RHO statistic and so are not reproduced in detail here; however, it is worthy of noting that the RHO values were consistently greater than 0.7 and the average RO was calculated as 0.86, indicating strong all round performance.

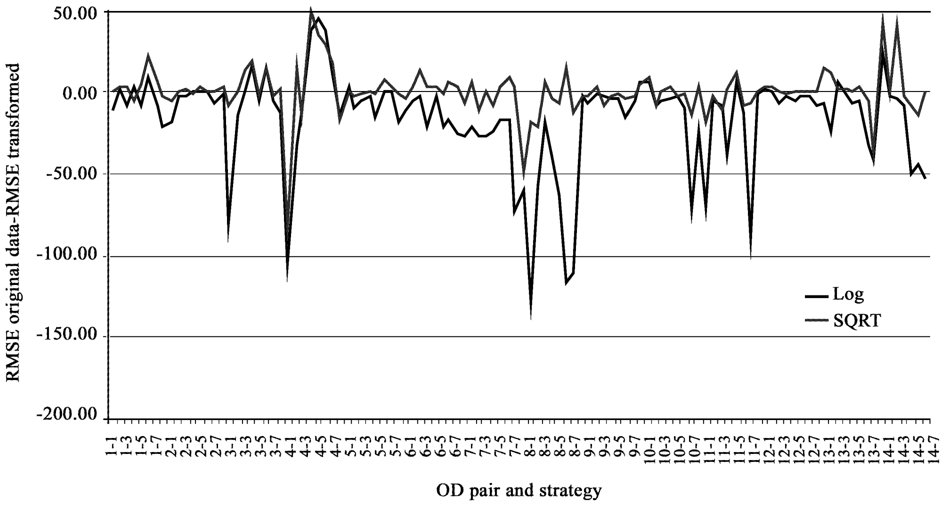


Fig.6 RMSE differences by transformation approach

The RMSE difference (Fig.6) does not consider the absolute value of the data and for this reason an evaluation in percentage terms was carried out. The ratio

$$\sqrt{\left[\sum_i \frac{1}{n} \frac{(x_i - y_i)^2}{y_i^2}\right]} \quad (4)$$

was calculated, which can be considered to be a percentage RMSE (RMSE%). For the individual OD model, the RMSE% was found to be never higher than 7%; the average value being 1.4%. The highest value of this statistic was found to be produced for OD pair 8 (JN 3a (42) to JN 7) whilst for other ODs, the RMSE% values are seen to increase in line with the increased standard deviation values in Table 2.

It can also be seen from Figs. 5 and 6 that:

• Applying a transformation to address non-stationarity can substantially improve performance for some OD pairs and offers modest improvements in the case of others. This is particularly true for OD pairs 4 and 14, both of which are of class 2 and characterised by high mean and standard deviation in ANPR counts;

• The best sampling strategy from those considered is to use the subset of lane 1 data as an input (strategy 7), with the second best strategies being to use either lane 3 (strategy 5) or lane 2 (strategy 6). This supports the use of a lane by lane analysis and may be as a result of lane 1 having consistent levels of demand regardless of traffic conditions;

• The 'All links' strategy generally produces the worst results compared with other strategies. This requires all detectors across all the lanes, whereby the data may be too heterogeneous to distinguish the target outputs.

Analysis based on the GEH statistic is reported in Fig.7 and from this it can be seen that the results are variable according to the OD pair, as was the case for the RMSE statistic. OD pairs 4, 8 and 14 (that have the highest standard deviation in the original data) have the worst GEH values. The other OD pairs indicate a good performance with the percentage of GEH≤5 always greater than 60% (and in many cases greater than 85%).

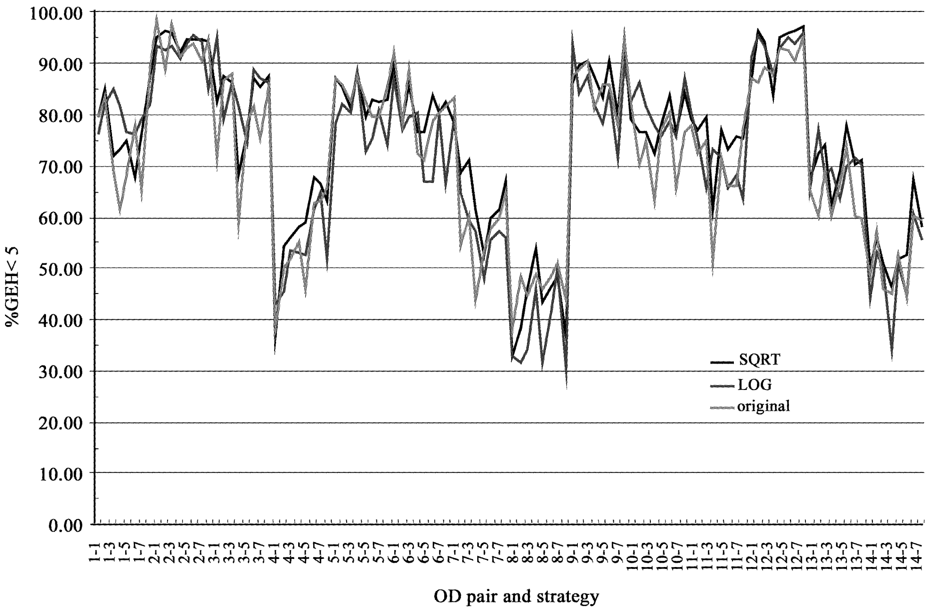


Fig.7 GEH statistics for individual OD model (% GEH values less than 5)

A SQRT transformation produces better GEH results than the alternatives of either no transform or a Log transform, though the latter performs better for some OD pairs and with particular data sampling strategies (for example OD pairs 10 and 13). Overall, however, the results support those reflected through the RMSE statistic.

5 Conclusions

A broad summary of the findings from this study is given below.

- A number of sampling strategies have been applied. In general it was found that where the model was intended to estimate individual ODs, a worse performance was found using all the data than using a more selective strategy, effectively based on one of the three lanes;
- The data used consisted of 14 ODs and it was possible through elementary data analysis to identify particular features of traffic demand, which resulted in four main OD types. The exact same patterns may not necessarily be observed if the method is applied with other data, but were an indication of the underlying variability in traffic flow levels. They also indicated that a model intended to simultaneously estimate all ODs may be less successful than one which attempted to estimate individual ODs;
- An investigation of the underlying stationarity properties of the training data (an assumption of the NN modelling process) revealed non-stationarity in most of the data. Two transformations were explored in detail, the square root transformation (SQRT) and Log transformation, with comparisons being drawn against the results obtained using the original, untransformed data. In general the results obtained using the SQRT transform outperformed those using either the original data or Log, although there were some notable exceptions to this.

Overall, the results indicate that the proposed method of using NN models for OD estimation achieved a good degree of success and shows considerable potential for further development and application. The results presented here have been achieved working with a considerable amount of missing or poor quality data and this reflects a realistic application of the methodology. For other sites, it is quite possible that the data may be more complete, offering the potential for a further improvement in results.

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