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ANALYSIS OF THE EVOLUTION OF TRAVEL DEMAND IN URBAN AREAS: A NEURAL-GEO-TEMPORAL MODELLING APPROACH

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1. INTRODUCTION

Considerable amount of research efforts has been dedicated to conceive forecasting models for predicting urban development and travel demand. Mainly originated from the application of economic theory, urban development models were initially conceived to explain the configuration and evolution of urban structures (Chapin, 1957). According to Ross (1988), these models are used to predict how future activities will be allocated, assuming that the land uses are determined by the location, the availability of services and proximity to other types of land uses. Based on these pioneer initiatives, Wegener (2003) identified and analyzed 20 integrated land use-transport models, which incorporated the most important spatial processes of development in conjunction with travel demand forecasting. Most part of them predicts land use separately to travel demand forecasting, i.e. each element (land use or transport) is modeled independently using its outputs for subsequent steps of the modelling process. Traditionally, planners have used these models to estimate future land use patterns and from them travel demand is estimated (Miller and Demestky, 1999), which is subsequently used to estimate traffic flows, congestion and pollution.

Nevertheless, travel demand models have been criticized due to the massive and costly data requirements for application to real problems (Harris, 1996), and due to the non-incorporation of temporal dynamic and realistic dimensions of urban reality (Rodrigue, 1997). Wegener (2003) points the travel demand models are still based on the traditional four-step approach, which ignores new techniques available in this information technology era. Many alternative approaches have been proposed. Some have argued that efforts should center on dynamic models, which should simultaneously consider land use and transport system interactions as part of the travel demand forecasting process (Handy, 1996). On the other hand, it is observed a growing concern over the need to incorporate the temporal dimension as part of travel demand modelling (Nihan and Holmesland, 1980). Ortuzar and Willumsen (1994) indicated that models should use temporal data series in order to better express the urban dynamic and its impacts on the transportation system demand.

In this paper, we present a Neural-Geo-Temporal Model (NGTM) that incorporates temporal interactions between transportation systems and land use patterns as the fundamental elements to express urban dynamics and its effects on travel demand. NGTM intends to reach an efficient representation of geographic, evolutionary and non-linear characteristics of urban interactions, without incurring on additional costs (data collection, processing time, personnel). NGTM combines Neural Networks (NN), which allows the creation of a mathematical model without considering *a priori* relations between dependent and independent variables, and Geographical Information System (GIS), which contributes on conducting spatial analysis that generate data/information on the evolution and characteristics of the urban area.

This paper is divided into five sections. After this brief introduction, we present a brief review on NN fundamentals, which is followed by the theoretical conception of the NGTM, the case study and the conclusions.

2. NEURAL NETWORKS

This section presents a brief review on the NN fundamentals, which understanding will be essential for the conception of the NGTM in the section 3.

Fischer (1998) has indicated that NN may be viewed as generalized non-linear extensions of conventional spatial statistical models (regression models, spatial interaction models, linear discriminant functions, etc.). The main consequence of the "generalized non-linear" capability is that a mathematical model can be reached without *a priori* assumptions regarding the interfering variables and their interrelationships.

Similar to traditional statistics modelling, NN is dedicated to obtain or compute a function that expresses the correlation between a set of independent (X) and dependent (Y) variables. Based on examples related to these variables, which are respectively incorporated into $\dot{X}$ and $\dot{Y}$ vectors, the obtained function is expected to produce results ($\hat{Y}$) similar to those observed in the samples. Despite the similarities, the whole process of computing the modelling function is totally different in its principles and procedures.

NN modelling consists on three main steps. Firstly, the architecture of the NN representing the relation between independent and dependent variables is selected and constructed. Next, NN parameters of the modelling function are obtained through a training process, which some scholars also call learning. Finally, the validity and efficiency of the modelling function is analysed based upon testing procedures (Fischer, 1998).

In order to conduct NN modelling, some assumptions have been adopted on developing an analogy of human brain processing even acknowledging its limitations. According to Fausett (1994), NN have been developed based upon the following assumptions:

- Information processing occurs at many simply elements called neurons;
- Signals (or sample value) are passed between neurons over connections links;
- Each connection link has an associated weight, which, in a typical NN, multiplies the signal transmitted; and
- Each neuron applies an activation function (usually non-linear) to its net input (sum of weighted input $\dot{X}$ signals) to determine its output $\dot{Y}$ signals.

In these assumptions, terms such as neurons, links, weight and activation function were introduced as part of the analogy to human brain processing that have now to be clarified in the NN context. In this sense, we make use of Haykin's (1994) description as following:

- A neuron is an information-processing unit that is fundamental to the operation of a NN. Figure 1 shows the model for a neuron, which is composed by three main elements (connecting links, adder, activation function);
- Each of which connecting links are characterized by a weight (or strength). Specifically, a signal x_j at the input of j connected to neuron k is multiplied by the link weight w_{kj};
- Adder processes the summing of input signals, weighted by the respective links of the neuron, which results in the u_k value, which is obtained by applying the equation 1

$$u_k = \sum_{j=1}^{p} w_{kj} x_j \tag{1}$$

where p is the total number of links connected to neuron k; and

- Activation function j (.) limits the amplitude of the output y_k of a neuron equation within pre-established intervals such as [0, 1] and [-1, 1] as shown in equations 2 and 3:

$$y_k = j(u_k) \tag{2}$$

$$j(u_k) = \frac{1}{1+\exp(-au_k)} \tag{3}$$

where a is the slope parameter of the sigmoid function (a=∞), which is the most common form of activation used in NN.

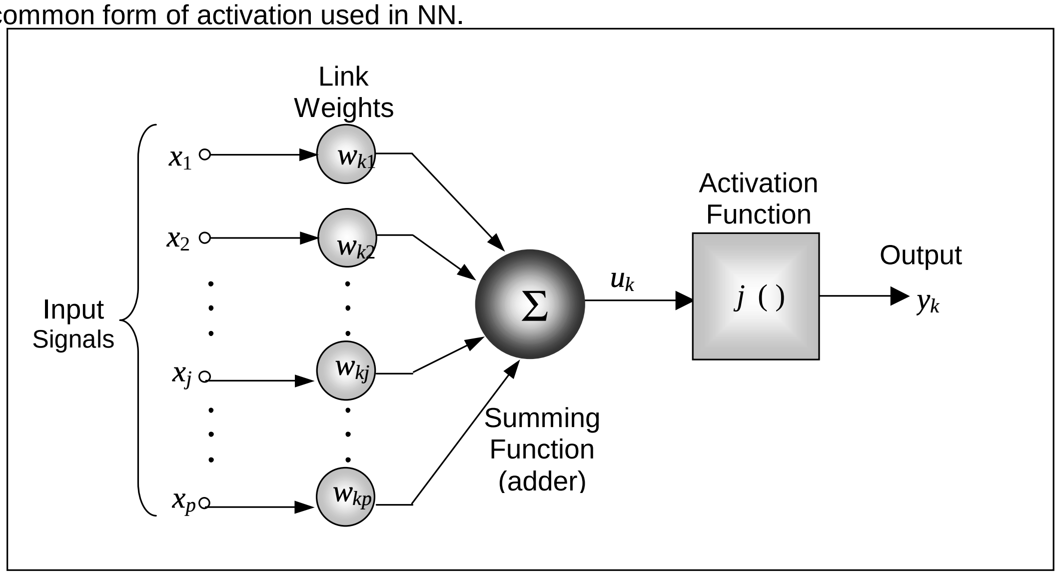

Figure 1: Non-linear model of a neuron
Source: adapted from Haykin (1994)

The learning process takes place in order to reach the compute of all link weights w_{kj}; which form a set W. Training is accomplished by sequentially applying input vector $\dot{X}$, while adjusting network weights W according to a predetermined algorithm, which is a prescribed set of well-defined rules. The most common approach for conducting the learning processing is the Supervised training, which is performed while the network "learns" to associate each input vector X to its corresponding output vector Y (back-propagation algorithm). In a typical supervised training, network weights are gradually adjusted in order to converge to values such that each input vector produces the desired output vector $\dot{Y}$ (Wasserman, 1989). This is reached by the minimization of the following equation:

$$e(q) = \frac{1}{2}\sum_{j=1}(y_j - \hat{y}_j(q))^2 \tag{4}$$

where e (q) is total error for the qth iteration, computing the differences between the desired output (y_j) and the calculated by NN ($\hat{y}_j(q)$) for all j neuron outputs, which is subjected to

$$e(q) \leq em \tag{5}$$

where *em* is the fixed error margin to be reached on adjusting the weights *W.*

Finally, once training is reached, one has to be concerned on the evaluation of NN modelling function. It is expected that this function is provides "generalization" on dealing with samples that have not been employed in the training process. In this sense, it is usual to conduct a testing phase that indicates if previous definitions (intervening variables *X* and *Y*, activation functions; architecture; and training algorithm) were correctly established or if they require a re-evaluation in order improve the efficiency of the NN. In this sense, Teodorovic and Vukadinovic (1998) points out that it is important to select part of the samples related to vectors *X* and *Y* in order to use them on testing tasks, which are usually separated into two-thirds for training and one-third for testing. Then, using testing vectors, the modelling function is applied and the efficiency of the NN can be considered.

3. THEORETICAL CONCEPTION OF NGTM

The description of the NGTM is presented in three steps: basic principles; mathematical formulation; and RN formulation as follows.

3.1. BASIC PRINCIPLES OF NGTM FOR TRAVEL DEMAND MODELLING TRIP GENERATION MODELLING

The first principle is: Trip Generation (*TG*) can be expressed as a parallel system formed by Urban Interactions (*UI*), which is the result of the interactions between Land Use patterns (*LU*) and the Transportation System (*TS*), Spatial Location (*SL*) and Population (*PO*) as shown in the Figure 2.

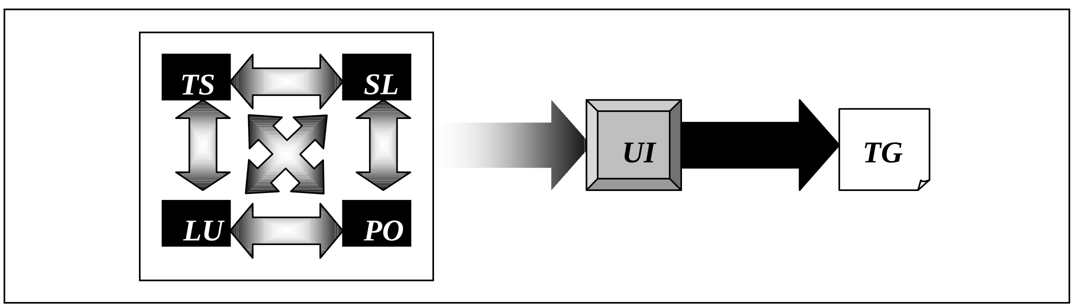

Figure 2: Trip generation as a parallel system

The second principle is: trip generation is the result of temporal interactions, which can also expressed using a parallel system. Figure 3 presents the representation of the temporal parallel system in which $\boldsymbol{TS}^{(t)}$, $\boldsymbol{PO}^{(t)}$, $\boldsymbol{LU}^{(t)}$, $\boldsymbol{SL}^{(t)}$, $\boldsymbol{UI}^{(t)}$ and $\boldsymbol{TG}^{(t)}$ are observed for each time z.

The third principle is: trip generation is the result of recursive interactions between the parallel system's elements. *TG* for any future time stage ($t=z+1$) will depend not only on present conditions but also on all previous time stages $\{1,2,...,z\}$ as shown in Figure 4.

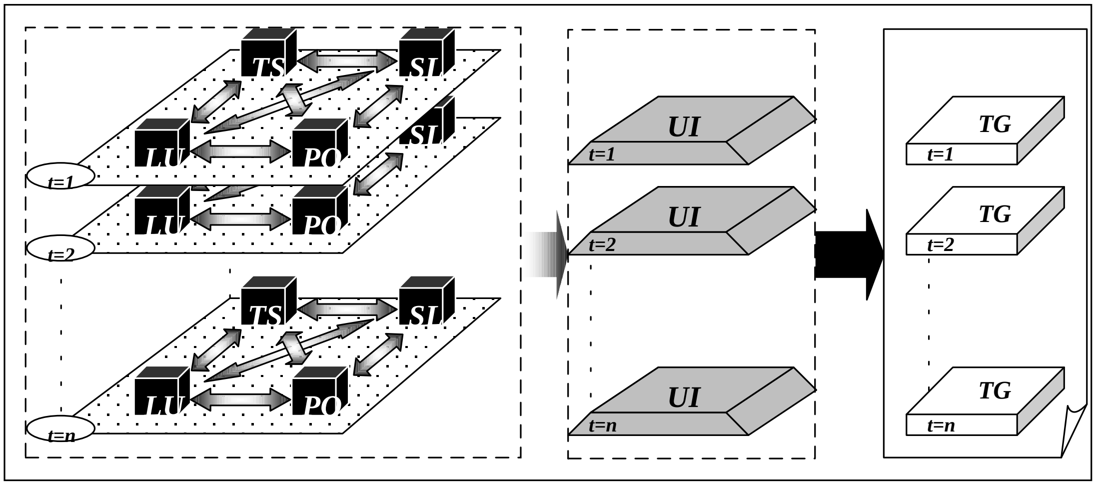

Figure 3: Temporal Parallel system for Trip Generation Modelling

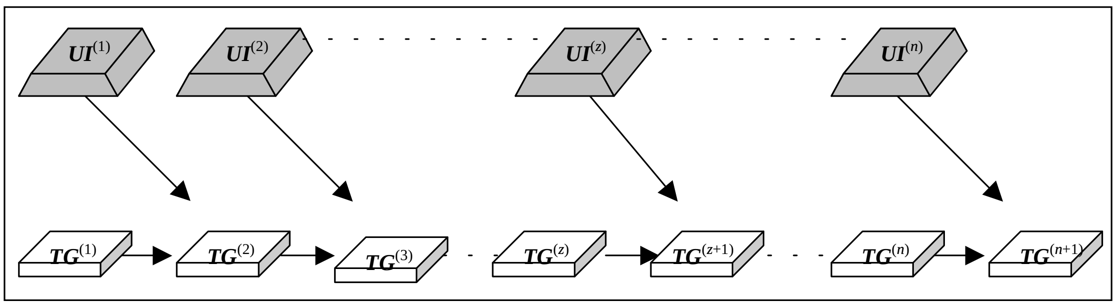

Figure 4: Future trip generation as a recursive process

3.2. MATHEMATICAL FORMAULATION OF THE NGTM FOR TRIP GENERATION MODELLING

Consider an urban area, which is divided in *z* zones. For any zone *i* and time stage *z*, urban interactions are expressed as shown in the equation 6.

$$\vec{UI}_i^{\,z} = \left\{ \vec{TS}_i^{\,z}, \vec{LU}_i^{\,z}, \vec{SL}_i^{\,z}, \vec{PO}_i^{\,z} \right\} \tag{6}$$

where

$\vec{TS}_i^{\,z}$ is the vector containing transportation system features of zone *i* at a given time *z*;

$\vec{LU}_i^{\,z}$ is the vector representing land use characteristics of zone *i* at a given time *z*;

$\vec{SL}_i^{\,z}$ is the vector for describing spatial location of zone *i* at a given time *z*;

$\vec{PO}_i^{\,z}$ is the vector with population information of zone *i* at a given point *z* of time;

From Equation 6, these interactions for a temporal perspective are represented as follows:

$$\vec{IT}_i^{\,n} = \left\{ \vec{UI}_i^{\,1}, \vec{UI}_i^{\,2}, \ldots, \vec{UI}_i^{\,z}, \ldots, \vec{UI}_i^{\,n} \right\} \tag{7}$$

where

n is the total number of time stages along the observation time period; and

$\vec{IT}_i^{\,n}$ is the set of interactions for *n* time periods for the *i*th zone.

At same time, TG_i^z is the trip generation at zone *i* and time *z* are observed as a travel demand-indicator for *i*th zone. Analogously to Equation 7, it is established

$$\vec{GT}_i^{\,n} = \left\{TG_i^{\,1}, TG_i^{\,2}, \ldots, TG_i^{\,z}, \ldots, TG_i^{\,n}\right\} \tag{8}$$

where

$\vec{GT}_i^{\,n}$ is the set of trip generation for *n* time stages for the *i*th zone.

Once the definition of land use-transportation interactions and travel demand indicator are reached, we concentrate now on the establishment of the forecasting paradigm. For each stage of time z, travel demand for a future scenario (*t*+1) can be obtained from incorporation of previous interactions (Equation 7) and demand (Equation 8) into NGTM as shown in the equation 9.

$$TG_i^{\,n+1} = f\left(\vec{GT}_i^{\,n}, \vec{IT}_i^{\,n}\right) \tag{9}$$

where

f is a function that establishes the relationships between the independent (TG_i^{n+1}) and dependent variables (GT_i^{n+1} and IT_i^{n+1}).

3.3. NN FORMULATION

In a NGTM, we apply NN to determine function f throughout a non-linear and recursive approach. This function represents the weight set *W* that establishes the relationships between input, hidden and output neurons of a NN as previously explained in the section 2. To conduct this calculation, firstly a NN architecture dedicated to efficiently process time-depending input vectors has to be defined. Derived from a Multi-Layer Perceptron (MLP) NN, Elman network is selected due to its simplicity of conception and because there is no need to develop sophisticated and complex training algorithms than the simple back-propagation (Elman, 1990; Haykin, 1994). Figure 5 illustrates the Elman NN for the NGTM.

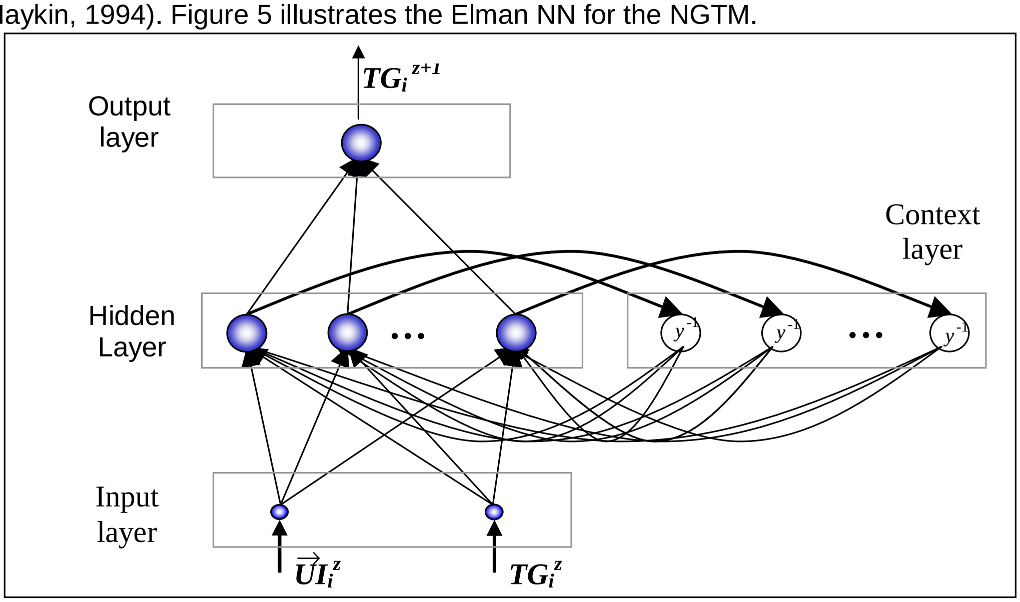

Figure 5: Application of an Elman NN for NGTM
Adapted from Elman (1990)

For the selected network architecture, the composition of input $\vec{X}_i$ and output $\vec{Y}_i$ vectors is described in Equations 10 and 11, respectively.

$$\vec{X}_i = \left\{ \vec{IU}_i^{\,z}, GV_i^{\,z} \right\} \tag{10}$$

$$\vec{Y}_i = \left\{ GV_i^{\,z+1} \right\} \tag{11}$$

4. CASE STUDY

Nagoya City is the fourth largest Japanese City. Located in Chubu (central) region, its current population is estimated on approximately 2.2 million people (1998) and it occupies 326.35 Km^2. Nagoya City is currently supported by massive production of automobile industries in its surroundings. Nevertheless, commercial and service activities are highly concentrated in the Central Ward (Naka-Ku) that comprehends Nagoya Station and Sakae.

In Nagoya City, one of the current challenges of urban planners has been the establishment of urban policies to control agglomeration of activities, which generate high levels of traffic flows in central and surrounding areas (Osukanon and Nagoya station). Actions have been taken in order to induct urban development in areas such as Kanayama, Ozone and Imaike. They have promoted new sub-centers that have concentrated many types of daily activities. However, agglomeration in central areas has remained high as well as congestion and pollution. Therefore, information on how these agglomerations have contributed for changes on person trip attraction, as well as how temporal evolution of urban conditions have affected the urban dynamics has to be obtained (CPB, 1997).

The description of the case study is divided into four sub-sections.

4.1. GIS DATABASE

Using 248 traffic zones (TZ), digital maps of the transportation system (bus, train, subway, road and Nagoya Highway - NH), land use information (commercial and parking area) and demographic (population) data, a GIS database as shown in Figure 6 was created.

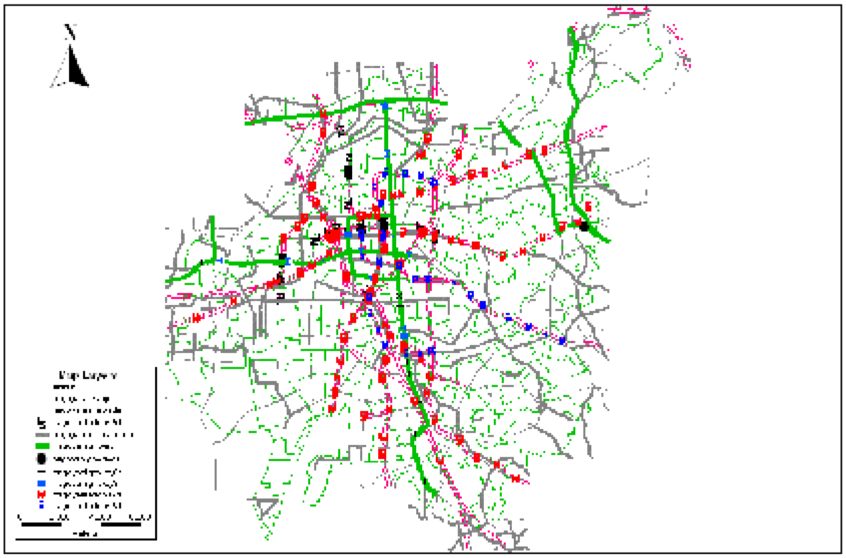

Figure 6: Temporal GIS database

This database is the result of multiple efforts to gather together data from three different sources at three different years (1971, 1981 and 1991). Land use, transportation system and demographic data were obtained from Nagoya Urban Institute (NUI), while person trip data (number of trips per zone in the peak-hour) was acquired from Nagoya's Road Planning Section and digital map data was purchased from a private company. In the construction of the GIS database, a time-base representation of spatial-temporal data was employed, since it is intended to evaluate dynamic changes over the years, considering the traffic zones as the main element of comparison (Peuquet, 1999). In this sense, for each time-state (1971, 1981, 1991), geographical maps were created containing their respective spatial objects.

4.2. TEMPORAL EVOLUTION OF THE URBAN AREA AND THE TRAVEL DEMAND

Based on the GIS database, we firstly identified 61 patterns of temporal changes on zone's characteristics in the 1971-1991 period. Table 1 summarizes the main patterns, which excludes the patterns that were not observed in more than 5 zones. From the Table 1, it is verified that Pattern 1 occurred in 57 zones, which represents approximately 23% of the total of zones. The Pattern 1 consists on population reduction in the 1981-1991 period ($PO^{1981}>PO^{1991}$). On the other hand, in the Pattern 13 population increase in the 1981-1991 period ($PO^{1991}>PO^{1981}$) accounting for 16% of the cases is observed. In addition to these cases shown in the Table 1, a large variety of patterns are observed due to the combination of changes on *LU*, *TS* and *PO*.

Patterns of changes on trip attraction were also identified. Table 2 presents four patterns of changes, their description and number of observed cases. It is clearly verified that Pattern 3 is predominant, which means that trip attraction has increased in the 1971-1981 period ($A^{1981}>A^{1971}$) and decreased in the 1981-1991 period ($A^{1981}>A^{1991}$).

Table 1 – The main patterns of temporal changes on zone's characteristics

Pattern No.	Pattern Description	No. Cases	No.Cases%
1	$PO^{1971}=PO^{1981}$ $PO^{1981}>PO^{1991}$	57	22.98%
13	$PO^{1971}=PO^{1981}$ $PO^{1991}>PO^{1981}$	40	16.13%
11	$PO^{1971}=PO^{1981}$ $PO^{1981}>PO^{1991}$ $PT^{1971}<PT^{1981}$ $PT^{1981}=PT^{1991}$	12	4.84%
3	$PO^{1971}=PO^{1981}$ $PO^{1981}>PO^{1991}$ $PT^{1971}=PT^{1981}$ $PT^{1981}<PT^{1991}$	10	4.03%
21	$PO^{1971}=PO^{1981}$ $PO^{1981}>PO^{1991}$ $RL^{1971}<RL^{1981}$ $RL^{1981}=RL^{1991}$	8	3.23%
14	$PO^{1971}=PO^{1981}$ $PO^{1991}>PO^{1981}$ $PT^{1971}<PO^{1981}$ $PT^{1981}=PT^{1991}$	7	2.82%
41	$PO^{1971}=PO^{1981}$ $PO^{1991}>PO^{1981}$ $RL^{1971}<RL^{1981}$ $RL^{1981}=RL^{1991}$	7	2.82%
6	$PO^{1971}=PO^{1981}$ $PO^{1981}>PO^{1991}$ $PT^{1971}=PT^{1981}$ $PT^{1981}<PT^{1991}$ $RL^{1971=}RL^{1981}$ $RL^{1981}<RL^{1991}$	7	2.82%
9	$PO^{1971}=PO^{1981}$ $PO^{1981}>PO^{1991}$ $PT^{1971}<PT^{1981}$ $PT^{1981}<PT^{1991}$	7	2.82%
22	$PO^{1971}=PO^{1981}$ $PO^{1981}>PO^{1991}$ $RL^{1971}=RL^{1981}$ $RL^{1981}<RL^{1991}$	7	2.82%
others		86	34.68%

Table 2 – The main patterns of temporal changes on trip attraction

Pattern No.	Pattern Description	No.Cases	No.Cases%
3	$A^{1971}<A^{1981}$ $A^{1981}>A^{1991}$	155	62.50%
1	$A^{1971}>A^{1981}$ $A^{1981}>A^{1991}$	59	23.79%
4	$A^{1971}<A^{1981}$ $A^{1981}<A^{1991}$	21	8.47%
2	$A^{1971}>A^{1981}$ $A^{1981}<A^{1991}$	13	5.24%

Taking into consideration the patterns presented on the Tables 1 and 2 as well as the spatial distribution of them as shown in the Figures 7 and 8, it can be preliminarily concluded that no general rule that explains changes in trip patterns based on changes on zones' characteristics.

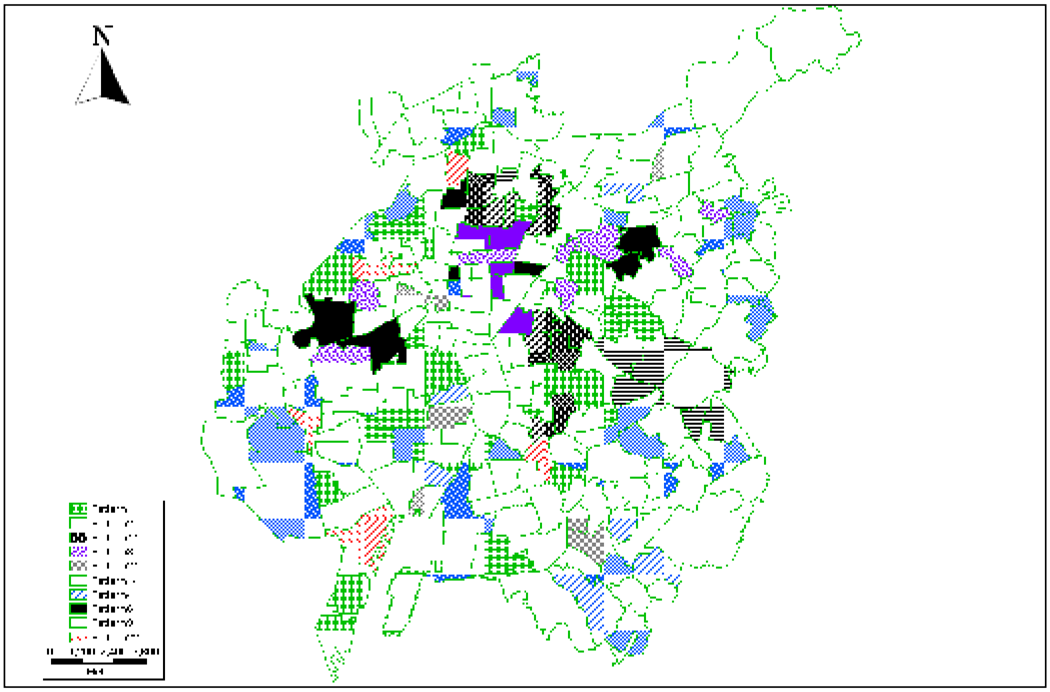

Figure 7: Spatial distribution of the main change patterns –Zones' characteristics

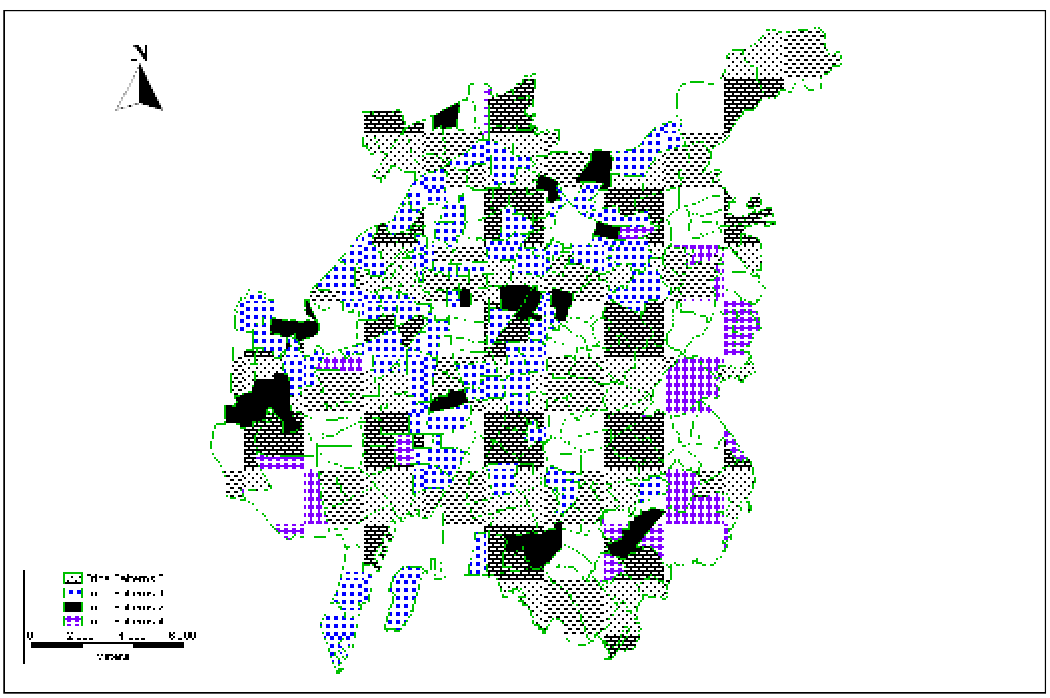

Figure 8: Spatial distribution of the main change patterns – Trip Attraction

4.3. APPLICATION OF THE NGTM FOR TRIP ATTRACTION MODELLING

Acknowledging the complexity of these temporal changes, NGTM was applied to establish the modelling of this phenomenon. Based on the GIS database, all the elements of the vectors $\vec{UI}_i^{\,n}$ and $\vec{GT}_i^{\,n}$ were specified as shown in the following equations:

$$\vec{TS}_i^{\,z} = \{PT_i^z, RT_i^z, NH_i^z\} \tag{12}$$

$$\vec{LU}_i^{\,z} = \{CL_i^z, PL_i^z, RL_i^z\} \tag{13}$$

$$\vec{SL}_i^{\,z} = \{SD_i^z, HD_i^z\} \tag{14}$$

$$\vec{GT}_i^{\,z} = \{A_i^{1971}, A_i^{1981}, A_i^{1991}\} \tag{15}$$

where

PT_i^z is the total extension (Km) of public transportation for zone *i* at a given time *z;*

RT_i^z is the total extension (Km) of road transportation for zone *i* at a given time *z;* and

NH_i^z expresses the existence or not of Nagoya Highway's ramp for zone *i* at a given time *z;*

CL_i^z is the occupied area (m^2) of commercial pattern for zone *i* at a given time *z;*

PL_i^z is the occupied area (m^2) of parking pattern for zone *i* at a given time *z;* and

RL_i^z expresses the regulation or not of zone *i* at a given time *z*. This regulation expresses an intervention by Nagoya' planning section that intended to establish a reticulated structure of the road system.

SD_i is the distance in kilometers from zone *i* to Sakae's TV Tower that is main reference located in downtown; and

HD_i expresses the distance (Km) from zone *i* to Nagoya Interchange of Tokyo-Nagoya highway were defined to represent spatial location*,*

$\vec{PO}_i^{\,z}$ is defined as the number of inhabitants in the zone *i* at a given time *z*.

A_i^{1971}, A_i^{1981} and A_i^{1991} are the trip attraction indicators expressed in number of trips attracted to the *i* during the peak hour (5:30 – 6:30 PM) for a given time 1971, 1981 and 1991.

The NGTM for trip attraction modelling was implemented in C++ language as independent module of *GeoConcept*, which was the GIS software used in this study. In this module, pre-processing, vectors separation, training and testing were conducted. The pre-processing consisted on the normalization of all the values of all variables within a 0.1-0.9 range. The data set was then randomly divided into two sets of training (X' and Y') and testing (X'' and Y'') according to a 75% (186 zones-vectors) and 25% (62 zones-vectors) distribution, respectively.

Finally, the training and testing of the Elman NN was conducted. We applied the back-propagation algorithm with a learning rate of 0.01 and using sigmoid activation functions. The NN was trained until the Minimum Square Error (MSE) was reached

(MSE=0.000229), i.e., after 36677 iterations. Using the trained network, trip generation in 1991 were estimated for the testing data set ($\dot{Y}''$) as shown in the Figure 9. The average error was 87.11 trips; the standard deviation was 128.35; and the average relative error was 23.58%.

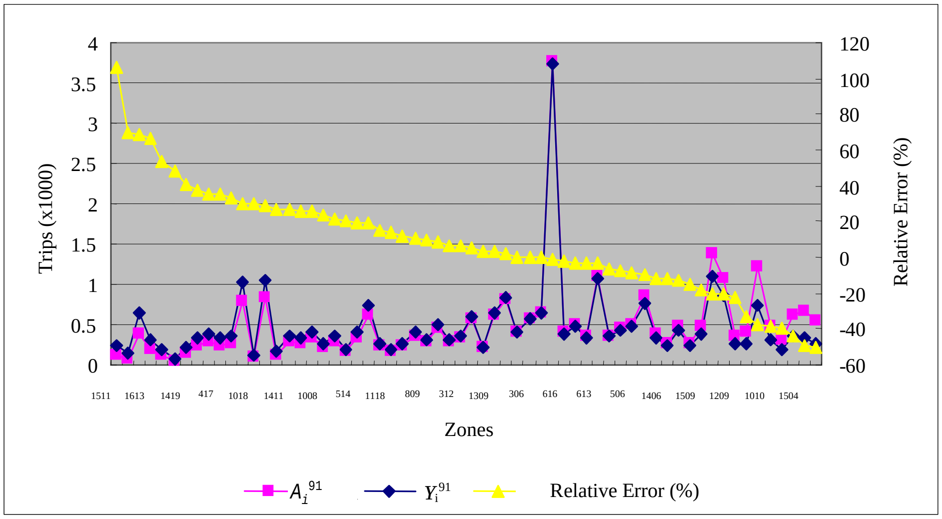

Figure 9: Comparison between the observed and estimated results for the testing data set

4.4. ANALYSIS OF THE RESULTS

Analyzing the Figure 9, it is verified that the modelling function generated by the NGTM provides estimated results, which are very close to the observed trip attraction in 1991. Despite the variation in the number of trips on the testing data set ($A^{1991}_{\max} = 3773$ and $A^{1991}_{\min} = 56$) the NGTM was capable of "understanding" the travel patterns observed over time.

For example, the zone 610, which had the testing vector with the greatest number of trips (3373), presented the second smallest relative error (-0.6%). This zone had a considerable increase on trip number in the 1971-1981 period, while in the 1981-1991 period the trip attraction was reduced (Pattern 3 – Table 2). This zone had also increase on transportation infrastructure and commercial area (Pattern 29 – Table 1 as part of "others"). This complex development pattern was fully incorporated into the temporal modelling and consequently NGTM was capable of predicting correctly trips in 1991.

Nevertheless, it is observed that in some cases the NGTM was efficient as expected. For instance, the complexity of the changes in zones 1511 (Hoshigaoka) and 1415 (Hirate), which presented relative errors of 106 and 50%, respectively, were not completely assimilated in the NGTM modelling function. Zone 1511 had population increase (21% in the 1971-1991 period), but the trip attraction reduced 10% since 1981 (A^{1971}=52, A^{1981}=126, A^{1991}=113). Therefore, the NGTM overestimated the trip attraction. On the other hand, zone 1415 experienced a 624% growth on demand in the 1971-1991 period and also increase on population numbers and commercial area. NGTM overestimated A^{1991}.

Still about the results presented in the Figure 9, it can be concluded that there is not a direct relation between the number of trips and the relative error. Despite of verifying relative errors greater than 20% in some cases with zones related to low A (A_{1022}=56, A_{406}=81, A_{1018}=98 e A_{1511}=113), in other cases (A_{806}=210, A_{1118}=168 e A_{1310}=230) relative errors lower than 20% were also observed.

Focusing on the spatial distribution of the relative errors per zone, it is verified that they are not related to a specific area of the city. In the Figure 10, it is noted that the relative errors are divided into 10 groups, which are randomly sprawled all over the urban area. This conclusion is particularly important for validating the model, especially for the zones in the urban area fridges. It can be concluded that the MNGT has no problems on generalizing the estimation of trip attracion independently of the spatial location.

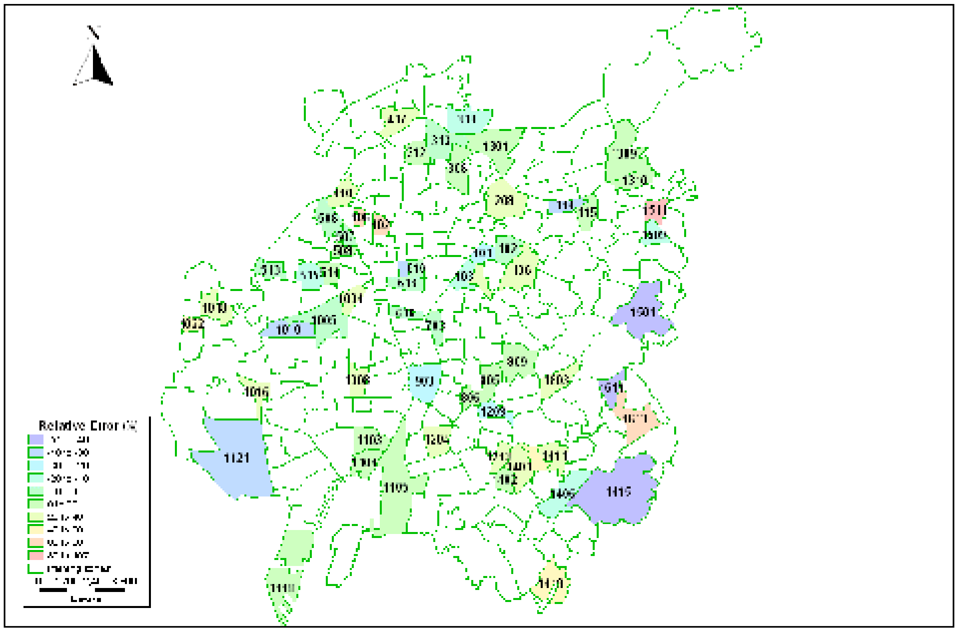

Figure 10: Spatial distribution of the relative error per zone

5. CONCLUSION

In this paper, a research effort to develop a NGTM for trip generation modelling was described. Combining NN and GIS technologies, this work intended to overcome limitations on the development of urban models for travel demand analysis. NGTM is a tentative to conceive models in a different way, i.e., adaptation of models to express urban reality, not the opposite. In this direction, innovative features of NGTM focused on establishing a non-linear, parallel system and recursive approach, which provided a spatial-temporal representation of urban interactions. This approach is considered essential for the obtainment of useful information related to urban developments and their effects on travel demand, which has been conducted in a static fashion and very limited in terms of the representation of urban dynamics.

The application of NGTM for conducting trip attraction modelling in a case study has shown its efficiency. The NN modelling function correctly calculated trip attraction for most part of the traffic zones of Nagoya City. Despite of few exceptions, it was capable to process a very complex situation of urban development as observed in

Nagoya City, which has presented different patterns of changes all over the urban area.

However, in a critical analysis, two main restrictions on employing NGTM are observed. The first one refers to NN formulation and the relationships between the independent variables that cannot be deeply understood. As NN establishes non-linear relationships and processing functions, it becomes a hard task to formulate a simple comprehension on the obtained weights *W*. In an opposite direction, linear modelling is rather simple on its understanding, since the number and the relations of function parameters are limited. Therefore, until scholars develop a form to reach some comprehension on the weights generated by NN modelling, the combination of both techniques would be an alternative way. Combination in the sense that after processing reaching a NGTM, planners should also verify linear relationships between the variables. In this sense, correlation analysis has much to contribute on exploring relationships between intervening variables. For example, the linear modelling of trip attraction in Nagoya City has shown that public transportation, road transportation and commercial land use have a considerable influence and correlation with zonal trip ends. Obviously, correlation analysis will not explain the whole nature of the process but at least they can provide additional information that is much more difficult to be obtained from the analysis of NN weights.

The second restriction is related to the practical issue of obtaining data for NGTM's simulations. In the information age, one would expect to face data-rich environment for conducting temporal analysis. However, it was remarkable the lack of a central geo-temporal database controlled by planning agencies in Nagoya City, which unfortunately is not a rare case. Many reasons could be argued here in order to justify or understand this situation, but the fact is that modelling advances are mostly likely not to appear until this is changed.

In future developments of this research, efforts could be concentrated in four main aspects. Firstly, alternative data sources such as Remote Sensing (satellite images and aerial photographs) should be considered and studied. Secondly, fuzzy theory could be applied to the classification of zonal trip ends (travel demand) into levels of attractiveness (low, medium, high, etc). Next, NGTM conception should be adapted in order to process the analysis of trip generation and distribution. Finally, evaluation of metropolitan effects in the trip attraction modelling should be conducted since due to data limitation only intra-urban trips were considered in this study.

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