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An Evaluation of Neural Spatial Interaction Models Based on a Practical Application

Alexandra Akamine and Antônio Nélson Rodrigues da Silva
University of São Paulo, School of Engineering of São Carlos, Brazil

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Abstract: One of the serious problems faced by the Brazilian municipalities is the scarcity of resources for building education infrastructure. This asks for an optimal allocation of the available resources that includes, among other things, a rational spatial arrangement of the supply points (i.e., schools) in order to increase the demand coverage (i.e., students). If it is possible to foresee the regions where the demand is going to be concentrated, it is then possible to plan the location of new facilities and to assess the impact on the future level of service of the entire system. Considering that one of the consequences of the location-allocation process is the distribution of trips from demand points to supply points throughout the city, therefore affecting the overall intraurban accessibility conditions to essential services such as education, there is a strong need of models that planners can rely on to predict the future trip distribution patterns. As a result, the objective of this work was to evaluate the performance of Artificial Neural Networks (ANN) when applied to spatial interaction models, the so-called Neural Spatial Interaction Models. This was done in a practical context, in contrast to the more theoretical works commonly found in literature. The practical application showed that the neural spatial interaction model had different performances when compared to the traditional gravity models. In one case the neural models outperformed the gravity models, while on the other case it was just the opposite. The explanation for this may be in the data or in the ANN model formulation, as discussed in the conclusions.

1. INTRODUCTION

The spatial interaction models were amongst the most studied topics in the field of Transportation Engineering in the second half of the last century. According to Black (1995), research in the area looks essentially for ways to improve the knowledge of the factors influencing trip flows. It also focuses in the development of methods that can help urban and regional planners to forecast the future displacements. There are different approaches for modeling the problem of spatial interaction, such as the intervening opportunities models, and the gravity models. While the use of the former is not very common in practical applications, the latter are largely employed in transportation planning practice and also in theoretical studies. The use of emergent techniques, such as the Artificial Neural Networks (ANN), for modeling the problem has also been tested in the last decade of the 20th century, as can be seen in the works of Openshaw (1993), Black (1995), Fischer, Reismann, et al. (1999), and Fischer and Reismann (2002).

According to Fischer and Reismann (2002), except for their high processing time, the neural models are better than the classical gravity models in terms of general performance. That statement was the starting point of the present study, which is a contribution for a larger project aiming the development of a Spatial Decision Support System for an integrated management of health and education facilities at the local level (Lima, Silva, et al., 2003). The objective of this particular study was to evaluate the performance of Spatial Interaction Models based on Artificial Neural Networks when dealing with different datasets taken from an actual situation. One of the challenges here is to deal with databases that although large are not always necessarily reliable.

This study, which is essentially based on a practical application, was meant to improve the knowledge about temporal and spatial changes of the demand for education infrastructure. That is a key point in the construction of planning scenarios for managing not only the demand but also the supply. In such a way, several alternatives can be tested, such as the reduction of travel distances due to demand relocation or the best locations for opening new educational facilities. Two datasets provided by the Secretary of Education of São Carlos, which is a medium-sized Brazilian city in the state of São Paulo, have been used to test the models performance in practical, real-world conditions. The datasets contain information about children attending day-care centers and elementary schools in two different years, 2000 and 2001.

The data of children from 0 to 6 years-old attending the municipal day-care centers in the year 2000 were initially used for training and validation of the ANN models. Later, these models were used for estimating future trip flows. The estimates were compared to the actual flows observed in 2001 in order to test the generalization capability of the models. The same procedure was carried out with the data of children from 3 to 6 years-old attending the EMEIs, which in Portuguese stands for *Escolas Municipais de Educação Infantil*, or Municipal Schools for Children Education.

The performance of the models was evaluated through a comparison of actual data with the results obtained for the different datasets analyzed with the two modeling approaches: the neural models and the gravity models.

In sections 2 and 3 of this document we discuss some aspects involving the data used in this study and the basic characteristics of the spatial interaction models. The evaluation of the models performance is carried out in section 4, in which the estimates of the gravity models are compared with the estimates of the neural models. Finally, in section 5 are presented the conclusions of the application, followed by the references, in part 6.

2. THE DATA

The data used in the present study show changes in spatial aspects of the demand for municipal educational services in the city of São Carlos throughout two years. The basic information gathered was the home address of the children registered in all public day-care centers and EMEIs and the corresponding locations of these educational facilities in the years 2000 and 2001.

Lima, Naruo, et al. (2001) were able to find the exact location of most children registered in the public educational system of São Carlos in the year 2000 using official data provided by the municipal government. The basic information used in that case was the home address of all students registered in the facilities under analysis. In order to correctly locate the children on a city map, that information was then combined with an address database built by the municipal agency in charge of water distribution and sewage disposal, which has an excellent address recording system based on geographic coordinates of land parcels.

The work started by Lima, Naruo, et al. (2001) was extended for the present study with data of the children attending the educational facilities in 2001. As in the case of the previous work, the data available in the databases used had to be carefully examined before trying to match the records using the address as a common reference. The students' addresses that were not properly typed were then fixed or replaced by the right street names. After that procedure, a Geographic Information System was used to spatially locate the new data. In practical terms, it means that we were able to find each precise address location on a map of the city streets.

That included not only the students but also the facilities they were assigned to, as shown in Figures 1 and 2. While Figure 1 shows the spatial distribution of the children attending day-care centers in the year 2001, Figure 2 displays the information of the demand per EMEI in the year 2001. Later on, GIS tools were also used to calculate the network distances from each demand point to the corresponding day-care center or EMEI.

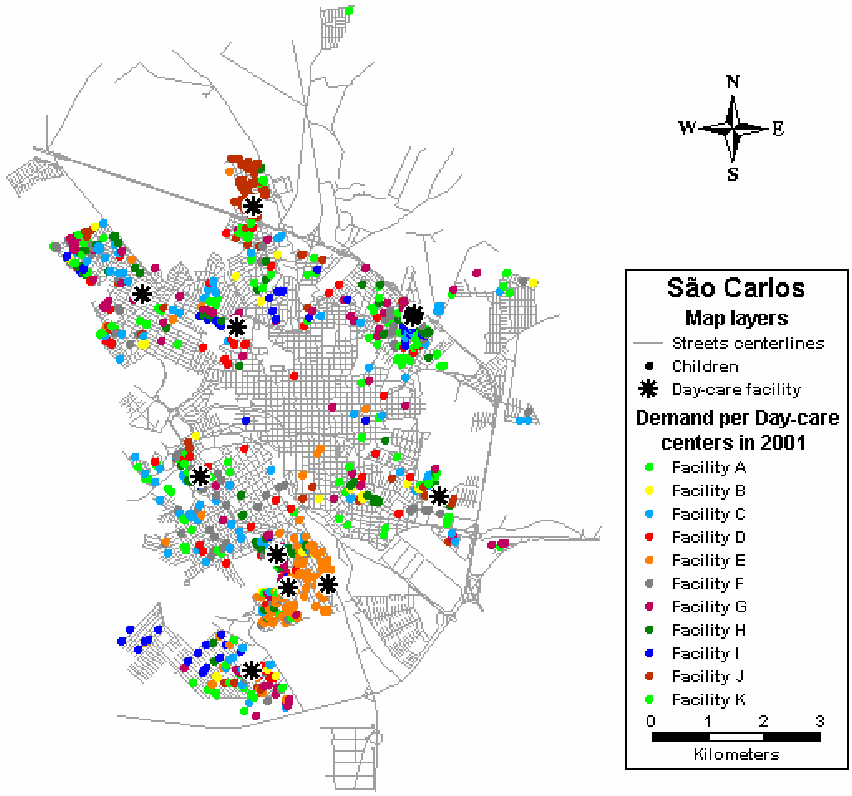

Figure 1. Spatial distribution of public day-care facilities in São Carlos in the year 2001 and respective demand

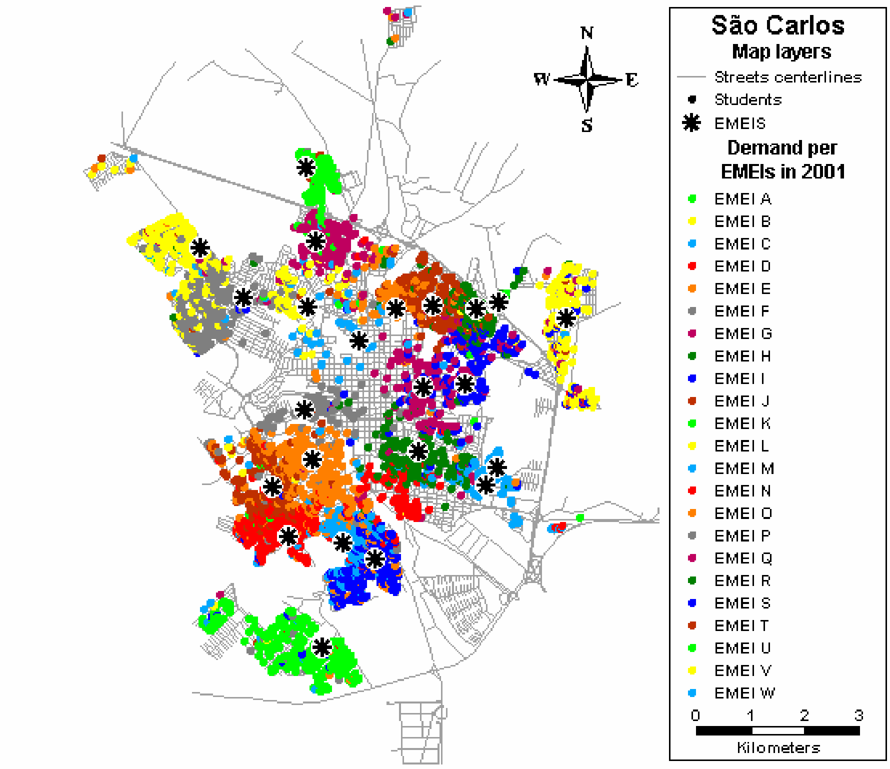

Figure 2. Spatial distribution of EMEIs in São Carlos in the year 2001 and respective demand

3. THE SPATIAL INTERACTION MODELS

Once the demand and supply points were located on the map, the identification of the flows among them was straightforward. The demand points were initially aggregated according to the limits of the 245 census tracts (CT) in which the city has been divided in the year 2000 by the Brazilian census bureau. The centroids of those CT were then assumed as the origin points of all displacements in each particular area. The same procedure was carried out for day-care centers and EMEIs in the years 2000 and 2001. Next, the number of trips attracted to each facility, the total number of trips produced in each CT, and the travel distances from all centroids to all facilities (day-care centers or EMEIs), was obtained. The location of all demand (centroids) and supply points is shown in Figure 3 for the case of day-care centers. An overview of the data is presented in Table 1.

Table 1. Summary of the data applied in the spatial interaction models.

Facilities	Year	Supply points	Demand points	O/D pairs
Day-care centers	2000	10	245	2450
	2001	11	245	2695
EMEIs	2000	22	245	5390
	2001	23	245	5635

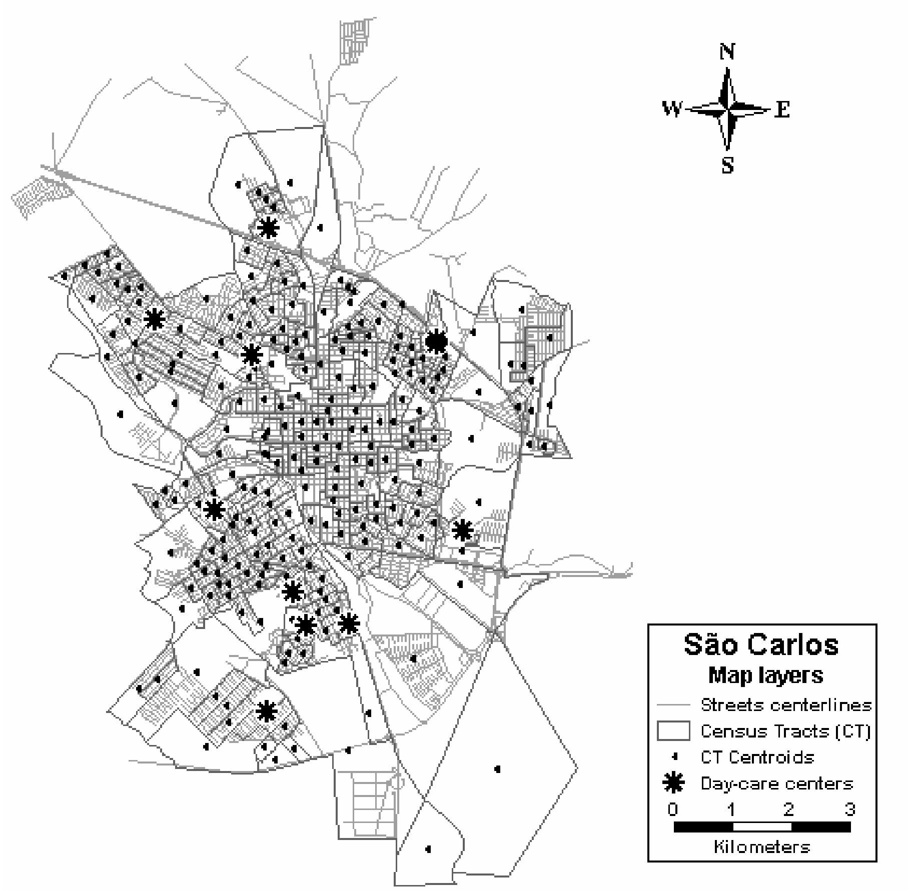

Figure 3. Demand (CT centroids) and supply points (public day-care centers)

The data of the year 2000 were randomly split in three data subsets for each of the two different kinds of facilities. While the first subset, which had fifty percent of the records, was used for training the neural networks, the second and third subsets, both with twenty-five percent of the records, were respectively used for validation and query. The absolute number of records in all subsets is shown in Table 2. Also shown in Table 2 is the total number of records of the year 2001. In order to test the generalization capability of the models, the total number of trips associated to the actual origins and destinations taken from those records were applied as input data in the trained networks for estimating the 2001 flows.

Table 2. Absolute number of records in the subsets used for training, validation, and query in the case of public day-care centers and EMEIs

Facilities	Year	Training	Validation	Query	Total
Day-care centers	2000	1225	613	612	2450
	2001	-	-	2695	2695
EMEIs	2000	2695	1348	1347	5390
	2001	-	-	5635	5635

Before introducing the data in the ANN, they were normalized as shown in Equations (1) and (2). The normalization interval was between 0.1 and 0.9 to avoid problems in the calculation (Equation (3)) of the mean relative error (MRE) if dealing with actual values equal to zero.

For distances: $$dist_{norm.} = \frac{dist}{\max(dist)} \qquad (1)$$

For production, attractions, and flows (as in Bocanegra, 2002):

$$Y_i = \left[\frac{(X_i - X_{\min}) * (Y_{\max} - Y_{\min})}{X_{\max} - X_{mín}}\right] + Y_{\min} \qquad (2)$$

where: Y_i = normalized value;
X_i = actual value;
X_{min} = minimum actual value;
X_{max} = maximum actual value;
Y_{min} = minimum normalized value (0.1);
Y_{max} = minimum normalized value (0.9).

$$MRE = \frac{1}{n}\sum_{t=1}^{n}\frac{abs(actual_t - estimated_t)}{actual_t} \qquad (3)$$

After the pre-processing phase the data were introduced in the software *EasyNN-plus*, which simplifies many of the steps needed for creating simple and efficient neural network models. The software can be used to build Multilayer Perceptron networks with up to three hidden layers, although the developer himself states that most real-world problems can be solved with one or two hidden layers (Wolstenholme, 2002). The *EasyNN-plus* package uses a backpropagation algorithm and a sigmoidal function to build the models. The data needed for training the network can be generated with simple text or spreadsheet software. In addition, the program can either assume values for the learning rate and momentum or let it up to the user. After the models are built, they can be used for estimating output values. The comparison of these values with the actual values making use of a performance measure (such as the MRE) makes possible to select, among the many alternatives built, the ANN model that produce the best estimates of the actual values.

4. EVALUATION OF THE MODELS

In order to evaluate the performance of the neural spatial interaction models, we have calculated the mean relative error (MRE) for each network configuration tested. The results are presented and discussed in this section. Starting with the parameters suggested by the package *EasyNN-plus* we have built networks with one or two hidden layers, with different number of nodes in each of the hidden layers, and with distinct learning rate (L) and momentum (M) values. The schemes shown in Figures 4 and 5 have the values of L and M grouped according to the distinct network topologies tested. In those Figures, the average and standard deviation of MRE values for the three groups of data randomly selected as training and validation subsets are also presented for each network tested, along with the results of the query data in the right-hand boxes. The latter are characterizing the generalization capability of the different ANN models.

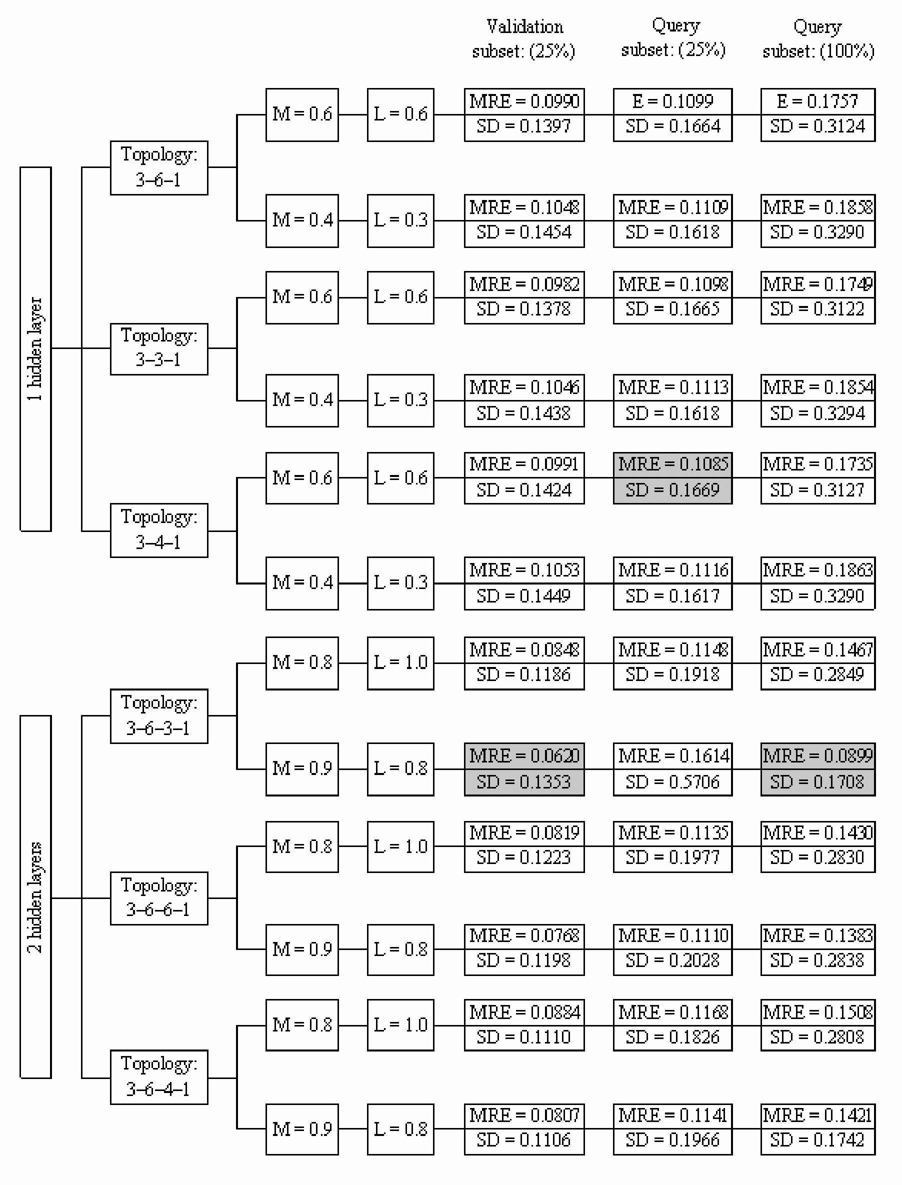

Figure 4. Performance of the neural spatial interaction models when applied to the case of day-care centers

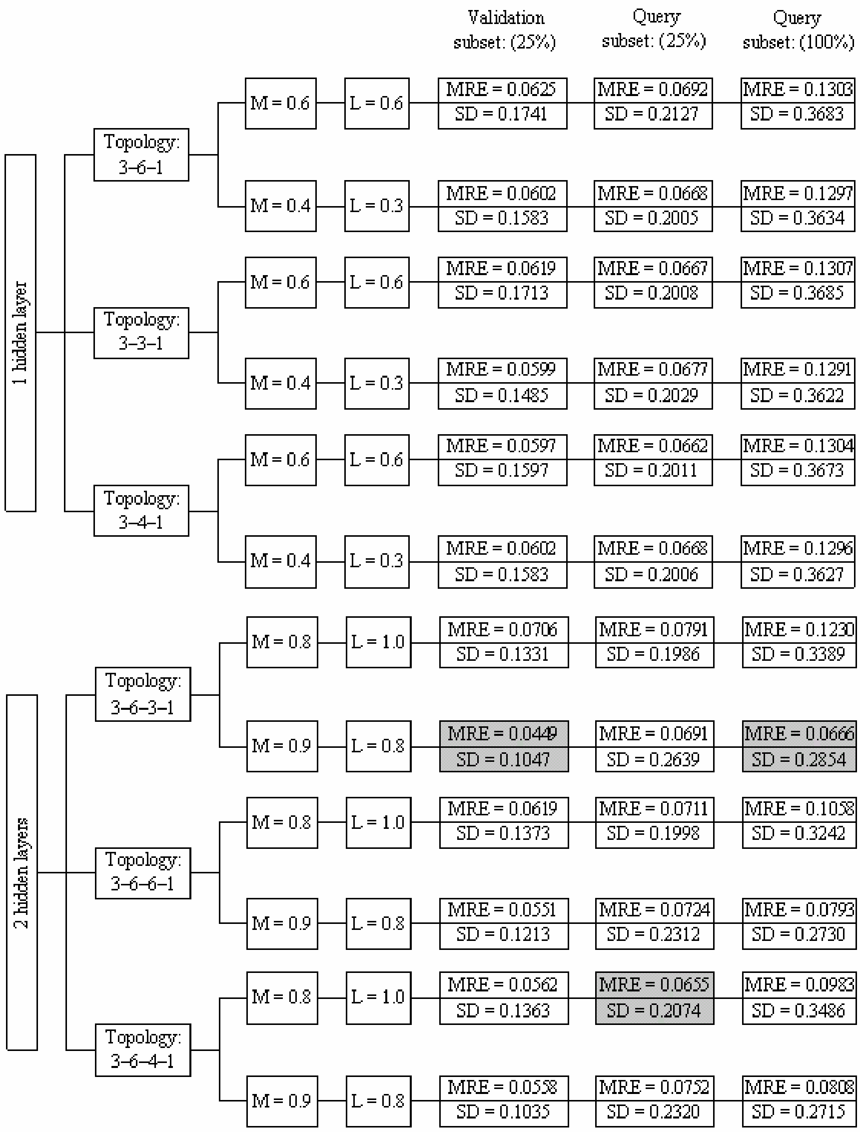

Figure 5. Performance of the neural spatial interaction models when applied to the case of EMEIs

4.1 Analysis of the results obtained with neural spatial interaction models and with gravity models

The data of the year 2000 were also used in both cases (i.e., day-care centers and EMEIs) to calibrate traditional doubly constrained gravity models, which were subsequently used for estimating the flows in the year 2001. Again, the average and standard deviation of MRE values were calculated in order to evaluate the models' performance.

Table 3. Results obtained with the gravity models and with the best neural spatial interaction models

Facilities	Model	MRE	
		Average	SD
Day-care centers	Doubly constrained gravity model	0.1353	0.3263
	Neural spatial interaction model	0.0899	0.1708
EMEIs	Doubly constrained gravity model	0.0456	0.1484
	Neural spatial interaction model	0.0666	0.2854

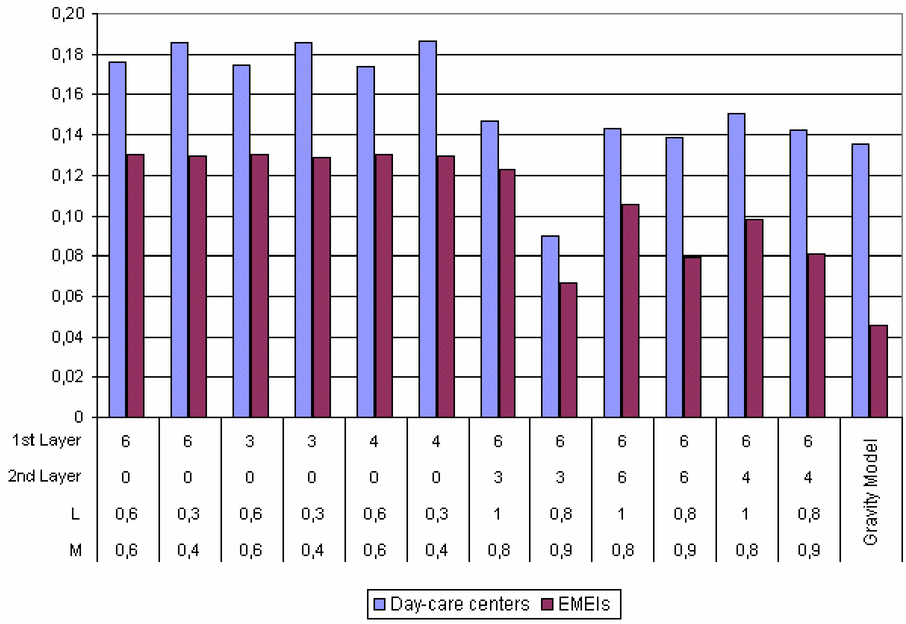

Figure 6. MRE values obtained with the neural spatial interaction models and with the gravity models

They are shown in Table 3, along with the best values obtained for the neural spatial interaction models. A visual comparison of the average MRE values of all models can be done in Figure 6. It is important to highlight that

we were referring in that case to the last column of Figures 4 and 5 (i.e., the 100% query subset), because of the focus of our analysis is on the generalization capability of the models.
The results presented in Table 3 and in Figure 6 showed that one configuration of the neural spatial interaction models had clearly outperformed the gravity model in the case of the day-care centers. In the case of the EMEIs, however, the best results were obtained with the gravity models. It is interesting to notice the fact that in all cases the models were more accurate when estimating the flows to EMEIs than to day-care centers.

5. CONCLUSIONS

The comparative analysis between the results obtained with the neural spatial interaction models and the doubly constrained gravity models for the case of day-care centers showed the superiority of the former, which produced more accurate estimates than the latter, although only in one configuration. In contrast, in the case of EMEIs the gravity models had the best performance. In addition, all models were more accurate in predicting the flows to EMEIs than to day-care centers. The explanation for that may be in the data or in the ANN model formulation, as discussed next.

The spatial distribution of the children in the case of day-care centers was quite irregular, while in the case of EMEIs they were clearly clustered around the facilities they go to, as shown in Figures 1 and 2. The likely explanation for the somehow unexpected spatial distribution pattern of the day-care center attendees (Figure 1) may be in the fact that the facility choice is more strongly influenced by the parents' work location than by their home location. As work location data is not available to the models, which rely only on the total trips produced in the CTs and attracted to the facilities, and on the distances between the points of demand (i.e., home locations grouped in the CT centroids) and supply (i.e., facility locations), this negatively impacts the models' performance. That is not the case of the EMEIs, however, where the students' home location is clearly connected to the school chosen (Figure 2). The regular spatial distribution of the children around the facilities made the prediction task easier for both model types, as indicated by the MRE results shown in Table 3 and Figure 6.

It is interesting to observe that the neural spatial interaction models were remarkably able to capture, although only in one case, the irregular spatial distribution pattern of the children in the case of day-care centers therefore producing better estimates than the gravity models. What is not clear, however, is their performance in the case of the EMEIs. Although better than the performance in the case of the day-care centers it was worse than the performance of the gravity model (Figure 6). Even though, the results of the neural spatial interaction models were not bad. Thus, the case discussed here stressed the promising role that those models can play in practical applications of education, and to a certain extent, health facilities management. The quality of their predictions is crucial in the evaluation of future scenarios of demand and supply spatial distribution aiming the reduction of travel distances obtained either by the demand relocation or by the creation of new facilities.

What seems to be an important conclusion of this study is the fact that certain ANN model configurations can outperform the gravity models. That was once observed in the case of day-care centers despite the irregular distribution of demand points, and it is probably the case with the EMEIs if more ANN configurations were tried. The challenge here lies on developing and applying in real-world conditions efficient methods to select the ANN configuration that better models the problem, such as Genetic Algorithms or the bootstrapping approach suggested by Fischer and Reismann (2002). In addition, given the results obtained in the case of the EMEIs, a point that deserves further investigation is the assumption that those models could be improved by any additional input data that also has influence on the facility selection process, such as the school attractiveness measures used by Almeida and Gonçalves (2001). Considering the difficulty for obtaining this sort of data, from a practical standpoint this may have, however, more costs than benefits. But it is certainly worth investigating. Moreover, the statement that both models performed better with the day-care centers data than they did with the EMEI's data is not necessarily true. It could be that the EMEI's data simply has a smaller variance, and so errors seem smaller when amalgamated using the MRE formula. Therefore, other performance measures should be also tested in the future.

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