MODELLING AND FORECASTING TRAVEL DEMAND IN AN URBAN AREA: A NEURAL-GEO-TEMPORAL APPROACH

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Abstract: A Neural-Geo-Temporal Model (NGTM) for travel demand modelling is presented. We combine the properties of Neural Networks (NN) and Geographical Information Systems (GIS) to construct a forecasting model, which is based on the incorporation of land use and transportation system interactions. Using a temporal database georeferenced in GIS software, including data of three surveys conducted in 1971, 1981 and 1991, NGTM is applied in Nagoya City and its efficiency is evaluated. It is also established a scenario for year 2001 that shows model's applicability and capability to conduct forecasting tasks.

Key Words: GIS, Neural Networks, and Travel Demand

1. INTRODUCTION

Resulting from temporal and dynamical evolution, complex structures of urban areas have been formed. According to Khisty (1990), urban areas over the years have changed as a result of the dramatic shift from agricultural to urban development, which is leading to more people and higher percentages of population but in less dense concentrations than ever before. Extremely heterogeneous combinations and organizations of urban environments substituted previous mono-centric structures, mainly due to decentralization of economic activity and advances in transportation technology (Wilson, 1974). In this context, a Central Business District (CBD) still plays an essential part in urban dynamic as main attraction pole of economical and social activities, but there has been considerable development of new sub-centers located both in suburban areas and peripheral districts.

These changes in urban form have created complicated commuting patterns as consequence of increasing on land use-transportation system interactions. The more these interactions become intensified and originate an extensive occupation of urban area, the greater is the proliferation of sub-centers. According to Taafle *et al.* (1996), one of the main consequences of this process is that contemporary cities are difficult to be covered by transit systems as they have been planned. Ortuzar and Willumsen (1994) point out that if urban development is not efficiently balanced, many problems to urban environment may be caused such as traffic congestion, pollution, degradation, decline on riderships of public transportation systems, etc.

Considering their role in urban structure, agglomerations can significantly affect the balance of urban areas. There has been an undergoing discussion whether the concentration or dispersion of urban activities will contribute to a better arrangement and achievement of life quality. Many actions have been deployed to establish control of urban development in order to define future planning and search for the achievement of a sustainable urban scenario. Basically, planners have to obtain reliable and representative information on travel demand increase and growing, affecting commuting patterns according to planned and accidental interventions. Nevertheless, travel demand modelling for analysis of agglomerations has been mostly dedicated to evaluate operational conditions of traffic flows, parking capacity, congestion and pollution in these areas (Carrese *et al.*, 1996). This approach is contrary to desirable focus towards incorporation of land use-transportation interactions and its impacts on daily movements.

Probably, the main reason for such a situation is the current conception of planning models. As acknowledged by Ortuzar and Willumsen (1994), forecasting models should use time-series data as a reasonable way to better express urban dynamics and its consequences on transportation and this has not been reached yet. In this sense, Miller and Demetsky (2000) emphasizes that modelers rarely evaluate the accuracy of their forecasts by using past data sets to predict present conditions. Furthermore, according to Fischer (1998), there was an overemphasis on the design of linear statistical model while nonlinearities prevail in reality. Just recently, transportation researchers have started to explore new technologies and techniques to overcome these limitations that are observed in current models.

In the direction of exploring technological developments and intending to adapt travel demand modelling to incorporate the evolution of urban areas, we present a Neural-Geo-Temporal Model (NGTM). It combines NN and GIS through a longitudinal data set analysis and incorporates land use-transportation interactions based upon geographical-spatial data, in opposition to traditional analysis that mainly concentrates on socioeconomic data. NGTM produces a recursive and non-linear regression function using NN, which generates quantitative information on travel demand expressed in terms of zonal trip ends. Additionally, it is possible to evaluate historical changes to be explored on the definition and analysis of future perspectives of urban area's development.

This paper is divided in five sections. After this introduction, section two presents the framework of NN-GIS integration for travel demand forecasting. Next, we describe the basic conception of NGTM for travel demand modelling. Section four presents a case study conducted in Nagoya City, Japan. Finally, section five concentrates on the conclusions and future perspectives of development for this research.

2. NN-GIS INTEGRATION FOR TRAVEL DEMAND MODELLING AND FORECASTING

Before establishing neural modelling of travel demand, we need to define an integration framework to take advantage of NN and GIS capabilities. According to Rodrigue (1997), the objective of NN modelling is to find a configuration of weights for a processor that produce estimated results similar to the observed results. However, despite of its recently application to solve many transportation problems as described by Dougherty (1995), NN by itself does not guarantee that urban characteristics are incorporated into modelling. In this way, GIS plays an essential role in our effort to express spatial urban characteristics previously collected and processed in this system.

Based upon this framework, we intend to follow the direction pointed up by Engelen *et al.* (1999) that geographical-based models are supposed to provide an exploration and thinking tool rather than to make definite statements about the future state of the modeled system. Therefore, this integration intends to contribute on the analysis of scenarios through the identification of patterns and tendencies observed on GIS database.

Next three subsections delineate the phases of NN-GIS integration, operations in GIS and NN processing. We focus on the general description of the framework in order to characterize steps that will be later explored in the mathematical formulation and case study.

2.1 Phases of NN-GIS integration

There are three phases in this integration as shown in Figure 1. Firstly, longitudinal (temporal) data sets originated from inventory and diagnosis activities are transferred into GIS. These data includes results of origin/destination surveys for person's trips, land use information, maps of the transportation system, and demographic information. As part of continuous planning process, it is expected that, along the time, incoming data will be gradually incorporated into GIS. As experienced by Miller and Demetsky (2000), due to variations on the geographical scope and levels of aggregation, one has to be aware that there will be many incompatibilities. Obviously, it is fundamental to process suitable corrections according to data limitations and perspectives on the application of the modelling.

The second phase is related to operations in GIS, which are responsible to generate a georeferenced-temporal data set to be used in NN processing. This processing can be either inside GIS or in an external module, according to the software. Finally, in the third phase, a NN is trained and tested generating a forecasting function and results that are stored into GIS database. In fact, evaluation and analysis process will initiate after the accomplishment of these phases.

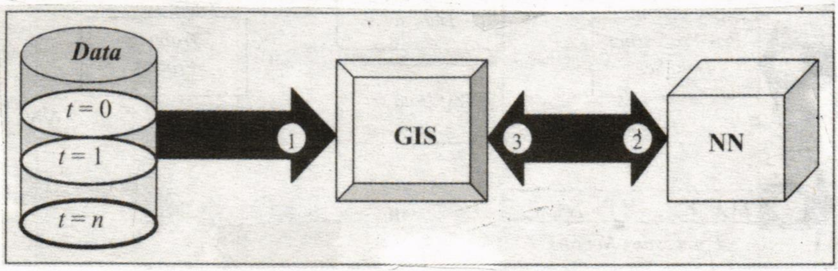

Figure 1. Phases of NN-GIS integration

2.2 Operations in GIS

As presented in Figure 2, operations in this system initiate on the georeferencing process of data that was previously collected. In the sequence, a georeferenced database is built, which consists of cartographic maps linked to attribute data. Maguire *et al.* (1991) present an extensive literature on these operations, so a detailed description of them is skipped. On this database, spatial-temporal queries are conducted and a new data set is obtained and transferred to NN processing. After NN processing, forecasting is performed and results are stored into the database. Finally, thematic maps are constructed and planners can conduct their analysis exploring visualization and spatial analysis resources.

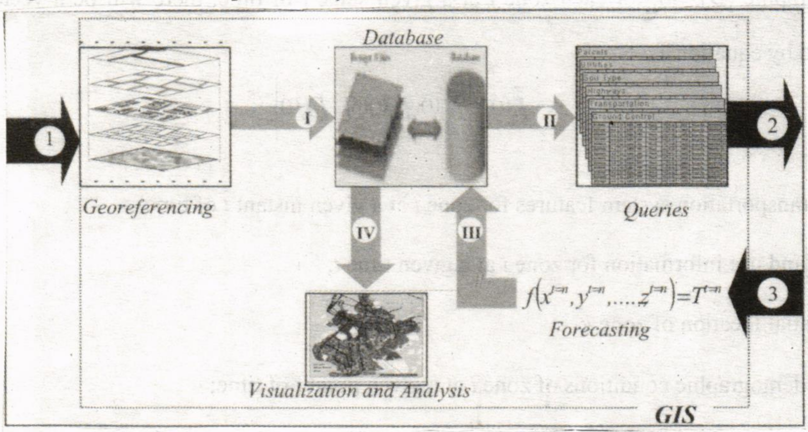

Figure 2. Schematic representation of operation in GIS

2.3 NN processing

The data set from GIS has to be pre-processed in order to fit original values such as areas, extensions and coordinates into a limited interval. Next, data is separated into training and test sets applying a random selection. Training process is performed in the sequence, but, as any typical modelling, dependent (input) and independent (output) variables have to be defined in advance as well as a training algorithm, a network topology (number of layers, input and outputs), activation functions and a learning rate. In Faghri and Sandeep (1998) the determination of these parameters is reported for many transportation problems and it can be concluded that each case has to be carefully examined. Obviously, these definitions can be adapted along the process in order to reach a better modelling performance. From the training process, a forecasting network is obtained, i.e., the training process establishes a function that is supposed to be capable of computing variations on dependent variables and then it can be used to forecast future scenarios. Figure 3 shows the activities of NN processing.

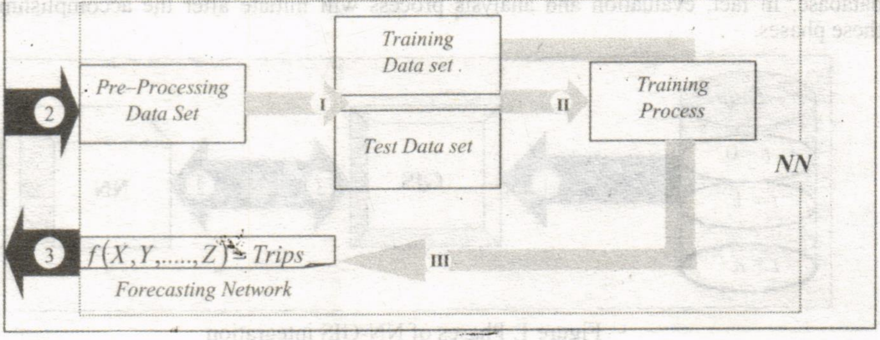

Figure 3. NN processing steps

3. FORMULATION OF NGTM

This modelling is based upon temporal and spatial interactions between land use patterns and transportation system. Firstly, we consider that these interactions can be expressed by the following indexes: transportation system (***T***); land use patterns (***L***); spatial location (***S***); and demographic (***D***). So, for each zone i at a given stage t of time, there will be a vector $\vec{I}_i(t)$ defined by equation 1.

$$\vec{I}_i(t)=\left\{\vec{T}_i(t),\vec{L}_i(t),\vec{S}_i,\vec{D}_i(t)\right\} \tag{1}$$

where

$\vec{T}_i(t)$ transportation system features for zone i at a given instant t of time;

$\vec{L}_i(t)$ land use information for zone i at a given time t;

$\vec{S}_i$ spatial location of zone i;

$\vec{D}_i(t)$ demographic conditions of zone i at a given point t of time;

From equation 1, we represent these interactions for a temporal perspective through equation 2.

$$\delta_i = \left\{ \vec{I}_i(1), \vec{I}_i(2), \ldots, \vec{I}_i(t), \ldots, \vec{I}_i(n) \right\} \tag{2}$$

where
n is the total number of time stages along the observation time period; and
δ_i is the set of interactions for n time periods for the ith zone.

Next, resulting from the interactions expressed by δ_i, travel demand is observed for each zone i and time t. As we are particularly interested on attractions into traffic zones, zonal trip ends a_i is defined as a travel demand-indicator for ith zone. So, analogously to equation 2, we establish

$$\alpha_i = \left\{ a_i(1), a_i(2), \ldots, a_i(t), \ldots, a_i(n) \right\} \tag{3}$$

where
$a_i(t)$ is the travel demand-indicator for ith zone at given point t of time; and
α_i is the set of zonal trips for n time periods for the ith zone.

Once the definition of land use-transportation interactions and travel demand were reached, we concentrate now on the establishment of the forecasting paradigm. For each stage of time t, travel demand for a future scenario (t+1) can be obtained from incorporation of previous interactions (equation 2) and demand (equation 3) into NGTM. This assumption is mathematically and graphically represented in equation 4 and Figure 4, respectively. They show that considering n previous stages and all traffic zones z, we want to calculate the demand for time n+1.

$$a_i(n+1) = f\left(\delta_i, \alpha_i\right) \tag{4}$$

where
f is a function that establishes the relationships between the elements.

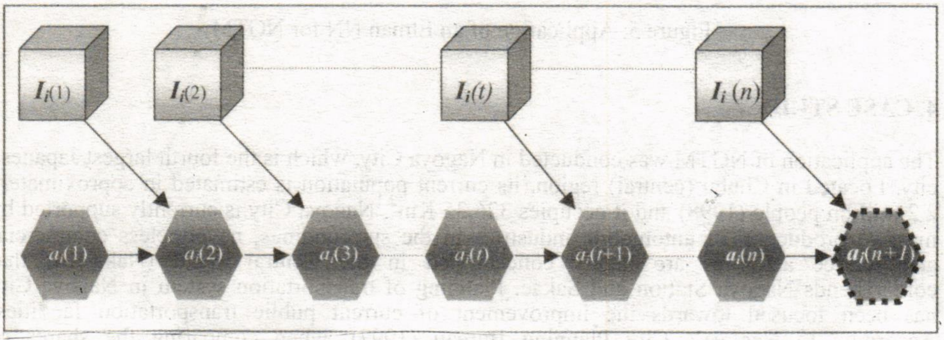

Figure 4. Recursive modelling and forecasting of travel demand

In NGTM, we apply NN to determine function f throughout a non-linear and recursive approach. To conduct this calculation, we have to define a NN architecture dedicated to efficiently process time-depending input vectors. 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 backpropagation. In order to represent time variations, Elman network makes use of recurrence technique, which is conducted using a *Context Layer* that makes a copy of inner states of the hidden layer and then feed it in the network in the next time step (Haykin, 1994). For the selected network architecture, we have now to establish the composition of input ***X*** vector and output ***Y*** as described in equations 5 and 6.

$$\vec{X}_i(t) = \left\{ \vec{I}_i(t) a_i(t) \right\} \tag{5}$$

$$Y_i(t) = a_i(t+1) \tag{6}$$

Figure 5 shows the structure of an Elman NN for NGTM, which is composed of four layers (Input, Hidden, Context and Output).

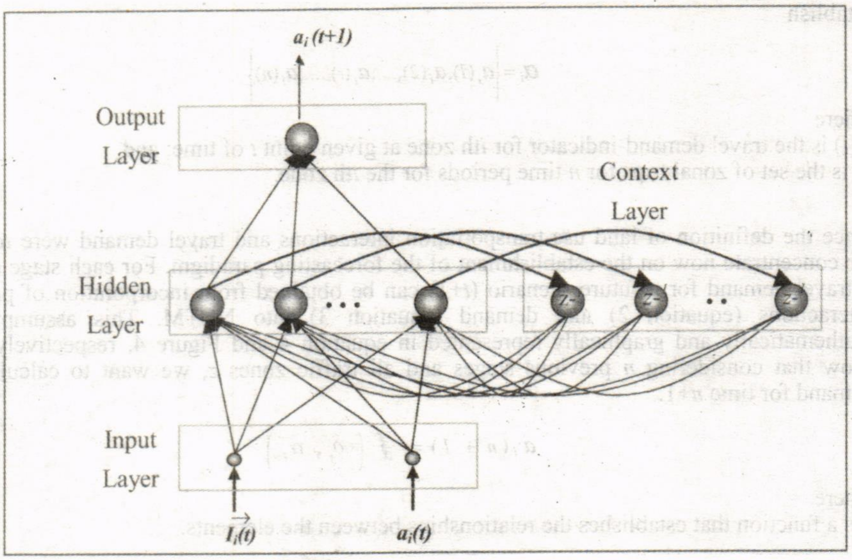

Figure 5. Application of an Elman NN for NGTM

4. CASE STUDY

The application of NGTM was conducted in Nagoya City, which is the fourth largest Japanese city. Located in Chubu (central) region, its current population is estimated in 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 the surroundings, nevertheless commercial and service activities are highly concentrated in the Central Ward (Naka-Ku) that comprehends Nagoya Station and Sakae. Planning of transportation system in Nagoya City has been focused towards the improvement of current public transportation facilities. According to Nagoya's City Planning Bureau (1997), when comparing the shares of transportation modes in Nagoya with those of Tokyo and Osaka, public transportation's participation is low due to delayed improvement of rail facilities and the urban structure that creates a dependency on cars.

The description of this case study is divided into three subsections. Firstly, we introduce the activities to construct the database in GIS. Next, we perform a brief analysis on the evolution of zonal trip ends along the years. In the third subsection, we report NN simulations and analyze the results in order to determine NGTM's efficiency and evaluate its forecasting for year 2001.

4.1 GIS database

Following the framework of NN-GIS integration as described in section 2.1 and 2.2, we constructed a geo-temporal database composed of 248 traffic zones, digital maps of transportation system (bus, train, subway and road), land use information (commercial and parking area) and demographic (population) data. Initially, efforts were taken in order to establish a geo-referenced database. We managed 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 was collected from Nagoya's Road Planning Section and digital map data was purchased from a private company. Figure 6 shows the main features of the GIS database.

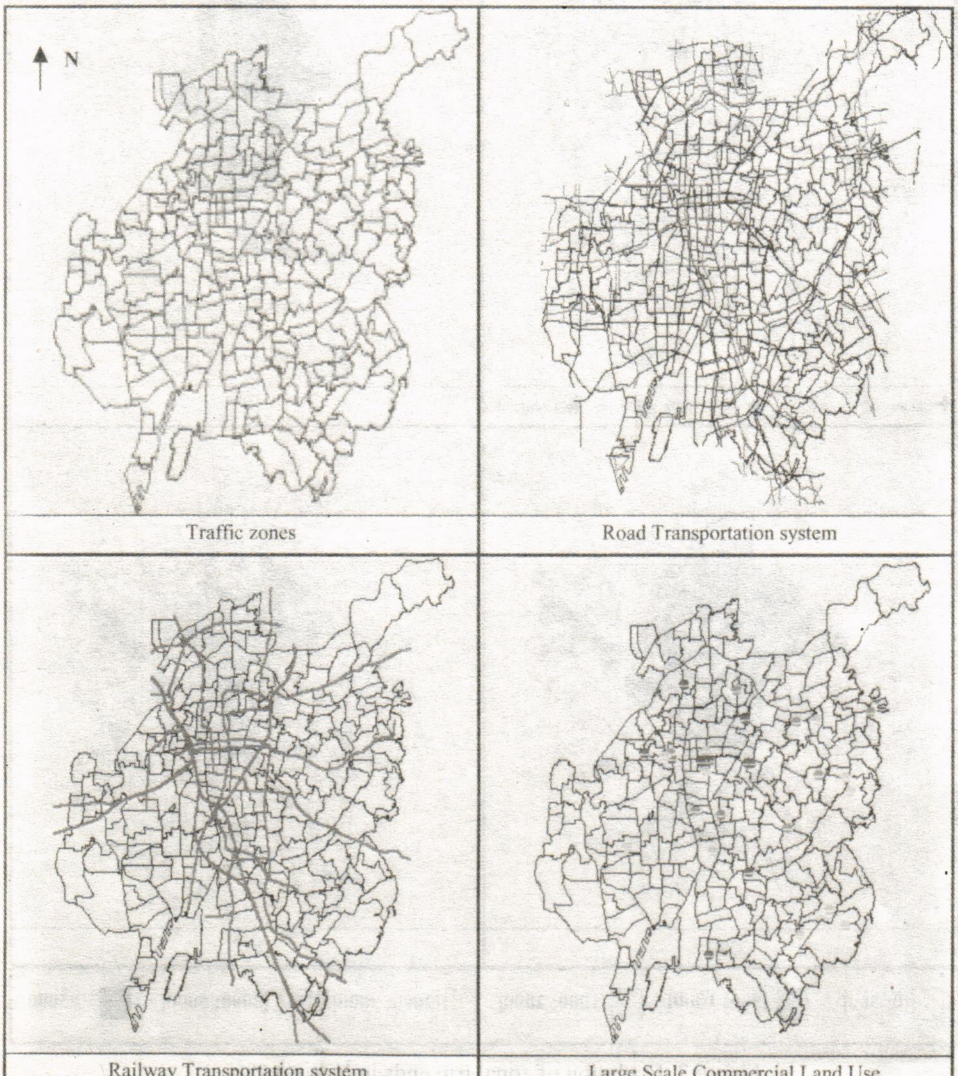

Figure 6. Main geographical features of GIS database for Nagoya City

4.2 Evolution of zonal trip ends

Planners are facing a perspective of decreasing on travel demand. In 1971-1981 period, 71% of traffic zones raised their zonal trip ends and there was an increase of 24% in the total number of zonal trip ends. In contrast, 1981-1991 period was marked by reduction in 86% of traffic zones and decrease of 18% on the total number of zonal trip ends. In Figure 7 and 8, it is observed that from 1971 to 1991 there has been a gradual reduction on zonal trip ends, despite of some cases with significant increasing in 1981. It is also observed that along the years Nagoya Station and Sakae regions have attracted the highest number of zonal trip ends. It is also observed that trip attraction into sub-centers have been, notably, in south (Kanayama), east (Hoshigaoka) and northeast (Ozone) region.

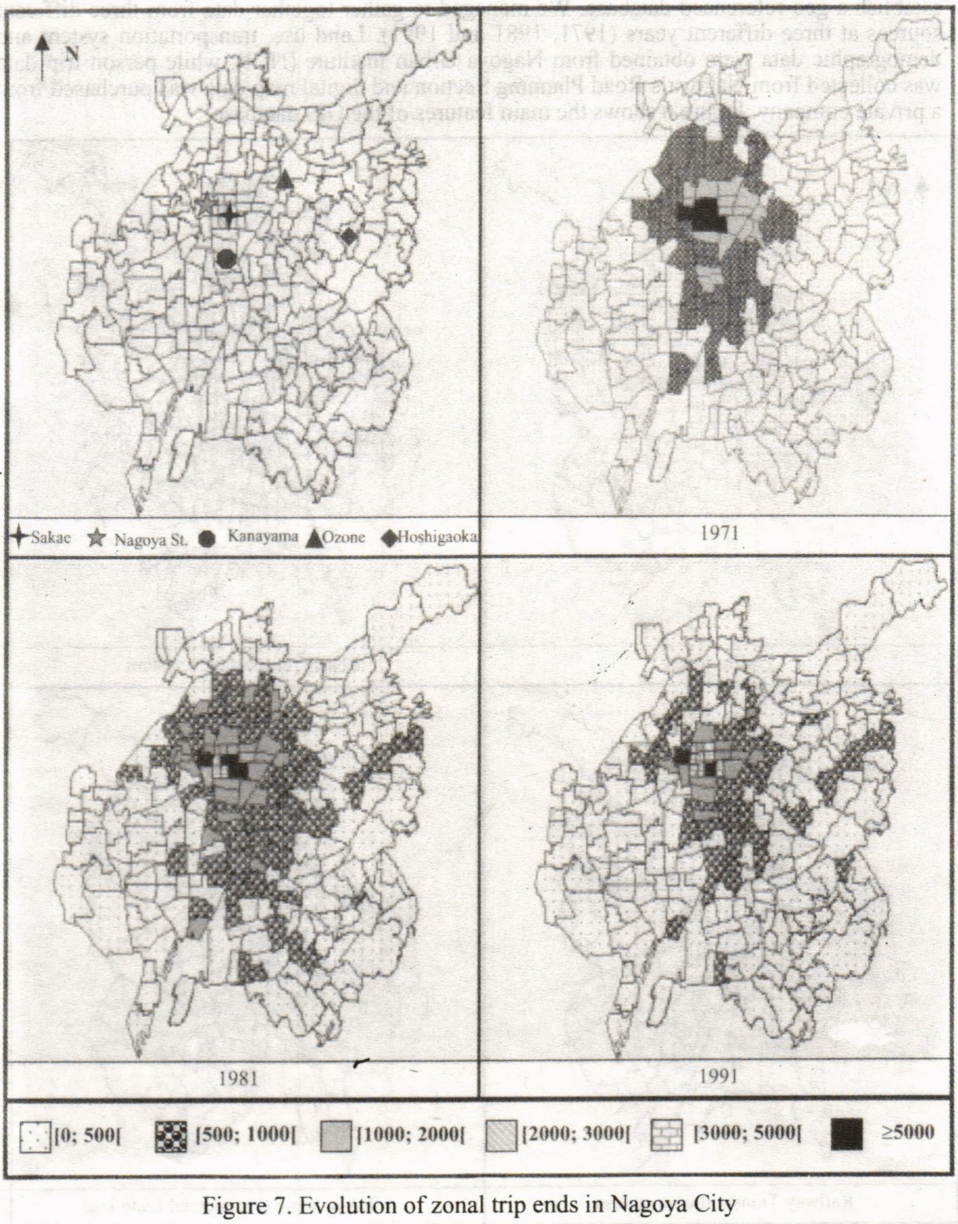

Figure 7. Evolution of zonal trip ends in Nagoya City

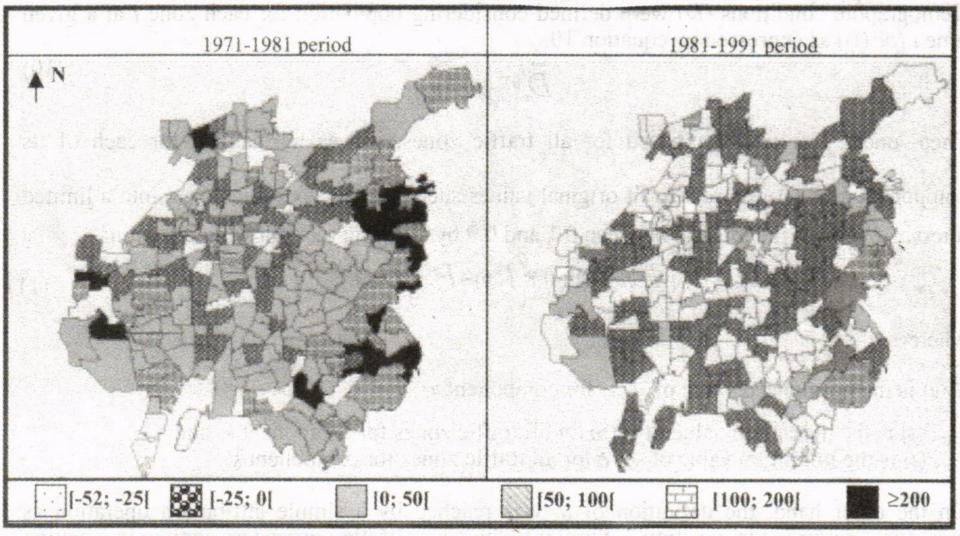

Figure 8. Relative variation (%) of zonal trip ends in Nagoya City

4.3 NN simulations

Based upon the GIS database, we were able to define vectors $\vec{I}_i(1971)$, $\vec{I}_i(1981)$, $a_i(1971)$, $a_i(1981)$ and $a_i(1981)$ for all traffic zones. A specification of both is essential since NGTM formulation was conceived in a general form allowing the incorporation of new variables according to planner's perception and data availability. Therefore, in this case study, we decided to use all collected data. So, transportation system was obtained by applying equation 7.

$$\vec{T}_i(t)=\{pt_i(t),pr_i(t),nh_i(t)\} \tag{7}$$

where
$pt_i(t)$ is the total extension (Km) of public transportation for zone i at a given time t;
$pr_i(t)$ is the total extension (Km) of road transportation for zone i at a given time t; and
$nh_i(t)$ expresses the existence or not of Nagoya Highway's ramp for zone i at a given time t.

Next, we defined the indexes related to land use patterns as presented by equation 8.

$$\vec{L}_i(t)=\{cl_i(t),pl_i(t),rl_i(t)\} \tag{8}$$

where
$cl_i(t)$ is the occupied area (m^2) of commercial pattern for zone i at a given time t;
$pl_i(t)$ is the occupied area (m^2) of parking pattern for zone i at a given time t; and
$rl_i(t)$ expresses the regulation or not of zone i at a given time t. This regulation expresses an intervention by Nagoya' planning section that intended to establish a reticulated structure of the road system.

In order to represent spatial location (S) for ith zone, we defined sd_i as the distance (Km) from zone i to Sakae's TV Tower that is main reference located in downtown; and id_i as the distance (Km) from zone i to Nagoya Interchange of Tokyo-Nagoya highway. Equation 9 defines S_i

$$\vec{S}_i=\{sd_i,id_i\} \tag{9}$$

Demographic conditions (D) were defined considering population for each zone i at a given time t ($pc_i(t)$) as expressed by equation 10.

$$\vec{D}_i(t) = \{pc_i(t)\} \tag{10}$$

Then, once $\vec{I}_i(t)$ was composed for all traffic zones, it was normalized for each of its component k ($I_i^k(t)$) in order to fit original values such as areas, extensions, etc into a limited interval. We used the interval between 0.1 and 0.9 by applying the following equation:

$$\bar{I}_i^k(t) = 0.1 + 0.8\left(I_i^k(t) - I_{\min}^k\right)\left(I_{\max}^k - I_{\min}^k\right)^{-1} \tag{11}$$

where

$\bar{I}_i^k(t)$ is the normalized value of $\vec{I}_i(t)$ for component k;

$I_{max}^k(t)$ is the maximum value of set δ for all traffic zones for component k; and
$I_{min}^k(t)$ is the minimum value of set δ for all traffic zones for component k.

On the other hand, the definition of a_i was reached by a simple attribution operation as previously described in equation 3. Similar to the normalization procedure applied in equation 11, a_i was processed by using equation 12.

$$\bar{a}_i(t) = 0.1 + 0.8\left(a_i(t) - a_{\min}(t)\right)\left(a_{\max}(t) - a_{\min}(t)\right)^{-1} \tag{12}$$

where
$\bar{a}_i(t)$ normalized value of $a_i(t)$ for all traffic zones;
a_{max} is the maximum value of set $a_i(t)$ for all traffic zones; and
a_{min} is the minimum value of set $a_i(t)$ for all traffic zones.

Next, gearing on the mathematical notion of equation 4, NN performed its simulations towards the obtainment modelling function capable to calculate trip zone ends for year 1991 considering previous time stages (1971 and 1981). In this sense, $I_i^k(t)$, $a_i(t)$ and $a_i(t+1)$ are associated to vector X and Y as conceived by equations 5 and 6. Normalized data sets were randomly divided into training and test, following a distribution of 75% (186 vectors) and 25% (62 vectors), respectively. Figure 9 shows the spatial distributions of training and test-related traffic zones.

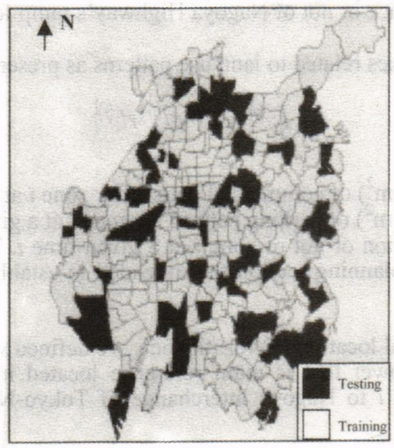

Figure 9. Spatial distribution of zones for testing and training

A four-layer NN structure as previously presented in Figure 5, containing 10 (input layer), 20 (hidden layer), 20 (context layer) and 1 (output layer) processing units was established. Applying a backpropagation algorithm with a learning rate of 0.01 and using sigmoid activation functions, the network was trained until a Minimum Square Error (*MSE*) in the test set was reached and the best results are shown in Table 1 and Figure 10 and 11.

Table 1. Best Training and Test results

	MSE	**Interactions**	**Maximum positive Error (%)**	**Maximum negative Error (%)**	**Average Error (zonal trip ends/ zone)**
Training	0,000346	117738			
Test	0,000344	122388	281	-91	36

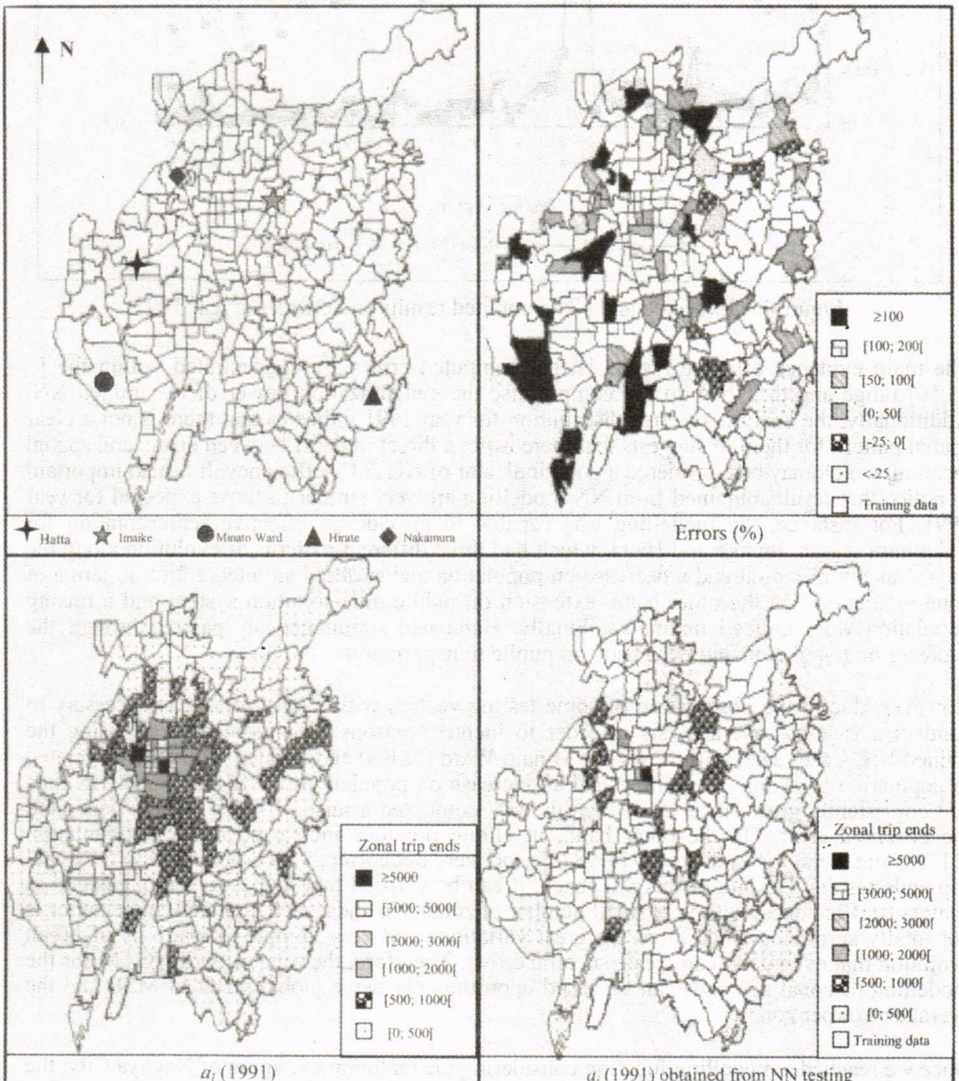

Figure 10. Simulation results and errors (%) for year 1991

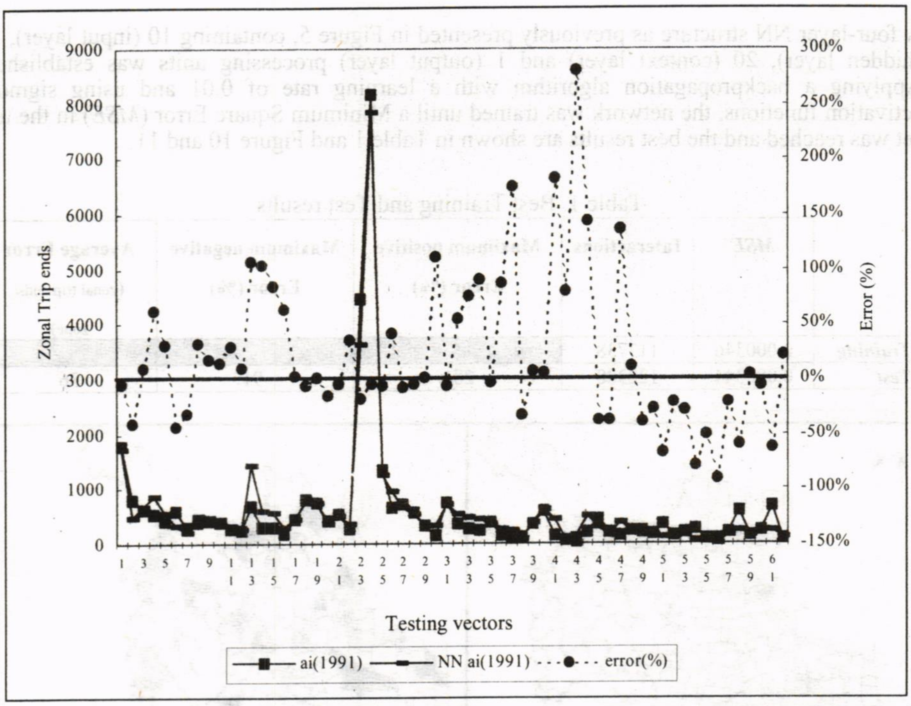

Figure 11. Expected and NN computed results and errors for year 1991

The main evidence of these results is that computed errors are concentrated within the [-25;50] range and that they do not compromise the generalization power of the trained NN. Additionally, the analysis of error distribution for year 1991 indicates that there is not a clear spatial pattern for them. It suggests that there is not a direct tradeoff between errors and spatial location, which may be considered a good indicator of NGTM's efficiency. It is also important to notice that results obtained from NN modelling are very similar to those expected for year 1991. For instance, the modelling was capable to provide an effective representation for Nakamura region, Imaike and Hatta, which had three different patterns of evolution along the time. Nakamura region had a decrease on population and suffered an intervention in terms of zone regulation. On the other hand, extension on public transportation system and a raising population were noticed in Imaike. Finally, Hatta had simultaneously passed through the decrease on population and expansion on public transportation.

However, due to the observation of some testing vectors with high errors, it is necessary to conduct a case-by-case analysis in order to identify reasons for miscalculations using the trained NN. Cases such as the error for Minato Ward (281%) and Hirate (-91%) are correlated to population growing. The former had an increase on population (65%) and zonal trip ends had consistently grow since 1971, then the NN computed a raise of 410%, which generated the observed error. On the other hand, in Hirate previous increasing on both population (117%) and zonal trip ends in 1971-1981 period were not correctly incorporated into the zonal trip ends results. Despite of this drawback, it can be verified that highest errors happened in vectors (traffic zones) with very small number of zonal trip ends, such a modelling behavior is not totally surprising since there are great variations and very complexes patterns of urban evolution that eventually can create specific errors. Therefore, the reliability of NGTM for the modelling of zonal trip ends can be based upon the expressive global result of MSE and the average error per zone.

Once we reached a modelling function considering the temporal evolution of Nagoya City, the next step is to process the forecasting for year 2001. In this sense, a new data set was obtained from the GIS database, which formed the vectors $\vec{I_i}(1981)$, $\vec{I_i}(1991)$, $a_i(1981)$ and $a_i(1991)$ for all traffic zones. Next, equations 11 and 12 were applied to normalize these vectors and using the network that was previously trained, we forecasted $a_i(2001)$ for all traffic zones as represented in Figure 12. It can be verified that few traffic zones have zonal trip ends increased and that only Minato Ward and Northeast region sharply present high rates of growing comparing to previous years. In the contrary direction, reduction on $a_i(2001)$ is largely observed but mostly they are within the [-2,5; 0[range. Such evolution directly reflects on the spatial distribution and agglomeration of zonal trip ends in 2001 following the tendency of previous years. In this sense, Sakae region and Nagoya Station area continue to be the main attraction poles but sub-centers are also noticed in Imaike, Ozone and Kanayama. This scenario of limited growing and almost keeping earlier urban configuration in terms of trip attraction is compatible to current policy of planing in Nagoya City, which did not present many modifications neither great interference related to transportation system and land use.

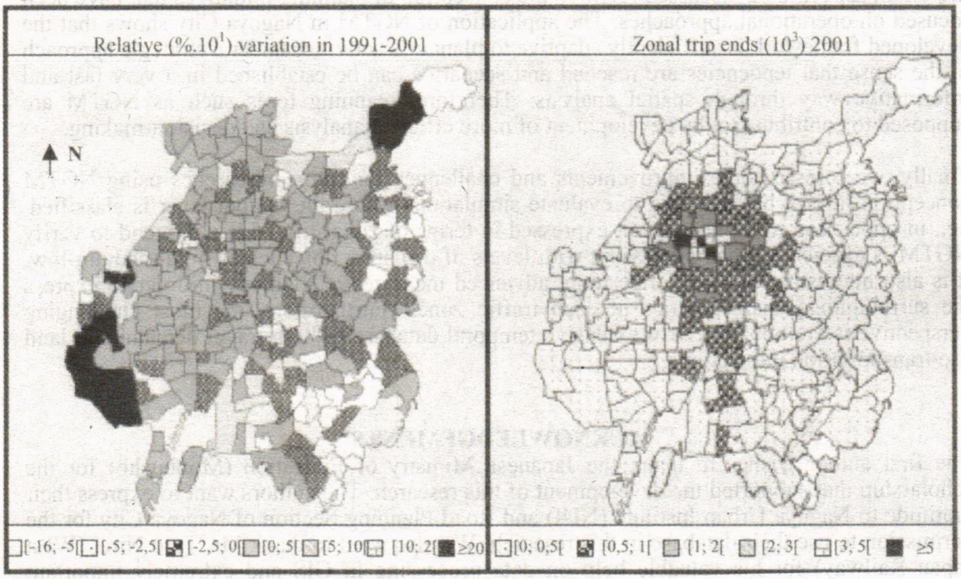

Figure 12. Forecasting for year 2001

5. CONCLUSION

In this paper, we present the development and application of a neural-geo-temporal modelling for the evaluation of travel demand agglomeration in urban areas. In a context of decentralization of urban activities, this modelling aimed to contribute to transportation planning towards efficient measures to assure a better life quality in metropolitan areas. In this sense, the obtainment of future patterns of trip attraction can contribute for the identification of evolutionary characteristics of traffic zones that have directly affected commuting patterns. Additionally and probably mostly important, NGTM intends to accomplish the incorporation of land use-transportation systems interactions through a non-linear and recursive approach, that extrapolates the potential of standard and traditional modelling techniques in order to represent the complex urban reality and its evolution along the time. This approach was possible due to the integration of NN and GIS that directly contributed to provide the essential capabilities of our modelling, which are deeply related to geographical processing of urban interactions throught these two advanced technologies and techniques.

In order to verify the efficiency of NGTM, the case study was conducted and results demonstrated that the proposed modelling was able to correctly represent the evolution from year 1971 to 1991. It is clear that NGTM provided a generalizing function that can be applied for all traffic zones of Nagoya City and that observed miscalculations are considered quite normal regarding the complex nature of this urban area. In the sequence, we applied NGTM to forecast zonal trip ends for year 2001 and its results express the current arrangement of trip attraction and urban agglomerations.

In addition to the evaluation of NGTM, there are two important aspects to be highlighted from the case study. Firstly, it was remarkable the lack of a central geo-temporal database that could be promptly used in a research project without any economical objective. It shows that planning agencies are not very well supported in terms of data organization, principally when evaluating a technological era with so much to offer and still very reduced exploration of them. Models such as proposed in this paper have to be improved and adapted to the dynamic of urban areas, but on the other hand it is fundamental to take advantage of databases that must be created under clear standards of organization, collection and processing. The second important aspect to be discussed refers to the conception of planning initiatives that have been focused on operational approaches. The application of NGTM in Nagoya City shows that the developed framework is sufficiently adaptive to planner's activities under a strategic approach in the sense that tendencies are reached and scenarios can be established in a very fast and informative way through spatial analysis. Therefore, planning tools such as NGTM are supposed to contribute to the development of more efficient analysis and decision-making.

Finally, we foresee some improvements and challenges for future researches using NGTM conception. It will be attractive to evaluate simulations where the Output layer is classified, i.e., in opposition to a linear result expressed in terms of zonal trip ends we intend to verify NGTM` s efficiency when processing with levels of trip attraction such as high-medium-low. It is also interesting to incorporate more advanced measures of topology in order to express the surroundings characteristics of each traffic zones. Furthermore, the most challenging perspective is the obtainment of extensive temporal database of both travel demand and land use-transportation interactions.

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