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NGSM-AP – MODELLING OF VEHICULAR POLLUTION WITHIN THE CONCEPT OF SUSTAINABLE TRANSPORTATION AND STRATEGIC PLANNING*

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1. Introduction

In the last decades the decrease of the urban quality of life due to the environmental matters stimulated international organizations to consider environmental problems based on the implementation of a Sustainable Development actions concerning social, environmental and economical interests. Experience, however, has shown that no Sustainable Development is possible without Sustainable Transportation, i.e., improving transport's benefits while reducing its environmental impact to sustainable levels [1]. Hence governmental policies on Sustainable Transportation have focused on reorganising the system while integrating it into the urban planning process, and trying to minimize the problem of vehicular pollution by various means. However, a brief literature review shows us that most of the studies in this field tend to concentrate on the use of specifics software[2], or on the development of complex mathematical formulations for pollution dispersion[3], generally focusing just the transportation network, without attempting to the application in more strategic (macro) approaches, as the sustainable principles require[4]. In those cases, the specificity of the studies, the number of the variables involved, and the complexity of the models, which try with traditional statistical methods to relate variables from different origins, makes its application in large cities studies hard to be performed by most of the researchers or planners, who need, in most of the time, just directives for the development and application of urban and transportation policies.

On the other hand, technological advances and the development of computational intelligence systems have helped problems related to urban and transportation planning in different ways, such as, in estimating origin-destination matrix or forecasting transportation demand, due to its efficiency and flexibility in correlating successfully different patterns of variables, something very difficult to reach by traditional models[5)-6)]. Therefore, it makes us believe that the use of tools such as Neural Networks (NN) could make possible the representation of the relationship between variables derived from both urban space and transportation systems, such as land use, and those variables' relation to the pollution indices, as a new approach to contribute actively in the studies of urban and transportation sustainability concerning the strategic planning process.

Thus, the purpose of this research is to present a flexible tool for diagnosis and macro analysis of the vehicular air pollution, the Neural Geo-spatial Model for Air Pollution (NGSM-AP), as a contribution to urban and transportation sustainable development within the concept of Strategic Planning. The NGSM-AP tries to analyse how some urban, transportation, and meteorological intervening factors affect vehicle emission levels by establishing non-linear relationships between variables, and also allows the management of these variables compounding different urban scenarios in order to forecast vehicular air pollution indices.

This paper initially discusses the principles of Sustainable Transportation within the process of Strategic Planning with the help of new technologies. Then, the concept of NGSM-AP for vehicular pollution within the context of strategic planning is presented. Next, the description of the NGSM-AP mathematical formulation on the modelling of vehicle emissions is showed. A case study has been conducted in Nagoya based on the performance of the NGSM-AP diagnosing and forecasting vehicular air pollution for different sets of scenarios, in order to validate its use as a strategic planning tool in the development of urban sustainable policies. At the end of the paper, the results of the study are discussed and some proposals are made for future improvement on the model.

2. Sustainable Transportation and Strategic Planning

* Keywords: Sustainable Transportation, Air Pollution, Neural Network
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The idea of Sustainable Transportation could be understood as a particular extension of international initiatives to react against the continuous process of degradation of the urban quality of life, systematized by actions of Sustainable Development in order to secure the quality of life of future generations[7]. Such actions, however, cannot be disassociated from interventions in the transportation system, one of the main agents related to urban activity, in an effort to improve urban displacements while minimizing the environmental impact. Sustainable Transportation was defined by the Centre for Sustainable Transportation as transportation which, "allows the basic needs of individuals and societies to be met safely and in a manner consistent with human and ecosystem health; ...is affordable, operates efficiently, offers choice of transport mode, and supports a vibrant economy, and; limits emissions within the planet's ability to absorb them..."[8].

On the other hand, the practical realization of those goals is only possible through a general and systemic comprehension of actual conditions that determines strategic policies which could be implemented in different time periods, i.e. within the Strategic Planning Process. Hence Strategic Planning could be briefly defined as a process which provides planners with policy options and implementation strategies to help them make informed decisions and strategic agreements[9], in the opposition of the traditional approaches of urban transportation planning, where, only recently, has changed on the way to a strategic approach. After a long period predominately geared towards evaluating traffic jams and road construction in day-to-day operations, planning agencies shift their focus to longer term (future visions) and to developing strategies to obtain more integrated transportation systems by exploring new technological potentials[10].

In this sense, linking the idea of Sustainable Transportation to the Strategic Planning Process means allowing planners, with the help of technological tools, to elaborate urban and transportation policies and make choices among different scenarios, based on urban and transportation sources, such as: land use, transportation system and environment conditions. It could be understood methodologically through five cyclical stages, according to the urban and transportation comprehensive planning processes[11)-12], with the difference in the weight attributed to the environmental matter. The stages could be briefly understood as following: 1)*System's Diagnosis and Monitoring* – Data collection; system diagnosis based on the relation of intervening variables; 2) *Formulation of Strategy* – Establishing principles for urban and transportation planning policies based on the system diagnosis; 3)*Future Scenarios Creation* – Creating future scenarios based on the defined principles; 4) *Evaluation and Decision* – Evaluating and choosing the most appropriate scenario based on the defined principles; and, 5) *Implementation, Management and Control.*

3. The concept of NGSM-AP within the Strategic Planning Context

Modelling techniques in a strategic planning context have assumed a complementary role in order to provide additional information in overcoming uncertainties. According to Ng[13], once the strategic approach is based on a discussion and dialogue between internal and external actors, analytical work does not assume primary importance as verified in traditional planning. In this sense, strategies are formulated and evaluated regarding multiple scenarios and alternatives in order to take advantage of available resources. In this sense, the development of an air pollution model plays a very important role in formulating air pollution control and management strategies by providing information about better and more efficient air quality planning[14].

Thus, the concept of the NGSM-AP[15], based formally on a Neural Network model applied to forecast person travel demand[16], is to establish a diagnosis of air pollution derived from mobile sources in the urban system allowing the composition of different urban scenarios in order to forecast the vehicular air pollution indices, based on the process of Strategic Planning on the way to develop a more sustainable city (Figure 1). The model will take into account the influence of urban dynamics such as land use and transportation system on demand for travel and consequently on the emission of air pollutants.

The idea of urban dynamics could be understood as the way in which the population displaces within the urban area in-between different patterns of land use in order to attend their economic or personal needs[17]. Most urban environmental problems, however, are a consequence of the way how these displacements are effected. A high volume of cars and buses on the roads, an aged fleet and long traffic jams are some of the main sources of pollution derived from mobile sources. With this in mind, studies have been trying to establish a relation among land use, transportation systems, traffic volume and pollution in order to minimize the effect of vehicles on the environment. However, the complex interaction of air pollution variables, which depend on various exogenous factors, with those urban with different levels of aggregation combined with high costs, makes measurement difficult to achieve.

Against this background, Neural Networks (NN) modelling attempts to fill the gaps in the traditional studies of urban transportation and environment. NN has come to be thought of as, "a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use"[18], i.e., it works as a powerful instrument of parallel processing with various degrees of liberty, which is able to learn and to generalize the "acquired knowledge" and so become a dexterous and flexible modelling tool.

Hence, due to the flexibility of the NN model, we believe it can be also helpful to attend some of the requirements of the sustainable transportation targets in promoting the balance among economic, social and environmental principles. These targets define some strategies of action, such as: improvement of the public transportation system; decrease of urban displacements; creation of "green zones; and, increase of accessibility, which are affordable to be performed by the NGSM-AP achieving different urban scenarios, based on the steps proposed in the strategic planning process.

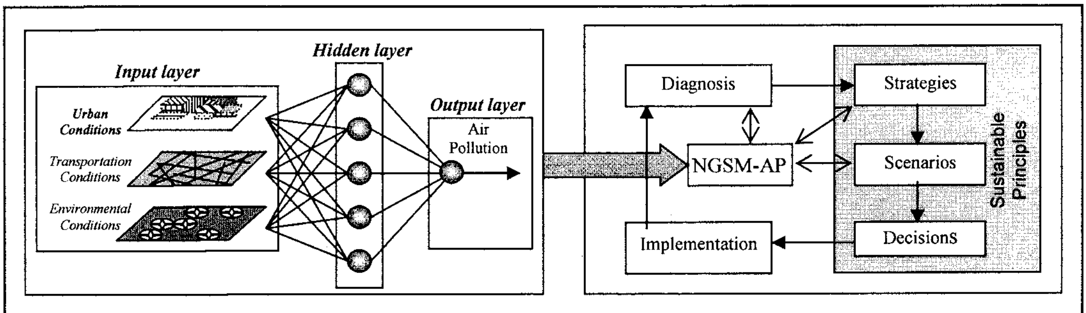


Figure 1: NGSM-AP and Strategic Planning Process based on Sustainable Principles

Thus, the purpose of this research is firstly to model the non-linear relation among urban, transportation and environmental conditions, using the NGSM-AP, in order to evaluate its possibility of use as a tool of diagnosis of urban system, and then, according to the new compound of urban scenarios based on the sustainable transportation principles, to perform the NGSM-AP trying to forecast lower vehicular pollution indices. These are the steps in defining the aims of the strategic planning process with the intention of developing urban and transportation sustainability.

4 – Definition of the Neural Network Model

Thus, in NGSM-AP, Air Pollution (*AP*) is obtained from a non-linear relation between Land Use patterns (*LU*), Transportation System (*TS*), Spatial Location (*SL*), Demography Conditions (*DC*) and Environmental Conditions (*EC*) as defined in Equation (1).

$$AP = f(LU;TS;SL;DC;EC) \tag{1}$$

where, f is a non-linear function establishing a set of weights W between the dependent variables (*LU, TS, SL, DC and EC*). These weights are determined through NN computation based on a Multi-Layer Perceptron (MLP) architecture. Similar to standard regression modelling, independent (input vector I) and dependent (output vector O) variables have to be defined in MLP architecture. Mathematically, an urban area, which is divided into *nz* unit of analysis (zones, macro zones, traffic zones, census borders, etc). For each unit of analysis I (zone), a vector $\vec{I_i}$ is defined as shown in Equation (2).

$$\vec{I_i} = \{\vec{TS_i}, \vec{LU_i}, \vec{SL_i}, \vec{DC_i}, \vec{EC_i}\} \tag{2}$$

where: $\vec{TS_i}$ vector containing transportation system features of i; $\vec{LU_i}$ vector representing land use characteristics of i; $\vec{SL_i}$ vector for describing spatial location of i; $\vec{DC_i}$ vector with demographic conditions of i; and $\vec{EC_i}$ vector with environmental conditions of i. On the other hand, AP_i expressing vehicular pollution of the unit of analysis i is assigned to the output vector $\vec{O_i}$.

Using training data sets, training process might be conducted until the NN reaches the convergence status. This happens if after a number q of iterations, additional increments on $\Delta w_{jh}(q)$ do not compute considerable improvement on the results ($y_j(q)$). Based upon the weights W obtained for the trained NN, testing has to be conducted in order to evaluate the learning capabilities of the modelling function. One of the measurements that is usually employed is the Minimum Square Error (*MSE*), which is computed as presented in Equation (3).

$$MSE = \sum_{i=1}^{nt} \sum_{j=1} \left(d'_j - y'_j\right)^2 / nt \qquad (3)$$

where: nt is the number of samples in the testing data set; d'_j is the desired output in the testing data set for neuron j; and y'_j is the calculated output in the testing data set for neuron j.

5. Case Study

The case study was conducted in Nagoya City, Japan. In 1991, when the statistics used here were gathered, the population was about 2,000,000 distributed over 326.35 Km^2. Nagoya has a radial and concentric urban structure divided into 16 wards and 248 traffic zones related to the predominant land use. The transportation system is formed by the interaction of the approximately 1,003 km of roads and 75 km of urban express highways and the public system, creating a high dependency on cars (around 70%)[19]. Thus, according to Nagoya City Environmental Affairs Bureau, in order to continually monitor air and water pollution 34 monitoring stations have been established at important spots, roadsides and rivers in Nagoya city, and densities of different types of pollutant are constantly measured. The pollutant used for the modelling was NO_x, collected in 26 stations, and the general average emission for vehicular source in Nagoya is around 65%, according to Nagoya City Environmental Affairs Bureau.

Concerning the pollution indices used in this research, since there are only 26 monitoring stations for 248 traffic zones, a simplified methodology was applied to estimate pollution indices for each zone. The monitoring stations are located close to areas where historically highest levels of pollution were detected[20], in that sense; there is a decrease in the concentration according to the distance, due to dispersion. The main variables which have influence in the air pollution dispersion are: morphology, environmental conditions and distance from the pollution source[14]. Since, the variables morphology (land use density) and environmental conditions were taken into account in the modelling process as part of the data set input, the use of the distance and its non-linear relation with the other variables would establish the behaviour, and, consequently, the dispersion of the vehicular pollution in the atmosphere. Thus, the distances of the centers of each traffic zone to the closest monitoring station were calculated using a Geographical Information System (GIS) (Figure 2), and included as an input of the NGSM-AP. The other data; land use, transportation system and demographics, were obtained from Nagoya City Bureau, while pollution, wind direction and velocity were obtained from Nagoya City Environmental Affairs Bureau.

(1) NN simulations for obtainment of NGTM-AP

Activities of this phase of the application of NGTM-AP comprise the creation of input and output vectors through pre-processing of data, definition of training and testing data sets, training and testing.

Initially, transportation system vector $\overrightarrow{TS_i}$ is defined as shown in Equation (4).

$$\overrightarrow{TS_i} = \{PT_i, RT_i, ET_i\} \qquad (4)$$

where: PT_i is the total extension (Km) of public transportation for zone i; RT_i is the total extension (Km) of road transportation for zone i; and, ET_i represents the existence of an express railway in the zone i.

Next, we defined the indices related to land use patterns in the Equation (5).

$$\overrightarrow{LU_i} = \{CL_i\} \qquad (5)$$

where: CL_i is the occupied area (m^2) of commercial pattern for zone i;

Spatial location vector ($\overrightarrow{SL_i}$) is expressed by SD_i representing the distance (Km) from zone i to Sakae's TV Tower, which is the main reference point located in the city centre as shown in Equation (6).

$$\overrightarrow{SL_i} = \{SD_i\} \qquad (6)$$

Next, as defined before the environmental conditions $\overrightarrow{EC_i}$ as presented by Equation (7).

$$\overrightarrow{EC_i} = \{WD_i, WV_i, CD_i\} \qquad (7)$$

where: WD_i is the wind predominant direction for zone i; WV_i is the average of the wind velocity (m/s) for zone i; and, CD_i is the distance between the centroid of the zone i and the closest monitoring station (Km).

Finally, $\overrightarrow{DC_i}$ was defined as the number of inhabitants in the zone i.

Then, once $\vec{I}_i$ was composed for all traffic zones, it was normalized for each of its component ς, in order to fit original values such as areas, extensions, etc into a limited interval. The interval between 0.1 and 0.9 was used by applying the following Equation (8):

$$\overline{I_i}[\varsigma] = 0.1 + 0.8\left(I_i[\varsigma] - I_{\min}[\varsigma]\right)\left(I_{\max}[\varsigma] - I_{\min}[\varsigma]\right)^{-1} \qquad (8)$$

where: $\overline{I_i}[\varsigma]$ is the normalized value of $I_i[\varsigma]$ for component ς; $\overline{I}_{max}[\varsigma]$ is the maximum value of $I_i[\varsigma]$ for component ς, inside $\overrightarrow{IT_i}$ (the set of interactions for the *i*th zone); and $\overline{I}_{min}[\varsigma]$ is the minimum value of $I_i[\varsigma]$ for component ς, inside $\overrightarrow{IT_i}$.

On the other hand, similar to the normalization procedure which was applied in Equation (11), AP_i was processed by using Equation (9).

$$\overline{AP_i} = 0.1 + 0.8(AP_i - AP_{min})(AP_{max} - AP_{min})^{-1} \quad (9)$$

where: $\overline{AP_i}$ is the normalized value of AP_i inside $\overrightarrow{AT_i}$ (the set of air pollution indices for the *i*th zone); AP_{max} is the maximum value of AP_i inside $\overrightarrow{AT_i}$; and AP_{min} is the minimum value of AP_i inside $\overrightarrow{AT_i}$.

Next, the NN was used to perform simulations towards the obtainment of modelling function capable to calculate the concentration of NO_x (AP) per zone of the year 1991 considering the vectors presented previously. In this sense, $\overline{I}[\varsigma]$ and $\overline{AP_i}$ were associated to $\vec{Y}$ $\vec{X}$ input and $\vec{Y}$ output vectors. As the data set was not large in terms of the number of sample vectors, it was divided in 4 groups and leave one out cross validation method was selected. In each interaction of the validation one group was selected for the testing set and the remaining for training the NN model. Thus, normalized vectors were randomly divided into training and test data sets, with the distribution of 75% (186 vectors) and 25% (62 vectors) for each group to obtain vectors $\vec{X}'$ $\vec{Y}'$ for training and $\vec{X}''$ input and $\vec{Y}''$ output for testing.

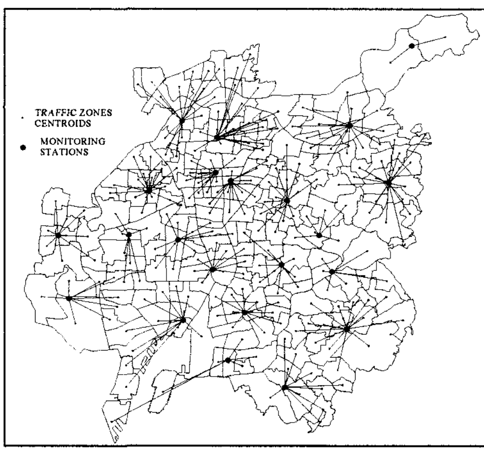
In the sequence, a three-layer NN structure was established. It was configured with 8-input, 8-hidden and 1-output processing units. Applying a back-propagation algorithm with a learning rate of 0.001 (η =0.001) and using sigmoid activation functions (α=∞), the network was trained until the minimums *MSE* in the test sets were reached. Thus, the group with the lowest *MSE* is selected for analysing. After 3,885,912 iterations of the NGTM-AP the best weights were defined with the *MSE* in 1.72 as the best optimisation. The application of the trained NN on a testing data set ($\vec{X}''$ and $\vec{Y}''$) generated a maximum positive error in 43%, a maximum negative error in -27% and the average error in 14%. It is also observed that the average error per zone (ξ), as defined in Equation (10), 62 air pollution indices per zone was reached.

$$\xi = \left(\sum_{i=1}^{nt} \left| AP_i'' - Y_i'' \right| \right) \Big/ nt \quad (10)$$

where: AP_i'' is the desired air pollution indices for zone *i* on the testing data set; Y_i'' is the measured air pollution indices for testing data zone *i*; and *nt* is the total number of vectors for testing.

Figure 3 shows the spatial distribution of relative error ξR_i(%), which could also be called the deviation of the expected pollution indices, for each zone *i* as defined by Equation (11). In the Table 1 the values of AP_i'' and Y_i'' were divided into five classes of results in order to better evaluate the performance of the model. It can be verified that the modelling function had more difficult to reach the pollution indices in the intervals [85;97) and [61;73) tending to concentrate the forecasting in the interval [49;61).

$$\xi R_1 = (AP_i'' - Y_i'')/AP_i'' \quad (11)$$



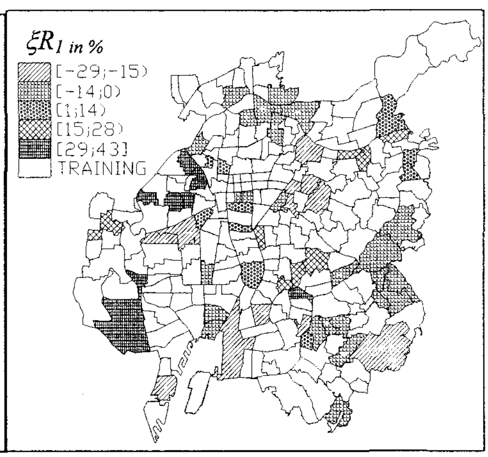


Figure 2: Distances between centroids and monitoring stations (GIS); Figure 3: Relative errors ξR_I (%) or deviation of the expected indices

Table 1: Distribution of Air Pollution Indices

	Classes of Results (air pollution indices)				
	[49;61)	[61;73)	[73;85)	[85;97)	[97;109]
AP_i"	25	16	7	9	5
Y_i"	18	33	6	0	5

(2) Creation of urban scenarios using NGTM-AP

After obtaining the NGTM-AP with the lowest *MSE* an urban variable was selected to be managed and to compound different scenarios based on one of the sustainable transportation targets in order to forecast the vehicular pollution indices. The parameter adopted was population density (residential use), owing to: a) the population of residential areas are exposed to air pollution during a longer period of time; b) population density defines not only a land use pattern (residential), but also an urban morphology (high densities are usually associated with verticality); c) the data used in the NGTM-AP formulation correspond to the night peak hour, i.e., the orientation of the displacements are from the centres to the residential areas; and, d) among the other variables considered in the NGTM-AP formulation (LU, TS, EC), density is the only parameter which doesn't depend on the atmospheric conditions (EC), doesn't require high amounts of investments in reordering transportation infrastructure (TS), and its targets could be reached through land use policies also taking advantage of the EC and the TS already existents.

Firstly, residential land use, density and high pollution indices collected in the monitoring stations were considered to define the residential districts with the highest pollution indices to be handled. Thus, two critical areas with high population exposed to the high pollution indices were identified: A – in Nakagawa Ward, with high density, and C – in Chikusa Ward, with high density. Concomitantly, a pair of districts close to the critical areas with the similar land use and transportation characteristics, but with low pollution indices and opposite densities, was selected for the interpolation: B – Nakamura Ward, with low density, and D – Mizuho Ward, with low density (Figure 4).

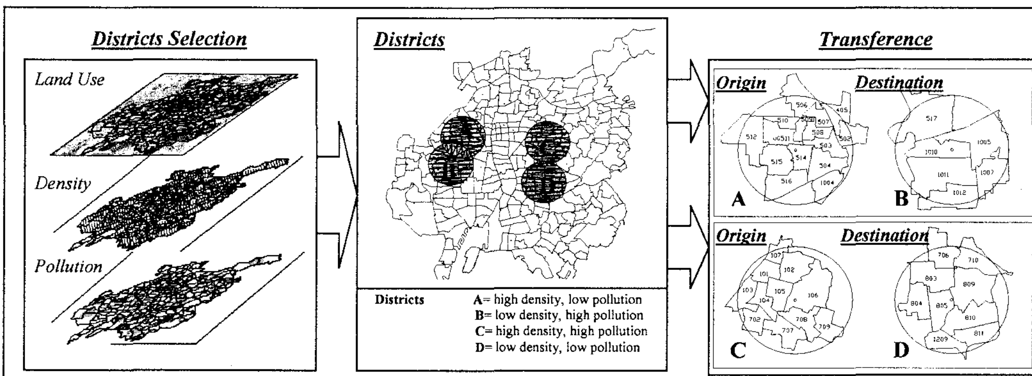


Figure 4: Districts selection for the residential population transference

A program was developed to make the transference of the population from the districts with high densities A and C, to those with low densities B and D, respectively. The sum of the population was withdrawn proportionally from each zone of the origin districts, and was proportionally reallocated in the zones of the destiny districts. In each simulation S_x, where x represents the number of the simulation, 2% of the population *DC* was replaced. Then, the NGSM-AP was performed and the vehicular pollution indices AP_i" were forecasted.

(3) Evaluation

The criterion selected for the evaluation of the urban scenarios obtained through the performance of NGSM-AP was the reduction of the NO_x indices with the transference of the residential population affected by high indices of pollution. Thus, in conformity with the results desired, the Figure 5 presented linear reductions of the NO_x indices in both districts where the residential population were withdrawn with a consequent increase in the indices in those in which the residential population were reallocated.

In order to evaluate the scenarios performed by the NGSM-AP, an indicator of pollution I (1/1000ppm) was calculated using the weighted average of AP" in function of the population *DC* considering each district itself in (D_i, Dj), or considering both districts (origin and destination) in (D_i+Dj). The results of the simulations S_x are presented for each 20%, (from 0% to 100%) of *DC* re-managed in the Table 2.

A previous analysis in the results of D_A+ D_B and D_C+ D_D, which take into account the higher amount of population exposed to the pollution indices, show initially the decrease of the I values. However, after reaching a minimum value, which occurs in the S_{10} for (D_A+ D_B) and S_{20} for (D_C+ D_D), where I began to increase. Thus, if just this criterion is regarded in the evaluation of scenarios resulted from the performances of the NGSM-AP, during the interpolation of population between districts with different indices of vehicular air pollution, the pairs D_A+ D_B, S_{10} and D_C+ D_D, S_{20} could be considered the most affordable for acquiring the target proposed by one of the transportation sustainable principles.

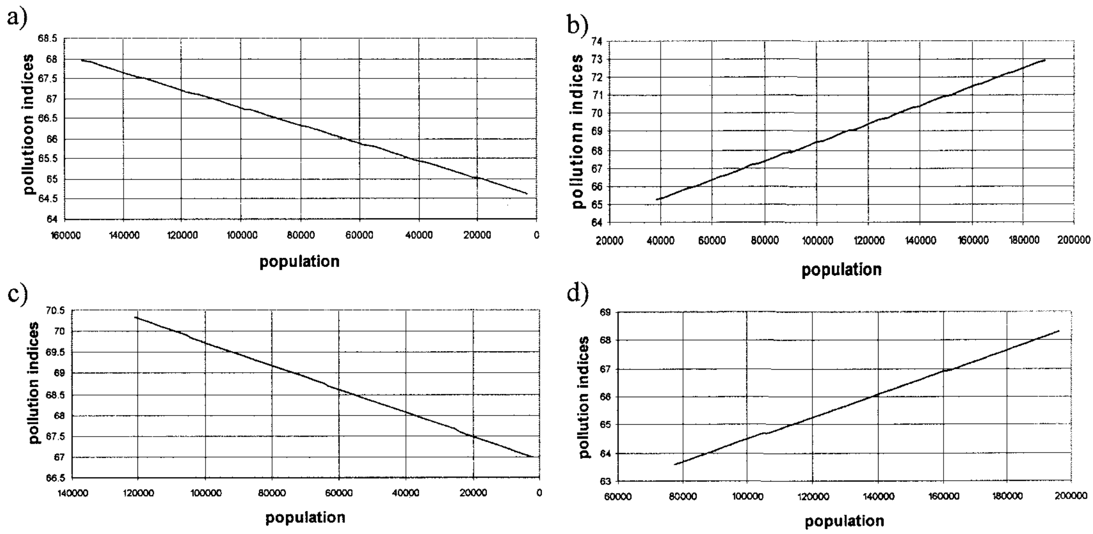


Figure 5: Pollution Indices x Population – Districts: a) from A; b) to B; c) from C; d) to D

Table 2: Simulations Results of the Urban Scenarios

Districts	*S_1 (0%)*		*S_{10} (20%)*		*S_{20} (40%)*		*S_{30} (60%)*		*S_{40} (80%)*		*S_{50} (100%)*	
	*I**	*DC*	*I**	*DC*	*I**	*DC*	*I**	*DC*	*I**	*DC*	*I**	*DC*
D_A	67.96	153797	67.42	123038	66.74	92278	66.06	61519	65.38	30759	64.71	0
D_B	65.23	38120	66.49	68879	68.06	99639	69.64	130398	71.21	161158	72.78	191917
D_A+ D_B	**67.42**	**191917**	**67.10**	**191917**	**67.41**	**191917**	**68.43**	**191917**	**71.21**	**191917**	**72.65**	**191917**
D_C	70.33	121011	69.71	96809	69.03	72607	68.35	48404	67.67	24202	66.99	0
D_D	63.59	87411	64.45	111613	65.41	135815	66.38	160018	67.34	184220	68.30	208422
D_C+ D_D	**67.69**	**208422**	**67.08**	**208422**	**66.78**	**208422**	**66.88**	**208422**	**67.38**	**208422**	**68.28**	**208422**

* *1/1000ppm*

6. Conclusion

The development of the NGSM-AP aims to contribute effectively as a new approach in the studies of urban and transportation sustainability concerning the concept of strategic planning, due to its potentiality in relating urban, transportation and environmental variables to the emission of vehicular air pollution, allowing a macro analysis of the environmental impact for changes in the urban layout.

With particular regard to NGSM-AP's formulations, the results of the simulations showed how the NGSM-AP could contribute as an efficient and flexible tool for the analysis in strategic approaches taking into account a relative simple set of data to establish directives of systemic actions. However, it must be stressed that the NGSM-AP cannot substitute the traditional environmental models in accurate studies, mainly those in which the extreme precision of the results are essential in the analyses, unless the formulation of the model be modified.

Concerning the urban scenarios obtained by the performance of the NGSM-AP, they were used mainly as a validation of the model, since actions like those proposed in this study, as the complete transference of the population from a district to another, will rarely be put into effect in the reality. However, the understanding of the relation among the variables, and their influence in the environmental matters, provide planners with important information for the development of urban and transportation policies in different levels.

The main drawback on employing NGSM-AP is that the relationships between the variables can not 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. On the other hand, linear modeling is rather simple on its understanding, since the number of parameters are limited. However, until scholars develop a form to reach some comprehension on the weights generated by NN modeling, the combination of both techniques would be an alternative way. Some errors and inaccuracy could be credited to the quality of the data and to the level of aggregation in which some data are disposed, such as, land use patterns and pollution.

Finally, we intend to improve the NGSM-AP through greater integration of the whole process of strategic planning within the concept of Sustainable Development and the use of new technologies, in order to contribute to the realization and consolidation of a more functional and clean – Sustainable – city.

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NGSM-AP – Modelling of Vehicular Pollution within the Concept of Sustainable Transportation and Strategic Planning*

By Dalve A. S. ALVES**, Koshi YAMAMOTO***, Yaeko YAMASHITA**** and Eizo HIDESHIMA*****

A strategic planning model for vehicular air pollution analysis is presented. The model is based on the representation of the urban, transportation and environment conditions interacting under a neural geo-spatial approach to forecast vehicular air pollution for the stages of diagnosis and scenarios creation as a part of the strategic planning process, within the urban and transportation sustainability principles. A case study in Nagoya City was conducted to verify the efficiency of the model. The result reached expresses an efficient definition of the NN, and also allows the continuance of the research.

持続可能な交通と戦略的計画のための自動車公害予測モデル*

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都市と交通の持続的発展を目的とする戦略的都市交通計画策定システムの一部である診断とシナリオ構築プロセスにおいて、自動車公害を予測するために Neural Geo-Spatial なアプローチを試みた。そして名古屋市域へのケーススタディを通してモデルの有効性を検証し、今後の発展性を明らかにした。
