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Trip Distribution Modelling Using Neural Network

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ABSTRACT

Trip distribution is the second important stage in the 4-step travel demand forecasting. The purpose of the trip distribution forecasting is to estimate the trip linkages or interactions between traffic zones for trip makers. The problem of trip distribution is of non-linear nature and Neural Networks (NN) are well suited for addressing the non-linear problems. This fact supports the use of artificial neural networks for trip distribution problem. In this study a new approach based on the Generalised Regression Neural Network (GRNN) has been researched to estimate the distribution of the journey to work trips. The advantage of GRNN models among other feed-forward or feedback neural network techniques is the simplicity and practicality of these models. As a case study the model was applied to the journey to work trips in City of Mandurah in WA. Keeping in view the gravity model, the GRNN model structure has been developed. The inputs for the GRNN model are kept same as that of the gravity model. Accordingly the inputs to the GRNN model is in the form of a vector consist of land use data for the origin and destination zones and the corresponding distance between the zones. The previous studies generally used trip generations and attractions as the inputs to the NN model while this study tried to estimate the trip distribution based on the land uses. For the purpose of comparison, gravity model was used as the traditional method of trip distribution. The modelling analysis indicated that the GRNN modelling could provide slightly better results than the Gravity model with higher correlation coefficient and less root mean square error and could be improved if the size of the training data set is increased.

Keywords:

Trip Distribution, Neural Network, Generalised Regression Neural Network, Gravity Model.

1 INTRODUCTION

Conventional transport modelling, known as 4-step modelling is highly depending on the input data used in different modelling steps. The trip distribution process is relatively complex in nature and difficult to model without adequate amounts of data. Errors that are generated during the trip distribution stage, distribute through the other stages of modelling which in turn affects the reliability of the modelling results. Therefore it is important to ensure that the trip distribution techniques are able to estimate accurate results.

A robust and efficient technique to estimate the trip distribution is always an essential part of the modelling process. There is no technique in trip distribution that is universally applicable, so attempts to develop alternative techniques are always needed. This includes the utilisation of approaches from other disciplines. Neural Networks are one of them and are proposed as an alternative method in this study. The problem of trip distribution is of non-linear nature and complex. Neural networks have been used successfully for solving the non-linear problems. This fact supports the use of artificial neural networks for trip distribution problem.

Since the beginning of nineties, neural network models were introduced as alternatives for traditional modelling approaches. The previous studies suggest that the NN approach is able to model the commodity, migration and work trip flows. However, its performance is not as good as the well-known gravity model. According to the literature review, the majority of the previous studies utilised the standard Back Propagation (BP) algorithm and there have not been enough attempts to utilise the GRNN approach. The knowledge required to develop the GRNN structure is relatively small and can be done without additional input by the user. This makes GRNN a very powerful tool in practice. This research aims to apply the GRNN model to test the ability of the neural network in prediction of the trip distribution problem. One of the differences in this approach with the previous studies is the use of land use data as an input to the NN model instead of using the trip generation and attraction. There is direct relation between the land use data and trip distribution between different land uses in a modeled area. Sometimes estimation of trip productions and attractions from the land use data involves simplistic assumptions that generate errors in the trip production and attraction stage. This error would distribute to the other stages of the modeling process including trip distribution stage which in turn affects the

reliability of the modeling results. Therefore estimation of the trip distribution directly from the land use data would remove the errors related to the trip production and attraction stage. This study also compares the GRNN approach with the gravity model and documents the outcomes of this comparison.

2 BACKGROUND

The use of NN is growing fast and covers many disciplines, including transport modelling. The literature indicates that NN were used in some 13 areas of transport modelling studies up to year 1990 where driver behaviour simulation models had the highest usage of NN applications (Dougherty, 1995). However, more recent research indicates a growing application of NN in travel demand modelling, mostly by Mode Choice and Trip Distribution problems.

It must be noted that the NN approach must be followed by logic and sensible theory, otherwise NN is just a naive tool. According to Black (1995), NN is an intelligent computer system that simulates the processing capabilities of the human brain. It is a forecasting method that generates output by minimizing an error calculated by the deviation between input and output through the use of a complex training process (Black, 1995; Zhang et al, 1998).

Various studies in transportation modelling prove the advantages and disadvantages of using NN. It is usually compared with the existing methods in relevant studies. For example, the neural network has been compared with the Discrete Choice Model as reported by Cantarella & de Luca (2005), Hensher & Ton (2000), Carvalho et al. (1998), and Subba Rao et al. (1998). Reviewing the literature indicates that there is less application of NN in trip distribution problem compared to mode choice studies. Black (1995) investigated the spatial interaction modelling using NN focusing on commodity flows. This model was structured similarly to the gravity model. Mozolin et al. (2000) utilised NN to model trip distribution for passenger flow modelling. The studies by Black and Mozolin et al. were based on multilayer perceptron neural networks.

NN is recognised by its important characters, such as learning algorithm, activation function, number of layers (input, hidden and output), number of nodes inside each layer, and learning rate (Teodorovic and Vukadinovic, 1998, Dougherty, 1995). The amount of data and the split of the

data which is used for training, validating and testing purpose are also essential for NN performance (Carvalho et al., 1998). Zhang et al. (1998) suggested that if there is not any appropriate guideline then NN model can only be developed through trial and error procedures. There is also a lack of reported researches on the behaviour of NN with respect to these properties. Lack of knowledge in structuring the main properties of NN could lead to disadvantages in using NN models, for example if the modeller is not able to enforce the network to simulate according to the existing constraints. This problem has happened in the study by Mozolin et al (2000). They reported that NN was not able to meet the double constraints and they provided adjustment factors for the output of the NN model so that the model satisfied the Production and Attraction constraints. They also reported that NN had slightly poor generalization capability. Although this was not comprehensively reported, Black (1995) provided a small report about this issue in commodity flow estimation using NN. It was not clearly reported if the model can properly satisfy the constraints.

Accordingly a number of different studies were undertaken to improve the ability of the NN to satisfy the production and attraction constraints. Gusri Yaldi, M A P Taylor and Wen Long Yue (2009) reported that a NN with simple data normalization and a linear activation function (Purelin) in the output layer could satisfy the two constraints, with average correlation coefficients (r) of 0.958 and 0.997 for Production and Attraction respectively. The test results of their research also proved that a validated NN could generate a similar goodness of fit as a doubly-constrained gravity model. However, the error level is still more than the gravity model as indicated by the average Root Mean Square Error (RMSE), where the RMSE for the NN and gravity model are reported 181 and 174 respectively.

In another research they tried to fix the testing performance of NN by training the models with the Levenberg-Marquardt (LM) algorithm, while the previous studies used standard Back propagation (BP), Quickprop and Variable Learning Rate (VLR) algorithms. The main difference between those algorithms is the method used in defining the optimum connection weights. The research results suggest that the RMSE are 168, 152 and 125 for model trained with BP, VLR and LM respectively, while the R^2 values are 0.194, 0.315, 0.505. The models trained by BP and VLR have underestimated the forecasted total trip numbers, while the LM algorithm

has slightly higher numbers. The research concluded that the testing performance of NN approach can be improved to the same level as doubly constrained gravity model when the model is trained by LM algorithm.

Fischer and Leung (1998) developed different models of NN by the use of different learning algorithms, and in conjunction with Genetic Algorithm (GA), to forecast traffic flows in a region in Australia. They found that GA can improve the NN modelling results.

3 A BRIEF DESCRIPTION OF NEURAL NETWORK

Neural Network is an artificial intelligence method that simulate the operation of the human brain (nerves and neurons), and consist of number of interconnected computer processors that perform simultaneously in parallel. NN was founded by McCulloch and co-workers in the early 1940s (Haque ME, Sudhakar KV, 2002). They developed simple neural networks to model simple logic functions.

Nowadays, neural networks are used for problems that do not have algorithmic solutions or problems that algorithmic solutions are too complex to be developed. In other words, it is not easy to establish a mathematical model for problems that with no clear relationship between inputs and outputs. To solve this sort of problems, NN uses the samples and will be trained to learn the relationship of such systems. The ability of NN to learn by samples makes them very flexible and powerful. Therefore, neural networks have been largely used for mapping regression and classification problems in many disciplines. In short, neural networks are nonlinear algorithms that perform learning and classification.

In general, neural networks are adjusted/ trained to reach from a particular input to a desired output. Therefore the neural network can learn the system. This type of learning is called supervised learning. The learning ability of a neural network depends on its structure and the training algorithm. Training algorithm can be stopped if the difference between the network output and actual output is less than a certain tolerance value. When the NN was learned, the network is then ready to estimate outputs based on the new inputs that are not used in the training data set. A neural network is usually consisting of three parts: the input layer, the hidden layer

and the output layer. The information saved in the input layer is transferred to the output layers through the hidden layers. Each unit can transfer its output to the units on the higher layer only and receive its input from the lower layer.

3.1 Generalised Regression Neural network

The Generalised Regression Neural Network (GRNN) is a feed-forward network. The use of a GRNN is especially helpful because it has the ability to converge to the desired outcome with only few training data available. The additional knowledge required to train the network and develop the NN structure is relatively small and can be done without additional input by the user. This makes GRNN a very powerful tool in practice.

The fundamentals of the GRNN can be found from Specht, (1991); Nadaraya–Watson kernel regression (1964), Tsoukalas and Uhrig (1997), also Schioler and Hartmann (1999). A schematic structure of the GRNN is illustrated in **figure 1**. A GRNN does not require an iterative training procedure. It can estimate any non-linear function between input and output vectors, learning the relationship between the input and output data directly from the training data. Furthermore, it is found that if the training set size becomes large, the estimation error approaches zero, with minimum restrictions on the function. The GRNN is used to predict the continuous variables as in standard regression methods.

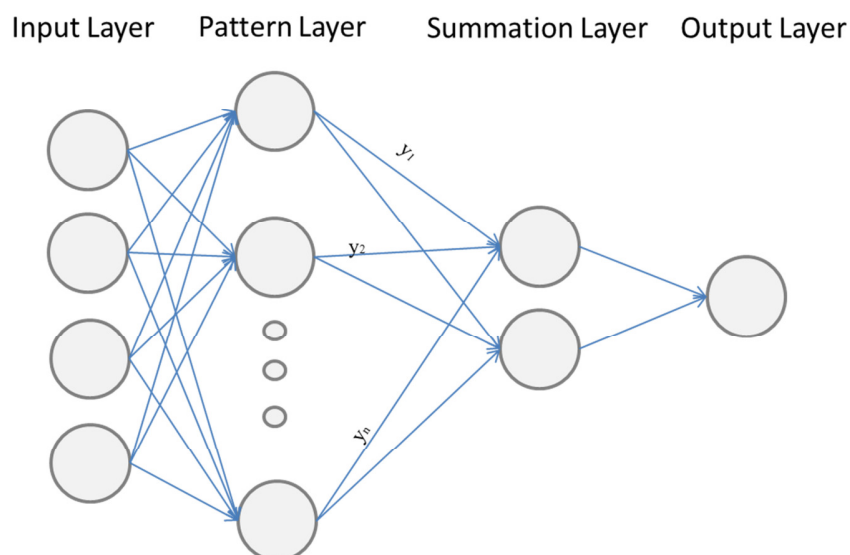


Figure 1: Schematic structure of GRNN

The GRNN consist of four layers: Input layer, pattern layer, summation layer, and output layer. The total number of parameters is identical to the number of input units in the input layer. The first layer is connected to the second, pattern layer. In pattern layer, each unit represents a training pattern, and its output calculates the distance between the input and the stored patterns. Each pattern layer unit is joined to the two neurons in the summation layer: S- summation neuron and D- summation neuron. Here, the sum of the weighted outputs of the pattern layer is measured by the summation and the un-weighted output of the pattern neurons is calculated by the D-summation. The linkage weight between the S-summation neuron and the i th neuron in the pattern layer is called y_i ; the target output value joint to the i th input pattern. The output layer just splits the output of each S-summation neuron by the output of each D-summation neuron, providing the predicted value to an unknown input vector x as:

$$y_i(x) = \frac{\sum_{i=1}^n y_i \exp[-D(x, x_i)]}{\sum_{i=1}^n \exp[-D(x, x_i)]}$$

In which the number of training patterns is specified by n and the Gaussian D function is calculated as:

$$D(x, x_i) = \sum_{j=1}^p \left(\frac{x_j - x_{ij}}{\delta} \right)^2$$

In which p represents the number of element of an input vector. The x_j and x_{ij} show the j th element of x and x_i , respectively. The δ is generally known as the spread factor, whose optimal value is often calculated experimentally for the problems. If the spread factor becomes larger, the function approximation will be smoother. If spread factor is too large, then a lot of neurons will involve fitting a fast changing function. If the spread factor is small then many neurons will be required to fit a smooth function, and the network may not generalize well.

4 MODEL DEVELOPMENT AND METHODOLOGY

The model development and methodology is illustrated in **Figure 2** and is described in the following sections.

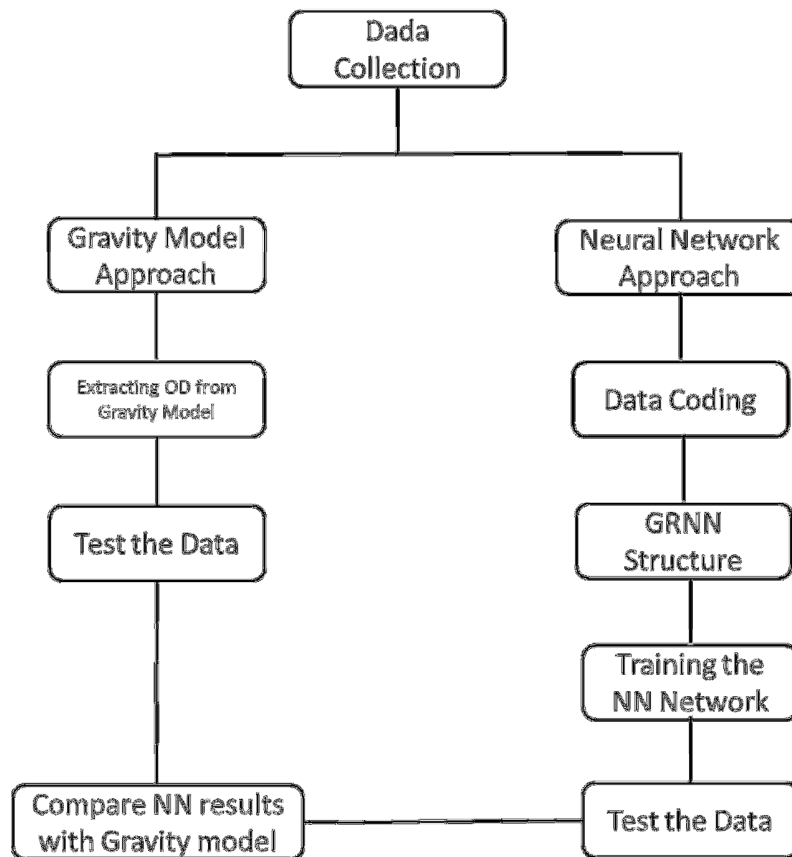


Figure 2: Model Development and Methodology

5 DATA COLLECTION

The 2006 Journey to Work dataset for the Mandurah Area in Perth WA was sourced from Australian Bureau of Statistics (ABS). Journey to Work (JTW) data are extracted from the five-yearly Census of Population and Housing conducted by the Australian Bureau of Statistics. It includes data on employment by industry and occupation, and method of travel to work at a small geographical level known as the travel zone.

At the time of preparation of this paper the 2011 JTW data was not available and therefore the 2006 JTW data was used. Considering that the strategic transport model for Mandurah area was

developed and calibrated for year 2011, then the 2011 JTW data was estimated from the 2006 data assuming the same travel pattern for the JTW in 2006.

6 O-D MATRIX ESTIMATION USING GRAVITY MODEL

6.1 Mandurah strategic transport model

Due to significant growth in recent years and anticipated future growth the City of Mandurah is faced with a number of challenges with planning and managing its movement network and transport system particularly within the City Centre. The City has ambitious plans for the future to deliver an attractive, dynamic and vibrant City. These plans will generate significant transport demand which will put pressure on the existing transport infrastructure and systems, particularly the road network within the City Centre.

In order to assist with its decision-making process, the City has engaged Transcore Pty Ltd to develop a strategic transport model for the greater Mandurah area. The strategic transport model will assist the City in establishing the future transport demand and test the impact of land use growth, major developments and road network options.

The modelled study area entails the Inner Peel Region including Mandurah, Pinjarra and Yunderup. The number of residential dwellings for the City of Mandurah was calculated for the 38 individual modelling zones as per **Figure 3**. According to the Australian Bureau of Statistics census results for 2011 the total number of dwellings in Mandurah is estimated to be about 35,372 with about 69,903 people residing in the municipality.

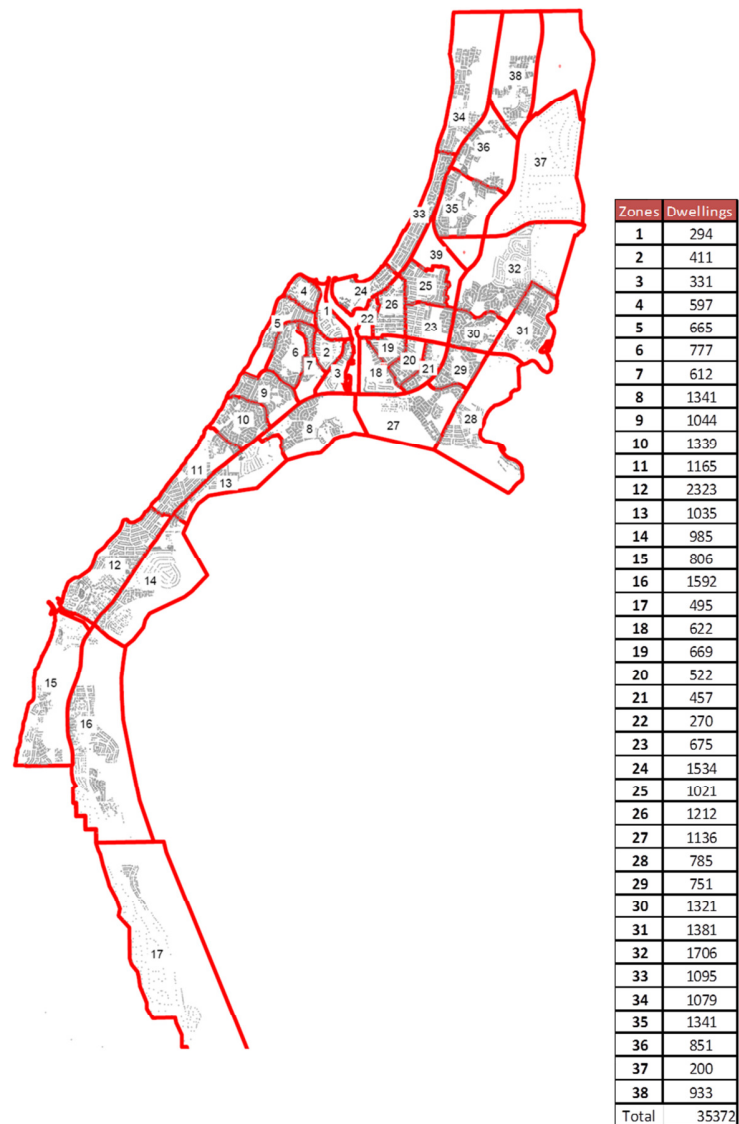


Figure 3: Mandurah Model Area and Zoning System

6.2 Model Structure

The traffic model 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. For the purpose of this study the trips were divided into 5 different categories based on the trip purposes: Work, Education, Social, Other and Non Home Based (NHB) trips.

Trips internal to the modelling area have been distributed based on the following gamma function:

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

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 reflects 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 EMME software.

Calibration of the model was based on the existing traffic volumes on the road links. The actual traffic data was provided by City of Mandurah. **Figure 4** shows the modelled traffic volumes against the actual traffic counts. The linear regression analysis for the 107 traffic count locations indicates that R^2 of the regression plot is 0.985 which shows how well the model is calibrated.

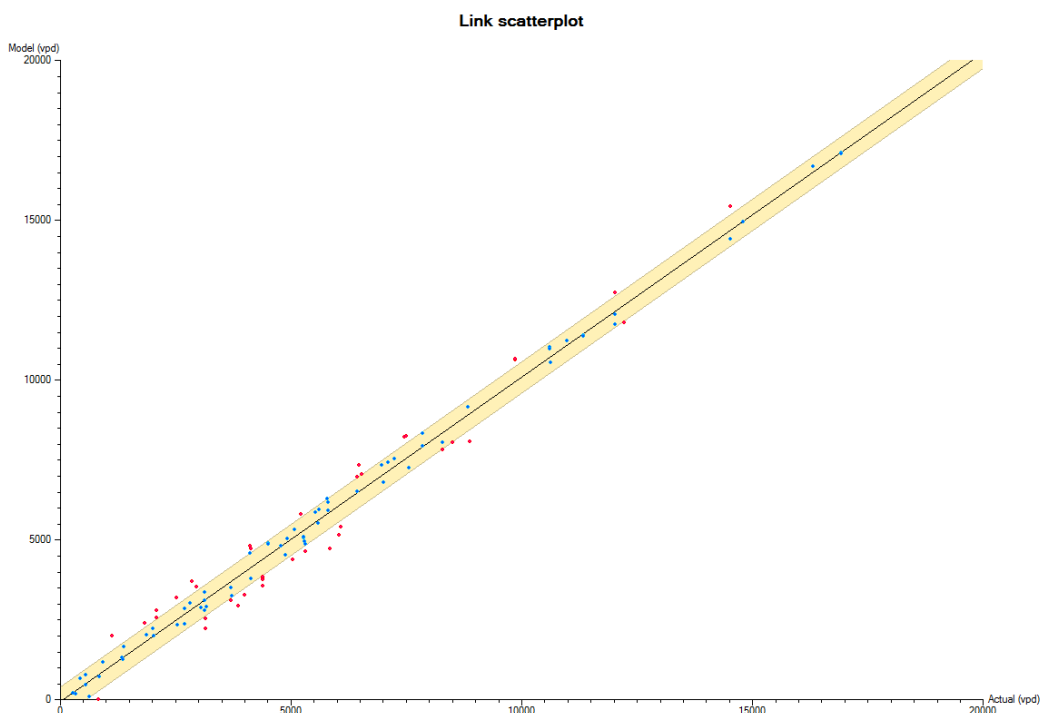


Figure 4: Regression Plot, Calibration of the Base Case (2011)

6.3 Extracting and comparing the journey to work OD matrix from Gravity Model

The journey to work OD matrix was extracted from the Mandurah strategic transport model and compared with the 2011 JTW OD matrix obtained from the ABS data. The R^2 for the trend line in Figure 5 is 0.59. According to the analysis undertaken the average Root Mean Square Error (RMSE) of the modelled trips were estimated to be 51.

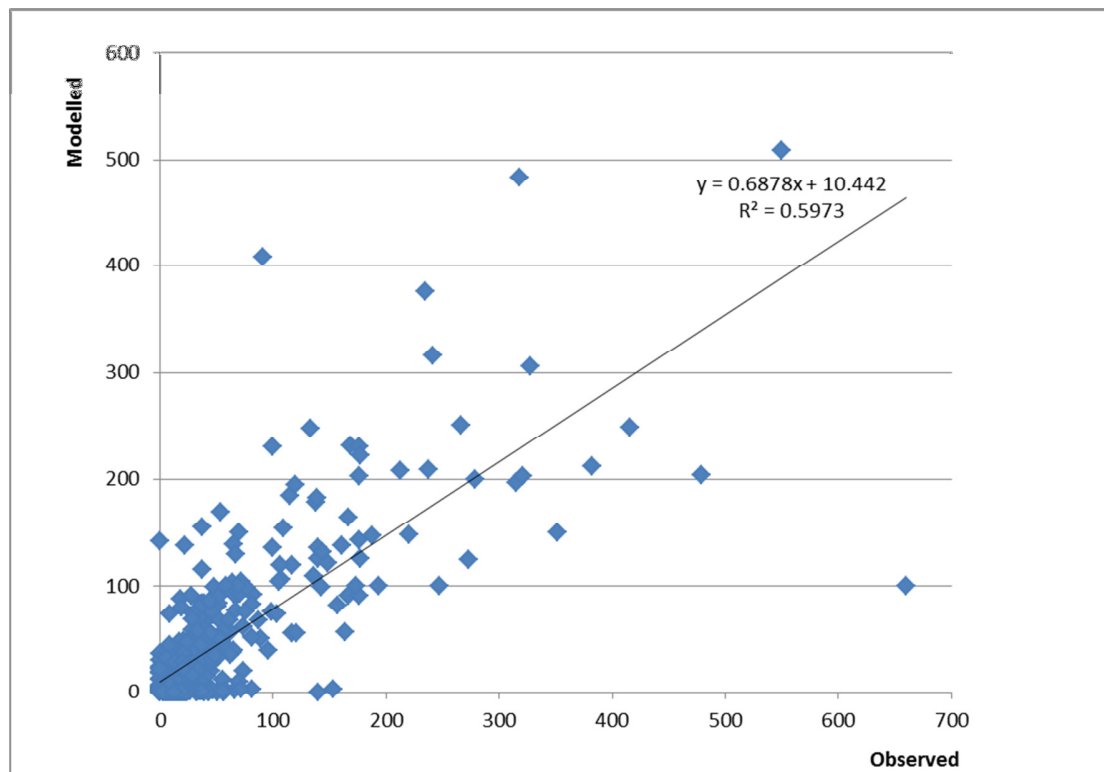


Figure 5: Observed and Modelled work Trips Base on Gravity Model

7 O-D MATRIX ESTIMATION USING NEURAL NETWORK

7.1 Neural Network Model Architecture

People's activities can be represented by land uses scattered on different zones that are separated by distance in an area. Therefore, trip distribution relates to the land use patterns in different zones inside that area. For instance, one zone which is typically occupied by residential land use patterns generates trips that are attracted to another zone which is formed by retail, industrial, commercial, etc.

On this basis the input layer of the neural network is represented by land use data in each zone, 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} (meters) between zones i and j is defined. Accordingly the input vector (X) 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 shows the origin and destination, respectively.

Trips (T_{ij}) between a pair of zones are considered as the output layer of the neural network. The GRNN has to be able to model the relation between trips T_{ij} and input vector X_{ij} . The model is developed to forecast the work trip. MATLAB R2011a is used to develop the network where the optimum spread factor was selected through try and error process. The model structure used in MATLAB software is illustrated by **Figure 6**. It has 11 input nodes representing the land uses for zone i and zone j , and distance between zone i and j (as defined in the above X_{ij} input vector). There is one node in the output layer which represents the estimated trip number (T_{ij}).

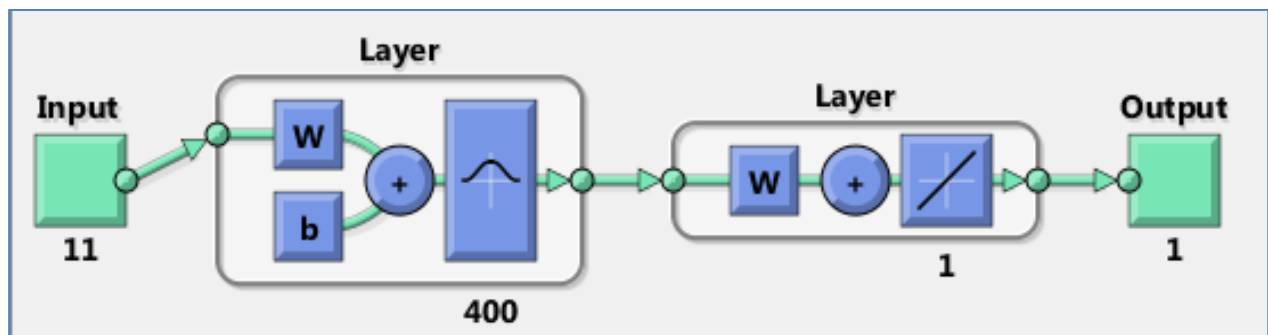


Figure 6: GRNN Model Structure Used in MATLAB Software

Simple data normalization method is used in this study for the input vectors. Simple normalization will convert the input data to the range [0,1].

There are usually two kinds of input data sets in neural networks, namely training and testing data sets. The training data set is used in estimating the model parameters/variables while the testing data set is for evaluating the forecasting ability of the model. For the purpose of this study 90% of the data (400 input vectors) were used for training and 10% were used for testing.

7.2 GRNN modelling results

The training data set (400 vectors selected randomly) were trained using the GRNN model and with different spread factors. The optimum spread factor of 1 was selected through try and error process. **Figure 7** illustrates the goodness of fit for the trained GRNN model; R^2 of 0.984 was obtained from the training process which shows how well the network is trained.

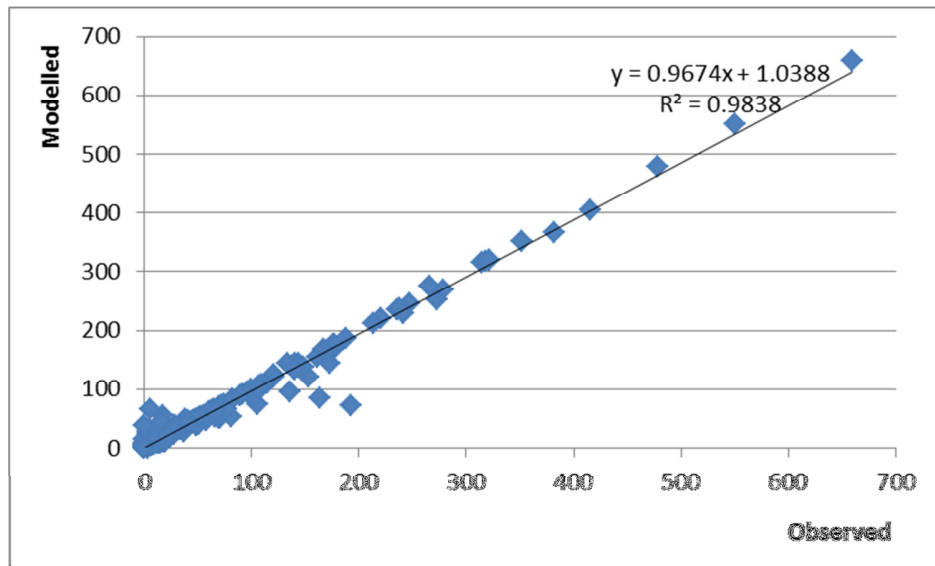


Figure 7, Modeled Tij through the Training Process against the Observed Ones

The trained GRNN model was then used to test the 41 unused vectors. **Figure 8** illustrates the modeled trip distribution against the observed data. The absolute difference (error) is also shown in this figure. The average RMSE for the tested data recorded as 38.

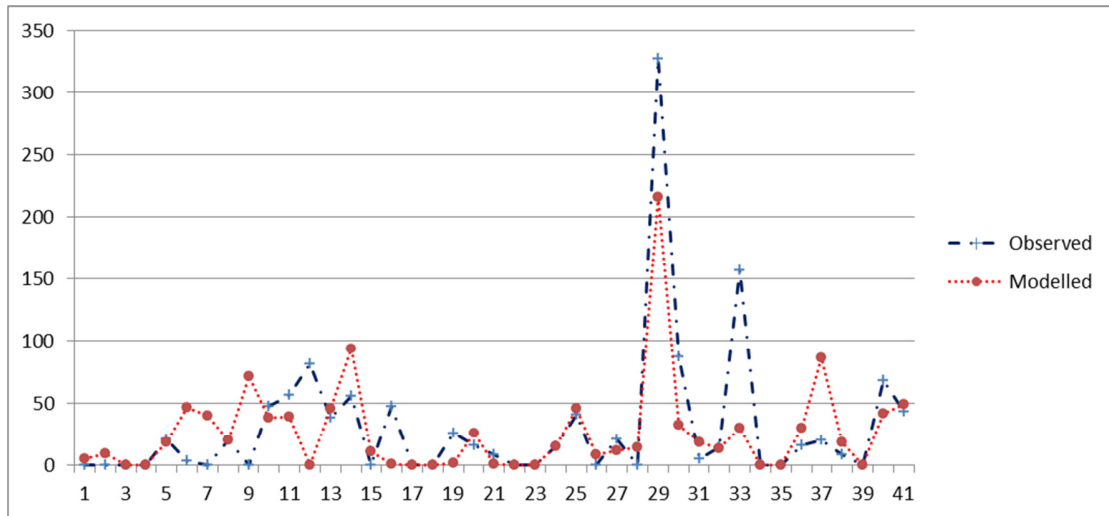


Figure 8, Error Estimation between the GRNN Modeled and Observed data

The R^2 of the tested model is reported as 0.575 as shown in **Figure 8**.

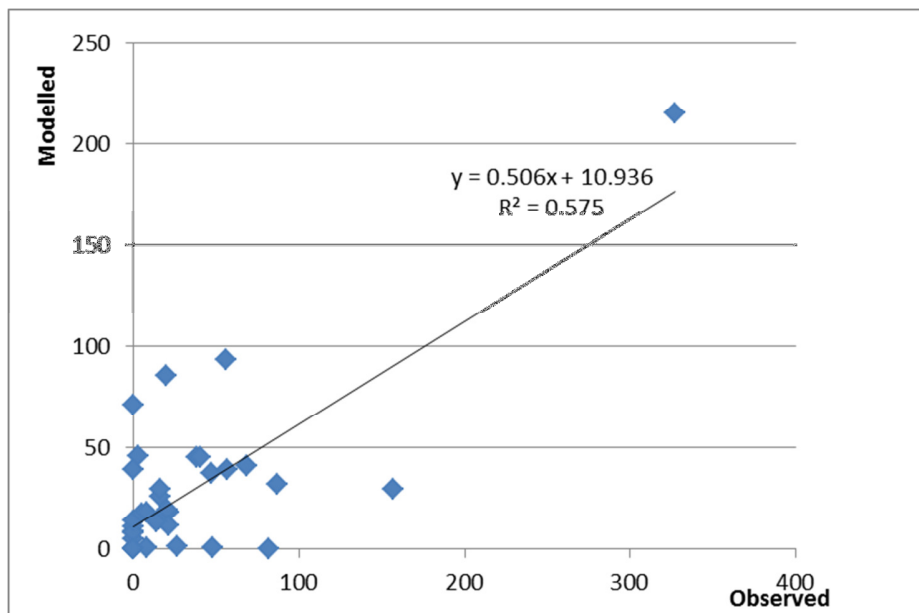


Figure 8, Modeled and Observed Tij for the Testing Data, GRNN Model

The R^2 of the tested data based on the Gravity model is estimated to be 0.446 (refer **Figure 9**) with the corresponding average RMSE of 46.

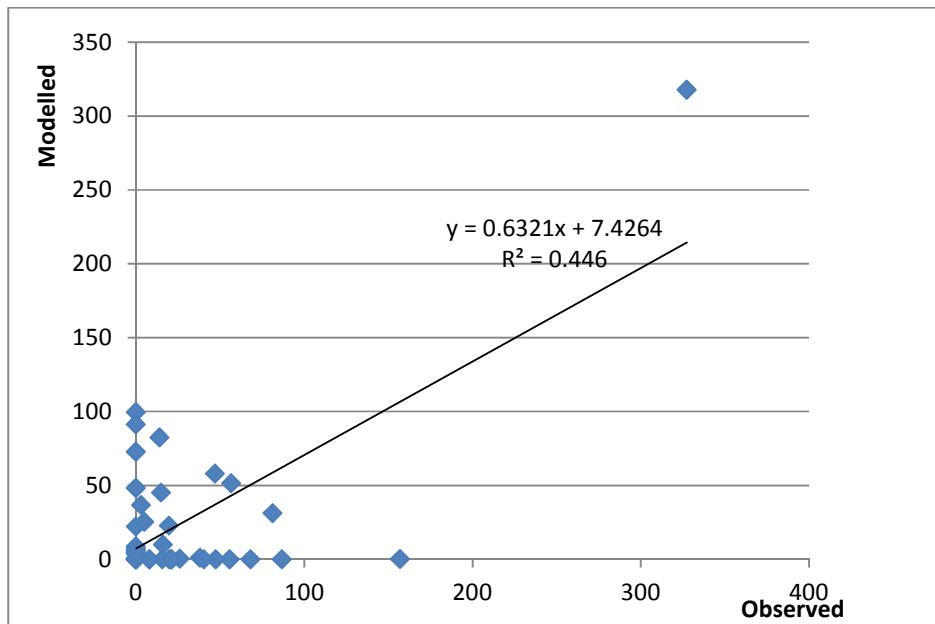


Figure 9, Modeled and Observed Tij for the Testing Data, Gravity Model

8 CONCLUSION AND RECOMMENDATION

Based on the results of the analysis undertaken, it can be concluded that the Neural Network model can be used to forecast trip distribution, especially for work trips. GRNN model could forecast the work trip distribution based on the land use data for each pair of traffic zones and the corresponding distance between the two zones.

The modeling results have also provided evidence that a validated GRNN could provide slightly better goodness of fit than a gravity model with the error level less than the gravity model as indicated by the average Root Mean Square Error (RMSE), where the RMSE for the NN and Gravity Model are 38 and 45 respectively. The estimated R^2 for the GRNN model and gravity model is reported 0.557 and 0.446 respectively.

The GRNN outputs highly rely on the amount of data available and the variety of the training data set vectors. The more the number of input vectors in the training data set the more accurate results in the output vector. Therefore it is recommended that the efficiency of the GRNN model be tested and improved with a bigger data set if available.

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