

Application of generalised regression neural networks in trip distribution modelling

Mohammad Rasouli and Hamid Nikraz

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Abstract

Trip distribution is the second step of the transport modelling process. Errors in this trip distribution step will propagate through the other stages of the transport modelling process and will affect the reliability of the model outputs. Therefore, finding a robust and efficient method for trip distribution has always been an objective of transport modellers. The problem of trip distribution is non-linear and complex. Neural networks (NNs) have been used effectively in different disciplines for solving non-linear problems. Accordingly, in this paper, a new NN model has been researched to estimate the distribution of the journey to work trips. This research is unique in two aspects: firstly, the training of the model was based on a generalised regression neural network (GRNN) algorithm, while the majority of previous studies have used a back-propagation (BP) algorithm. The advantage of the GRNN model over other feed-forward or feed-back neural network techniques is the simplicity and practicality of the model. The second unique aspect is that the input data for the GRNN model was based on land use data for each pair of zones and the corresponding distance between them, while the previous NN models used trip productions, trip attractions and the distance between a pair of zones as inputs. As a case study, the model was applied to the journey to work trips in the City of Mandurah in Western Australia. The results of the GRNN model were compared with the well-known doubly-constrained gravity model and the BP model.

INTRODUCTION

Neural network (NN) models were introduced as alternative methods to traditional modelling approaches, and have been increasingly used since the 1990s (Tillema, van Zuilekom & van Maarseveen 2006). The use of NN models has been researched for the prediction of trip distribution.

Previous studies show that the NN method has been used successfully to model commodity flows (Black 1995), inter-city passenger flows (Xie 2000) and work trip flows. Other researches indicated that the NN performance is not as good as the well-known gravity model (Mozolin, Thill & Lynn 2000). According to our review of the literature, the majority of previous studies utilised a back-propagation (BP) algorithm to solve the trip distribution problem. Most recent studies tried to improve the performance of neural networks by training the models with different training algorithms, such as the Levenberg-Marquardt (LM) algorithm or different activation functions (Yaldi, Taylor & Yue 2011).

Although the recent studies were able to improve the performance of the NN models, there have not been enough attempts to utilise other NN models such as the generalised regression neural network (GRNN). The advantage of GRNN models over other NN models is their ability to converge to the target data with only limited training data available. Also, the additional knowledge needed to develop and train the GRNN is relatively small and can be done without additional input by the user (Specht 1991). This makes the GRNN a very useful tool in practice. In this research, a GRNN model has been developed as a new approach and the performance of this model has been compared with back-propagation and gravity models. This study is unique in two aspects:

- The input data for the GRNN model was based on the land use data for each zone and the corresponding distance between a pair of zones, while the previous NN models used trip productions, trip attractions and the distance between a pair of zones as input into the model.
- The training of the model was based on a GRNN algorithm, while the previous studies used a BP algorithm.

As a case study, the new approach was applied to journey to work (JTW) trips for the Mandurah area in Western Australia. The 2006 JTW data set for the Mandurah area was sourced from the Australian Bureau of Statistics (ABS). Accordingly, three different models were developed: the GRNN, BP and gravity models. MATLAB¹ was used to train and develop the GRNN and BP models. The gravity model used in this research was based on the strategic transport model developed for the Mandurah and Peel Region in Western Australia with EMME software (Rasouli 2012).

Simple data normalisation, linear transformation, and statistical normalisation methods were used in this study for the input vectors. The root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) between the modelled output and target data for training and testing data sets were used as indicators of goodness-of-fit of the model estimates.

BACKGROUND

The application of neural networks in the transport modelling area is growing fast. The literature indicates that NNs have been used for driver behaviour simulation models, mode choice and trip distribution problems. *Table 1* summarises the major studies undertaken so far to estimate trip distribution by applying the NN technique. This table indicates that all the studies undertaken used trip production, trip attraction and distance between a pair of zones as the inputs to the NN model. BP was the main training algorithm used for the majority of studies undertaken, and RMSE was the main performance measurement used in the majority of research.

Black (1995) investigated the application of NNs for commodity flows. Black's model was developed the same as the gravity model, with trip production, trip attraction and distances between each pair of zones as inputs to the NN model. The model developed by Black was a back-propagation model with three layers (input, output and hidden layers). He compared the RMSE of the NN model with the gravity model for the data of commodity flows between nine regions. Based on this comparison, he demonstrated that the errors from the proposed NN model were as much as 50% lower than those from the gravity model.

Xie (2000) undertook an NN approach to model inter-city passenger flows. Xie extended the work undertaken by Black by using the same NN architecture. In this study, a back-propagation neural network model with a gradient descent search algorithm was used to predict monthly intercity Amtrak passenger flows between various stations in order to evaluate the model's predictive ability. According to the analysis, the application of neural networks to large data sets produced satisfactory performance results and the neural network model outperformed the fully-constrained gravity model in terms of RMSE for some volume groups.

Mozolin et al. (2000) researched the performance of NNs and doubly-constrained gravity models for the distribution of commuter trips. Their research indicated that the NN models performed better to fit the data, but their accuracy in predicting

1 <http://www.mathworks.com.au/>

Table 1
Application of neural networks for trip distribution estimation

Author	Date	Input Data	Network detail		
			Network Structure	Training	Performance
Black	1995	P, A, D	MLF	BP	RMSE
Xie	2000	P, A, D	MLF	BP	RMSE, R
Mozolin et al.	2000	P, A, D	MLF	BP	RMSE, AE
Tapkin	2004	P, A, D	Revised MLF	GD	RMSE
Tillema et al.	2006	P, A, D	NA	NA	RMSE
Yaldi et al.	2009	P, A, D	MLF	BP	RMSE, R
Yaldi et al.	2011	P, A, D	MLF	LM	R ²

Abbreviation definitions: P: Production, A: Attraction, D: Distance, MLF: Multi-Layer Feed-forward, BP: Back-propagation, RMSE: Root Mean Square Error, AE: Absolute Error, NA: Not Available, R: Correlation Coefficient R²: Coefficient of Determination, LM: Levenberg-Marquardt, GD: Gradient Descent.

the target data was not as good as the doubly-constrained models. They further claimed that the analysis undertaken proves that the accuracy of the NN models was poorer in comparison with that of doubly-constrained gravity models with the distance decay of exponential function format. They referred to different reasons for NN under-performance, including 'model non-transferability, insufficient ability to generalise, and reliance on sigmoid activation functions'.

In a study by Tapkin (2004), a recommended neural trip distribution model (NETDIM) was developed and its performance was compared with three different models, including the back-propagation network, modular neural network and unconstrained gravity model. The objective of this research was to demonstrate the performance of the three models by comparing their levels of prediction, rather than by comparing outputs of the models for a specific data set. RMSE has been used as an indicator for comparison of the levels of prediction of the models. The analysis undertaken indicated that NETDIM provided more accurate predictions than the modular approach, unconstrained gravity model and the back-propagation neural network.

Tillema et al. (2006) undertook a study to compare the results of the NN and the gravity model in predicting trip distribution. This study researched both synthetic data and real-world data. Calibration of the neural network and gravity models was based on different percentages of hold-out data. This research demonstrated that neural networks outperformed gravity models in both synthetic and real situations. The modelling results indicated that the gravity model only gives better results when

the model is very well calibrated. But in reality, with scarce data, neural networks showed their capabilities and outperformed the gravity model.

Yaldi et al. (2009) reported that in order to satisfy the production and attraction constraints in NN modelling, a linear activation function can be used in the output layer of the model. Their recommended model used simple data normalisation for the inputs of the NN. Their analysis proved that a validated NN model could perform the same as a doubly-constrained gravity model with a similar R². However, the error level of an NN model is still more than the gravity model in terms of the average RMSE.

In another study, Yaldi, Taylor and Yue (2011) used the Levenberg-Marquardt (LM) algorithm to improve the performance of NN models. They compared the results of the new model with standard back-propagation, Quickprop and variable learning rate (VLR) algorithms. Their research demonstrated that with the use of the LM algorithm, the testing performance of the NN model can be improved to the same level as the doubly-constrained gravity model.

A brief description of the neural network

The neural network is an artificial intelligence method that simulates the operation of the human brain (nerves and neurons). The NN approach was developed by Warren S. McCulloch and co-workers in the early 1940s (Haque & Sudhakar 2002). They developed simple neural networks to model simple logic functions.

Nowadays, neural networks are used for complex problems that do not have algorithmic solutions. In

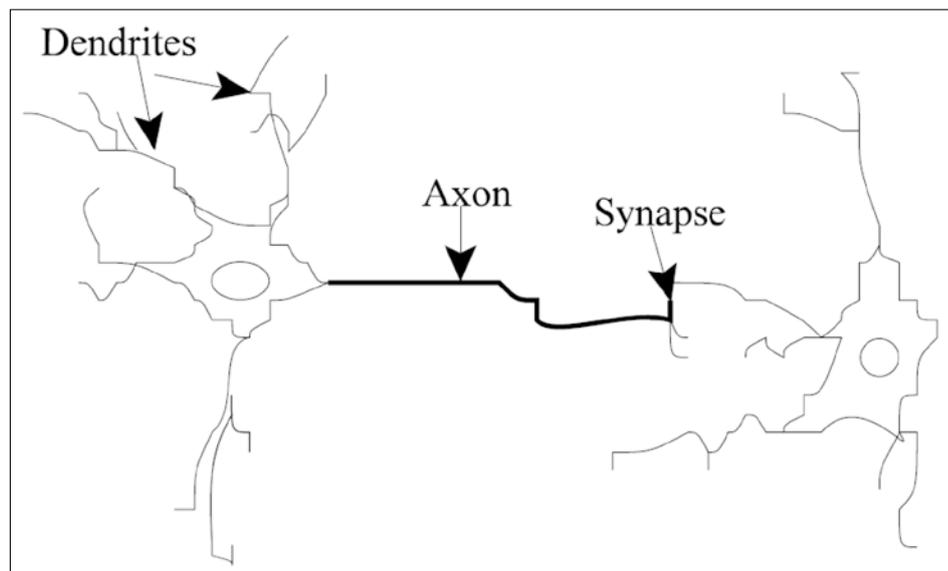


Figure 1
Natural neuron

other words, it is not easy to establish a mathematical model for problems with no clear relationship between the inputs and outputs of a system. To solve this sort of problem, the NN uses input samples and is trained to learn the relationship between the input and output data.

The ability of an NN to learn by samples makes this a very flexible and powerful tool. Accordingly, neural networks have been largely used for mapping regression and classification problems in many disciplines, and their usage is growing fast.

There have been a number of different NN models developed since McCulloch's first NN model. The differences in the NN models are related to the activation functions, the topology, the learning algorithms, etc. The back-propagation algorithm is one of the most common methods used in NN modelling, and many others are based on it. The GRNN is a feed-forward network. The advantage of a GRNN over the other NN models is simplicity and practicality of the GRNN. The required knowledge for a user to develop a GRNN model is relatively small. Another advantage of the GRNN is its ability to converge to the desired outcome with only limited training data.

Basic concept of neural networks

The artificial neural network (ANN) is a computational approach inspired by real neurons. Real neurons have synapses located on their dendrites or membrane to receive input signals (Figure 1). Once the received signal becomes strong enough (exceeds a certain threshold), it can activate the neuron, which then generates an output signal and transfers it through the axon of the neuron. The output signal can be received by other synapses,

which might activate other neurons successively (Gershenson 2003). Artificial neurons are highly abstracted models of complex real neurons. These neurons consist of three basic parts: inputs (as synapses), which are multiplied by weights corresponding to the strength of the signals; a mathematical function, determining the activation of the neuron; and an output layer (Figure 2).

The higher the weight of an artificial neuron, the stronger the input multiplication result will be. There are negative weights, so signal inhibition becomes possible. The computation inside each neuron is different, depending on its weight. Through adjustment of the weight of an artificial neuron, any desired output can be obtained for specific inputs. However, it would be quite difficult to manually determine all of the necessary weights in an ANN with hundreds or even thousands of artificial neurons. There are algorithms which can calculate the weights for an ANN in order to generate the desired output. This weight adjustment process is known as the learning or training procedure (Gershenson 2003).

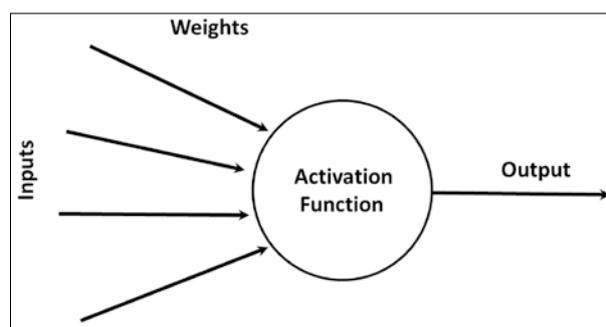


Figure 2
Artificial neuron (Gershenson 2003)

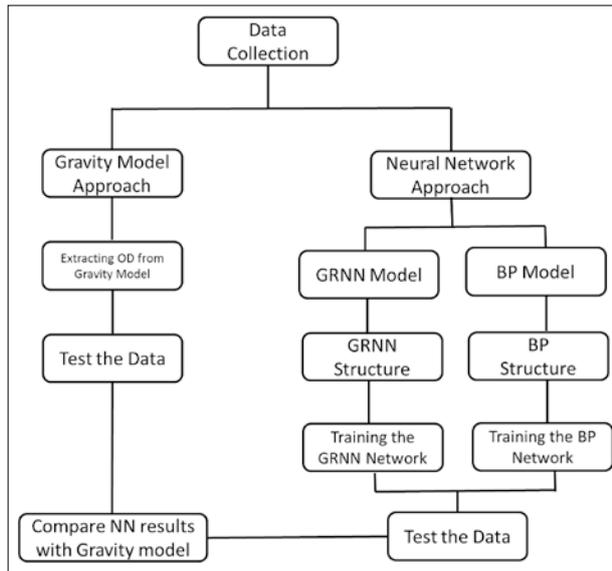


Figure 3
Model development and methodology

MODEL DEVELOPMENT AND METHODOLOGY

For the purposes of this research, three models were developed for estimation of the trip distribution. GRNN modelling is the new model, which is the focus of this research. The BP and gravity models are the other approaches. The results of the GRNN model have been compared with the BP and gravity model. The root mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R²) between the modelled output and measures of the training and testing data set have been used to compare the modelling results.

At the time of preparation of this paper, the 2011 JTW data was not available; hence, the 2006 JTW data was used. Taking into consideration that the strategic transport model for the Mandurah area was developed and calibrated for the year 2011, the 2011 JTW data was estimated from the 2006 data assuming the same travel pattern for the JTW in 2006. The model development and methodology is illustrated in Figure 3 and is discussed in the following sections.

GRNN model architecture

The input layer of the GRNN model is represented by land use data in each zone (Rasouli & Nikraz 2013), which is assigned to RD (residential dwellings), RE (retail), CO (commercial land use), SH (showroom) and SC (schools). In order to represent the spatial distribution of a pair of zones, the distance D_{ij} (metres) between zones i and j is also defined. Accordingly, the input vector (X_{ij}) is defined as:

$$X_{ij} = (RD_i, RE_i, CO_i, SH_i, SC_i, RD_j, RE_j, CO_j, SH_j, SC_j, D_{ij})$$

where i and j show the origin and destination, respectively.

Trips (T_{ij}) between a pair of zones are considered to be the output layer of the neural network. The GRNN has to be able to model the relationship between trips T_{ij} and the input vector X_{ij}. The model was developed to forecast the work trip. MATLAB R2011a was used to develop the network, where the optimum spread factor was selected through a trial and error process. Simple data normalisation, linear transformation and statistical normalisation methods were used in this study for the input vectors. Simple normalisation uses the following formula:

$$x_n = \frac{x_0}{x_{max}}$$

where:

- x_n = normalised input
- x₀ = each data input
- x_{max} = the maximum among all the data.

Linear transformation will convert the input data to the range [0, 1] with the following formula:

$$x_{(scaled)} = \frac{x_{(actual)} - x_{(min)}}{x_{max} - x_{min}}$$

where:

- x_(scaled) = normalised input
- x_(actual) = each data input
- x_{max} = the maximum among all the data
- x_{min} = the minimum among all data.

Statistical normalisation will convert the input data based on its mean and standard deviation using the following formula:

$$x_i = \frac{x_0 - x_{(mean)}}{SD}$$

where:

- x_i = normalised input
- x₀ = each data input
- x_(mean) = the mean value of all data
- SD = standard deviation of all data.

Table 2
GRNN modelling results for the training data set

Indicators	RMSE	MAE	R ²	Optimum Spread
Simple Normalisation	10	4	0.984	0.1
Linear Transformation	10	4	0.984	1
Statistical Normalisation	10	4	0.984	0.7

There are two kinds of input data sets in neural networks: the training data set and the testing data set. The training data set is used to calibrate the model parameters, while the testing data set is used to evaluate the forecasting ability of the model. For the purpose of this study, out of a total 440 vectors, which cover all the origins and destinations in the City of Mandurah, 90% (400 input vectors) were used for training and 10% were used for testing. The training data set was selected randomly, and because it contained 90% of the data, it would cover a wide range of work trip conditions in Mandurah. The remaining 41 vectors were checked to ensure that they also covered a different range of work trips (a few to a large number of trips between different pairs of zones). The process of random data selection for training and checking the testing data set was repeated a few times to insure that the testing data set represents a good sample of different trip conditions.

The testing data set was hold-out and was not used in the training process. This set of training data was used for BP and gravity modelling as well, to compare the results for one set of testing data. The RMSE, MAE and R² between the modelled output and measures of the training and testing data set were used to demonstrate the performance of the model according to the following equations:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^n (A_i - T_i)^2}$$

$$MAE = \frac{1}{N} \sum_{i=1}^n |A_i - T_i|$$

$$R^2 = \frac{\frac{1}{N} \sum_{i=1}^n (A_i - T)^2}{\frac{1}{N} \sum_{i=1}^n (T_i - T)^2}$$

where:

N = number of observations

T_i = observed value

A_i = predicted value

T = average value of the explained variable on N observations.

RMSE and MAE provide a general idea of the difference between the observed and predicted values and, therefore, are used as an indication of the residual errors. R² is the proportion of variability or sum of squares. When the RMSE and MAE are at a minimum, and R² is high (R² > 0.80), a model can be judged as very good (Kasabov 1998).

The training data set (400 vectors selected randomly) was used for training by the GRNN model and with different spread factors. *Table 2* summarises the modelling results for the training data set.

Analysis indicates that the GRNN model can produce the same results for different normalisation methods with different optimum spread factors as indicated in *Table 2*. Therefore, for simplicity, the simple normalisation method has been used for the testing data set. *Figure 4* illustrates the modelled T_{ij} through the training process against the observed data. The R² of 0.984 was obtained from the training process, which shows how well the network is trained.

The trained GRNN model was then used to test the 41 unused vectors. *Table 3* summarises the modelling results for the testing data set. *Table 3* indicates that the average RMSE for the tested data was 38.

BP model architecture

The input and output vectors to the BP model were kept the same as for the GRNN model. The standard network used for this study was a two-layer feed-forward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The number of hidden neurons was set to 10. The training algorithm was back-propagation based on a Levenberg-Marquardt minimisation method.

The initial set of data was divided into three subsets: training, validation and testing. For the purpose of

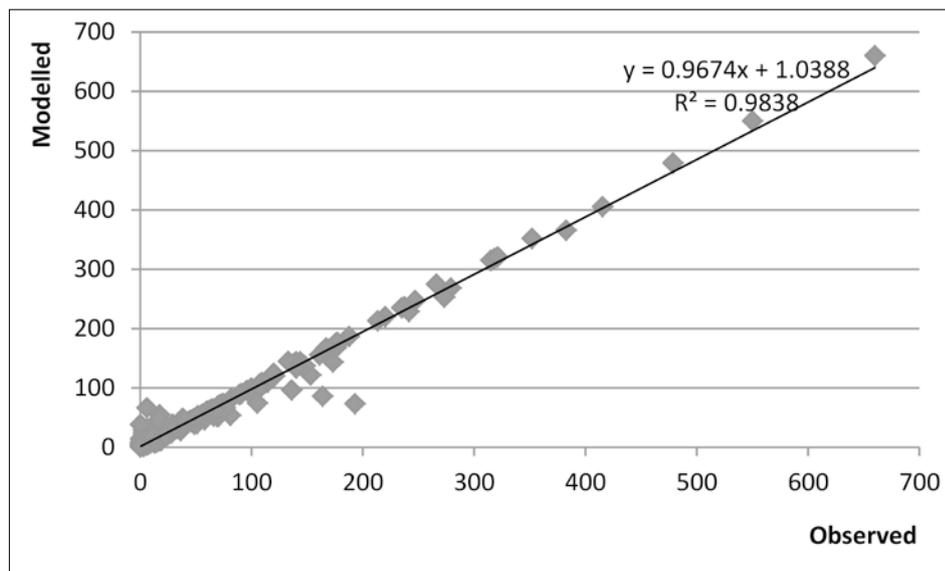


Figure 4
Modelled T_{ij} through the training process against the observed data

Table 3
GRNN modelling results for the testing data set

Indicators	RMSE	MAE	R ²
Simple Normalisation	38	22	0.575

Table 4
Performance of the BP model for different seeds

Seeds	Training data		Validation data		Testing data	
	RMSE	R ²	RMSE	R ²	RMSE	R ²
1	47	0.74	54	0.50	52	0.46
2	73	0.17	84	0.20	72	0.02
3	49	0.62	60	0.62	53	0.45
4	50	0.67	65	0.46	46	0.47
5	51	0.62	46	0.45	39	0.46
6	52	0.59	60	0.55	56	0.35
7	43	0.76	47	0.59	64	0.38
8	60	0.46	61	0.34	49	0.32
9	45	0.77	57	0.42	64	0.48
10	45	0.74	46	0.48	72	0.37

validation, 15% of the total 400 training data set was selected randomly. The testing data set was similar to the data set used in GRNN modelling. The testing vectors were not used in the training or validation process. Simple data normalisation was used for the input vectors. The BP network was trained with 10 different seeds and the performance of the training, validation and testing data sets is reported in *Table 4*.

According to the analysis of the different seeds, the reported R² for the training data set was between 0.17 and 0.77. The highest R² recorded was 0.77 for seed number 9. The corresponding R² for the validation and testing data was reported as 0.42 and 0.48. *Table 4* indicates that only in one case (seed number 2) was the BP model not well trained (i.e. very poor correlation for training), and subsequently produced poor validation and testing results.

Table 5
Performance of the BP model for different hidden layers

Hidden layers	Training data		Validation data		Testing data	
	RMSE	R ²	RMSE	R ²	RMSE	R ²
5	50	0.62	39	0.40	49	0.47
10	45	0.77	57	0.42	64	0.48
15	65	0.41	73	0.22	45	0.40
20	59	0.56	62	0.29	94	0.25

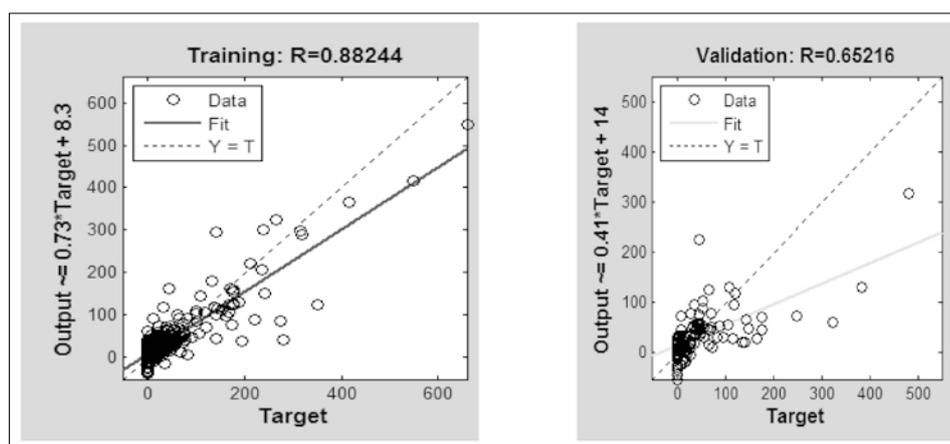


Figure 5
Reported R² for training and validation data sets for Seed Number 9 and 10 layers

The best training results are related to seed number 9 with an R² of 0.77 and RMSE of 45. Accordingly, better validation and testing results are also produced by seed number 9. The reported R² and RMSE for seed 9 are 0.48 and 64, respectively.

In order to investigate the impact of the different number of hidden layers on the performance of the BP model, different hidden layers were tested, with the performance of the model being reported in Table 5 for the various hidden layers.

Table 5 indicates that the best performance is related to the BP network with 10 hidden layers. Increasing the number of hidden layers to 15 or 20 did not improve the performance of the BP model. Figure 5 illustrates the BP model outputs against the actual trip distributions for the training and validation data sets for the preferred BP model structure with 10 hidden layers.

Gravity model structure

The strategic transport model for the Mandurah area is based on the traditional four-stage model process (trip generation, trip distribution, mode split and traffic assignment); however, the trip generation within this model considered only private vehicle trips and, therefore, the mode split stage was not adopted. The mode split was taken into

consideration when generating the trip production rates for the trip generation stage (Rasouli 2012). For the purpose of this study, the trips were divided into five different categories based on trip purpose: work, education, social, other and non-home based (NHB) trips. Trip distribution of the model was based on the doubly-constrained gravity model in the EMME software. The following gamma function was used to reflect deterrence in the gravity model:

$$W_{ij} = a * d_{ij}^{b * \exp(-c * d_{ij})}$$

where:

- W_{ij} = weight between zone i and zone j
- d_{ij} = distance between zone i and zone j.

Parameters a, b and c were calibrated for each trip purpose so that the model reflected the proportion of trips for each length, as observed in the travel surveys. Assignment of the trips was based on the fixed demand traffic assignment module in the EMME software. Calibration of the model was based on the existing traffic volumes on the road links. The actual traffic data was provided by the City of Mandurah. Figure 6 shows the modelled traffic volumes against the actual traffic counts. The R² for

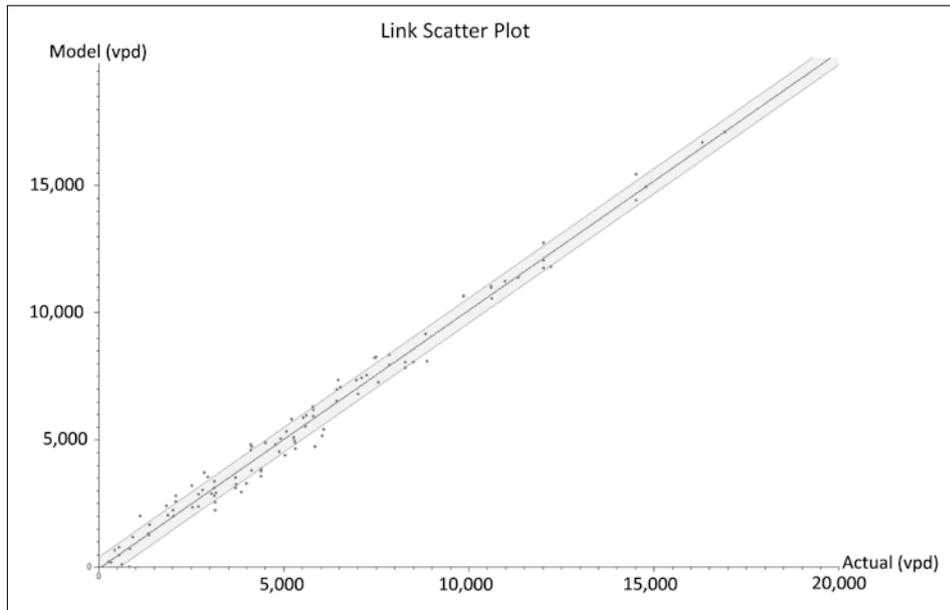


Figure 6
Regression plot, calibration of the base case (2011)

Table 6
Gravity modelling results

Indicators	RMSE	MAE	R ²
Gravity Model	50	23	0.59

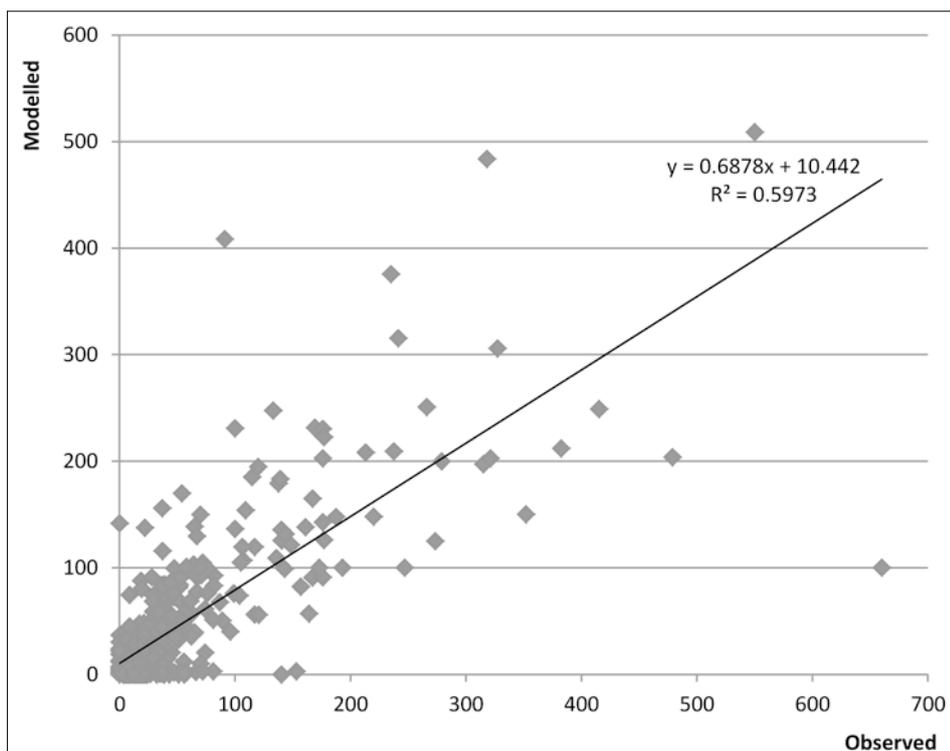


Figure 7
Observed and modelled work trips based on the gravity model

the 107 traffic count locations is 0.985, which shows how well the model is calibrated (Rasouli 2012).

The JTW origin-destination (OD) matrix was extracted from the Mandurah strategic transport model and compared with the 2011 JTW OD matrix obtained from the ABS data. The extracted

OD matrix for JTW from the gravity model was compared with the OD matrix from the ABS data. Table 6 summarises the modelling results for the gravity model.

Figure 7 illustrates the comparison between the trip distribution (T_{ij}) extracted from the gravity

Table 7
Gravity modelling results for the testing data set

Indicators	RMSE	MAE	R ²
Gravity Model	46	31	0.446

Table 8
GRNN, BP and Gravity modelling results for the testing data set

Indicators	RMSE	MAE	R ²	Regression parameter
GRNN Model	38	22	0.575	0.51
Gravity Model	46	31	0.446	0.63
BP Model	64	31	0.48	1.08

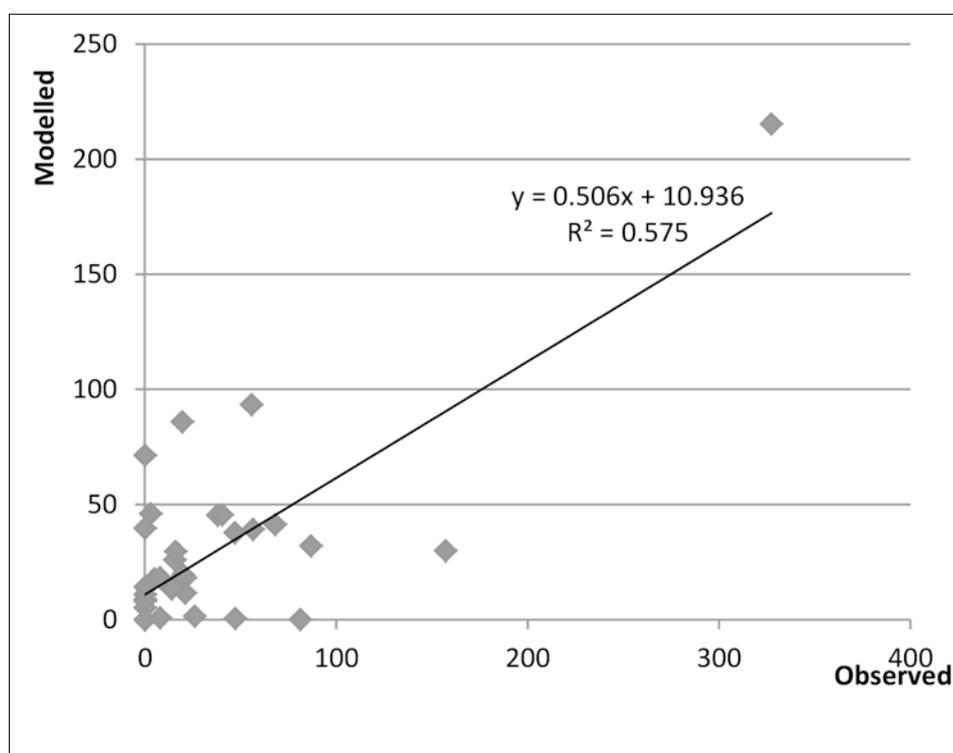


Figure 8
Modelled and observed T_{ij} for the testing data, GRNN model

model and the ABS data. The R² is reported as 0.59. According to the analysis undertaken, the average RMSE of the modelled trips is estimated to be 51.

The gravity model developed for the Mandurah area was then used to estimate the trip distribution of the testing data set used in the GRNN and BP models. Table 7 summarises the modelling results for the testing data set.

COMPARISON OF MODELS

In order to compare the performance of the GRNN, BP and gravity models, the tested data set was used to estimate the trip distribution based on the various models. The RMSE, MAE and R² indicators were

calculated for each model and are compared in Table 8.

Table 8 indicates that the GRNN model provides slightly better results than the BP and gravity models for all the performance indicators. However, the regression parameter value for the GRNN model is lower than that for the BP and gravity models, which means that the GRNN model would underestimate the observed value.

The R² of the BP model is slightly higher than that of the gravity model, while the reported RMSE for the BP model is higher than for the gravity model. The MAE for both the BP and gravity model is reported as 31. Therefore, it is expected that the BP

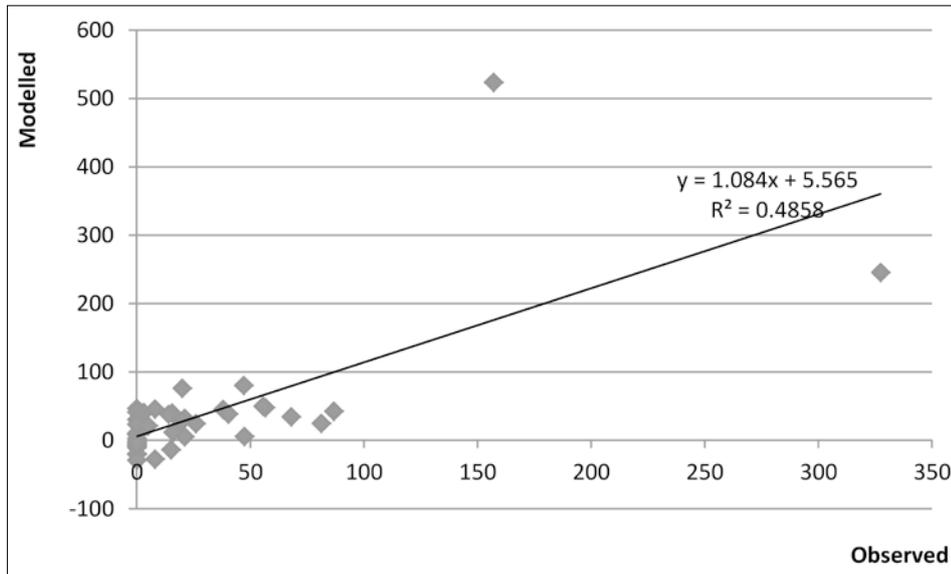


Figure 9
Modelled and observed T_{ij} for the testing data, BP model

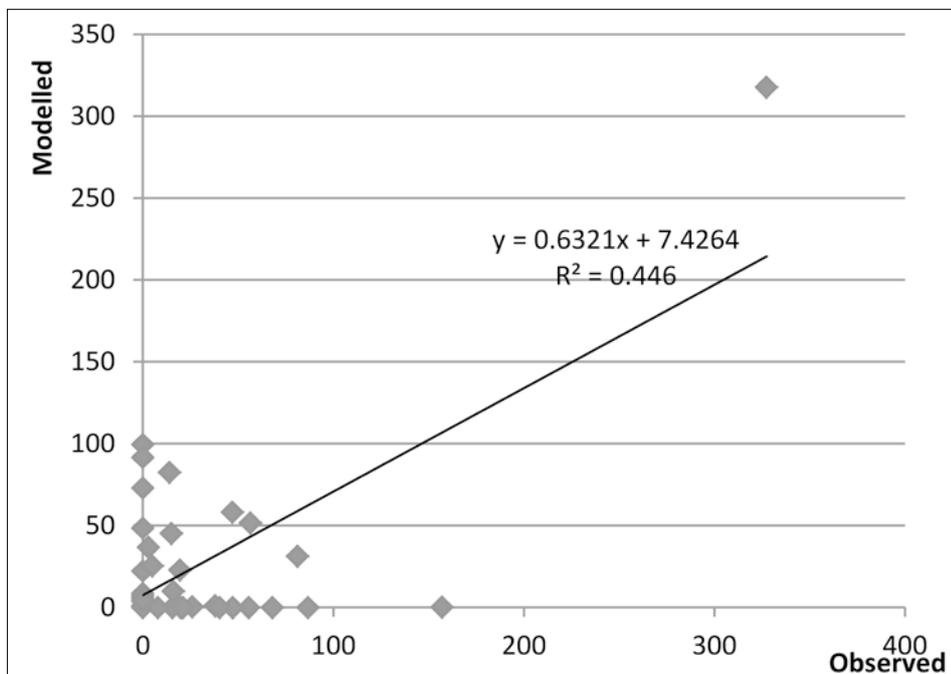


Figure 10
Modelled and observed T_{ij} for the testing data, Gravity model

and gravity models will perform the same. The BP model provides the closest regression parameter (x parameter) to 1, indicating that the modelled values match the observed values over the range of data.

Figures 8, 9 and 10 illustrate the modelled and observed T_{ij} for the testing data set for the GRNN, BP and gravity models, respectively. The distribution of points in these figures indicates that the majority of the points are clustered at low values, with one or two at much higher levels, which represent the variety of the work trip conditions in Mandurah. Therefore, the regression parameters (and thus the level of bias) are strongly dependent on these points.

CONCLUSION AND RECOMMENDATIONS

In this paper, a generalised regression neural network (GRNN) model was developed as a new approach, and the performance of this model was compared with the back-propagation and gravity models. The modelling and analysis undertaken indicate that:

- The neural network (NN) models can be used to forecast trip distribution directly from the land use data for each pair of traffic zones, instead of production and attraction for each pair of zones.
- The modelling results indicated that a validated GRNN model could provide a slightly lower

error level than the BP and gravity models, as indicated by the average root mean square error (RMSE); however, it might underestimate the observed values compared with the BP and gravity models.

Despite the efforts devoted to analysing all of the approaches discussed in this paper, there are major areas that still need to be researched. The following recommendations are put forward for future studies:

- The GRNN outputs rely heavily on the amount of data available and the variety of the training data set vectors. The greater the number of input vectors in the training data set, the more accurate the results in the output vector. Therefore, it is recommended that the efficiency of the GRNN model be tested and improved with a larger data set if available.
- The GRNN model needs to be tested with trip generation, trip attraction, and the distance between pairs of zones as inputs to the model, instead of the land use data, and be compared with the gravity and BP models.

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**Mohammad Rasouli**

Mohammad is a Chartered Professional Engineer (CPEng) with a first degree in Civil Engineering and a Master of Science (Hons) degree in Transportation Engineering. He is currently undertaking PhD research work at Curtin University, WA. Mohammad has gained invaluable experience across a wide variety of projects including transportation modelling, traffic engineering and impact assessment for clients in Western Australia and abroad. He has developed strategic transport models for a number of regions of Western Australia including major parts of the metropolitan area, Peel region, Busselton, Karratha and Port Headland/ South Headland. These models have been used successfully by local governments and a range of private sector organisations. Mohammad has substantial experience in transport modelling using both strategic transport modelling platforms such as EMME and VISUM and micro simulation platforms including PARAMICS and VISSIM Models. Mohammad is also able to assess the outputs of the models using SYNCHRO and SIDRA intersection analysis software.

**Hamid Nikraz**

Prof. Hamid Nikraz is Head of the Department of Civil Engineering, Curtin University and has particular expertise in pavement materials and soil stabilisation techniques. Prof. Nikraz has made efforts to attract the highest quality students to achieve strategic R&D initiatives. This currently includes leading 10 research teams with a total of 78 research students and research fellows. He is recognised as an authority in the sustainable use of industrial by-products in geotechnical, pavement and geopolymer concrete engineering, spanning research interests in Geomechanics, Soil Stabilisation, Pavement Design and Construction, and Waste Management. The outcomes of his research and that of the students and research staffs under his supervision have led to the publication of five book chapters, 90 papers in international refereed journals, 300 papers in refereed conference proceedings, and many reports for industry.

CONTACT

Mohammad Rasouli
Senior Traffic & Transport Engineer/Modeller
Transcore
61 York Street, Subiaco WA 6008
PO Box 42, Subiaco WA 6904
Tel: 08 9382 4199
Email: mrasouli@transcore.net.au