AN ANALYSIS OF ENERGY CONSUMPTION FOR TRANSPORTATION IN PORTUGUESE CITIES USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Empirical studies carried out in several parts of the world have highlighted the existence of a strong relationship between the physical planning of cities and energy use for transportation. Despite the economic and environmental costs produced by urban sprawl, several countries have not yet started to study the phenomenon in order to better understand it and to somehow control it. Thus, this study tries to bring a contribution to the subject through an analysis of the situation found in some of the main Portuguese cities, which however do not include Lisbon and Oporto. The main objective of this work is to identify the variables related to physical aspects of the cities and socioeconomic characteristics of urbanized areas in Portugal that significantly influence energy consumption for transportation. After the spatial and socioeconomic data were combined in a single database, they were analyzed using Artificial Neural Network models, in order to identify variables that are relevant to energy consumption for transportation, along with their relative weights. The results found in the current study confirmed the trend observed in several countries worldwide, in which the *characteristics of urban form and population distribution* played an important role influencing energy use for transportation.

Keywords: Energy consumption; Urban transportation; Portuguese cities; Artificial Neural Networks
Topic Area: F3 Transport and the Environment: Energy Use, Greenhouse gas Emission and International Impacts

1. Introduction

Starting from the year 1990 and mainly after the first Earth Summit, which was held in Rio de Janeiro in 1992 focusing in general terms on the sustainability issue, and also in the urban sustainability problem in particular, the interest for the compact city concept has been increasing. The following planning strategies and policies came along with the compact city concept: high population densities, mixed land use, urban redevelopment and reorganization of public transportation systems. The concept is somehow a reaction to the extreme urban sprawl conditions observed in several parts of the world.

One of the main consequences of this urban sprawl seems to be the excessive fuel consumption resulting from the large number and length of trips conducted every single day by

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millions of people worldwide. Internationally known cities, such as Houston, Phoenix, Los Angeles, Perth, Adelaide, and Sydney are examples of urban areas in which transportation systems are directed to the automobile use as a result of their sprawled patterns. That is one of the reasons why authors like Newman & Kenworthy (1989a and 1989b) and Næss (1995), for instance, stand for the compact city concept. Although other researchers (such as Gordon & Richardson, 1989, for example) do not agree that the concept may be a solution for the present problems of urban areas everywhere, the results found in a significant number of references describing empirical studies already accomplished in several parts of the world suggest strong relationships among variables describing urban form characteristics and the consumption of energy for transportation purposes.

A commonly observed pattern is that sprawled cities have significantly higher consumption levels of energy for transportation than compact cities. In addition, the consumption of energy is not only kept at very high levels in the developed countries, but it is still growing. However, despite all economic and environmental costs produced by this situation, many of these countries still did not carry out studies to better understand the phenomenon and to somehow control it. The situation becomes a reason for even greater concern when one verifies that these aspects are usually not taken into account in the planning process of developing countries cities, which are currently also affected by the urban sprawling process. As a consequence, the energy required for transportation in those cities has grown considerably and some of them present today very high levels of energy consumption (Silva *et al.*, 1999; Costa *et al.*, 2001).

Cities of several countries have been analyzed in the various studies that tried to relate urban form with energy consumption for transportation. Among those countries are: Australia, Canada, some countries of Europe and Asia, and the United States (Newman & Kenworthy, 1989a and 1989b; Næss, 1995; Kenworthy & Laube, 1999a and 1999b; Snellen, 2002). One of the few developing countries with studies in this area is Brazil (Pampolha, 1999; Costa, 2001). Some of the studies above mentioned compared the energy consumption patterns of cities located in different countries. That is the case of the works of Newman & Kenworthy (1989a and 1989b) and Kenworthy & Laube (1999a and 1999b), in which the values observed in cities of the United States, Canada, Australia, and of European and Asian countries were cross-compared. Other authors studied cities within a particular area or country, such as Næss (1995), in the case of the Nordic countries; and Pampolha (1999), in Brazil. Costa (2001), for example, restricted his research only to one state in Brazil, namely São Paulo, in which he analyzed the municipalities with a population of 50,000 inhabitants and over.

In the case of Portugal, there are only a few studies dealing with this subject (for instance, Costa *et al.*, 2002; and Costa, 2003), notwithstanding the extreme relevance of the issue. The small number of studies in the country was indeed the main motivation for the present work, which is a summarized and revised version of the original research paper of Costa (2003). The analysis carried out in both cases involved the main Portuguese cities, with the exception of Lisbon and Oporto, because they represent very particular cases among the country's urban areas. This paper is intended to be a contribution to the theme, through the identification of some of the main urban planning related factors that may influence the levels of energy consumption for transportation in the specific case of Portugal.

Therefore, the main objective of this work is to identify some of the variables characterizing physical and socioeconomic aspects of the urban areas that can significantly influence the energy consumption for transportation in the case of Portuguese cities. Artificial Neural Networks are used as the modeling tool for the analysis, thus making possible the determination of the relative importance of the different variables in the energy consumed for transportation purposes.

This document is organized in five items, including this introduction. A brief review of the most important concepts concerning the technique employed in the study, the Artificial Neural Networks (or simply ANN), is presented in the second item. The case study is introduced in the sequence, in three main parts: the data used, the first ANN models, and the strategies used for improving the performance of those models. The document ends with some brief conclusions based on the results, just before the list of references cited in the text.

The analysis based on Artificial Neural Networks required the determination of a set of parameters that can produce the best performance of the model. Thus, more than 110 different configurations were tested already in the initial phase of the study, varying the number of hidden layers, the number of neurons in each hidden layer, the Learning Rate, and the Momentum. From the several networks tested, the one that produced the smallest MRE was assumed as the best possible model at that point, given the variables used as input data. However, as the model performance was not satisfactory, further analyses were subsequently carried out in order to look for a different mix of input variables that could produce a better model.

2. Artificial neural networks

Artificial Neural Networks were used in this study for analyzing the relationships between a few selected variables and energy consumption for transportation. The ANN models appear as potential substitutes for the conventional statistical models, due to the fact that no previous knowledge of the relationships among the involved variables is needed and also to the userfriendly interface of some computer programs developed for practical applications (Brondino, 1999). The efficiency of this kind of tool can be found in several studies conducted in the transportation engineering field (e.g., Brega, 1996; Furtado, 1998; Brondino, 1999; Wermersch & Kawamoto, 1999; Coutinho Neto, 2000; Raia Jr., 2000; and Bocanegra, 2001), which showed the good performance of the technique when compared to conventional mathematical models.

In general terms, an Artificial Neural Network can be defined as a system made up by several interconnected processing elements, also called artificial neurons, which are arranged in layers (an input layer, one or more intermediate or hidden layers, and an output layer). These elements are responsible for the characteristic of non-linearity observed in the network when internally processing mathematical functions. One can certainly say that ANNs learn with examples. The process is hence based on a learning rule, which is responsible for changing the connection weights after each iteration cycle, trying to match the examples that were initially introduced for training the network (Costa, 2001). Some of the characteristics of the problem under analysis that were not easy to treat with conventional statistical tools or computer programs made the use of this tool particularly interesting for the present study.

The use of Artificial Neural Networks for solving a problem starts with a learning phase, through which the net extracts important information from the data initially introduced for training it. Based on the patterns of information found in the available data it then creates a particular representation of the problem under analysis, which is not necessarily a known mathematical function. The learning phase consists of an interactive process of adjustment of some network parameters, mainly the weights of the connections among the processing units. In the end of the process, these elements keep the knowledge that the network got from the environment in which it is operating (Queiroz, 1999).

The examples presented to the ANN in the learning (or training) phase are randomly chosen from the entire set of data. The weights are modified in a process that tries to minimize the differences between the actual values and the estimates produced by the neural network. The training process is repeated until the net arrives to a stable state, in which there are no more significant changes in its internal weights. In such a way, the ANN learns through examples building a map of the input-output patterns of the problem under analysis. In this training technique, called supervised training, not only the input data but also the actual output data have to be provided to the ANN. The process goes on in a simple way, starting with random values assigned to the weights for getting the first output estimates from the ANN. They are compared with the target values in order to evaluate the estimation error. If the errors are not acceptable, the weights have to be accordingly adjusted in order to reduce them. There is an algorithm responsible for adjusting the weights of the ANN in order to reduce the errors after a finite number of iterations. In the case of the ANN software used in this study the algorithm is called *backpropagation*.

One of the biggest difficulties in building an ANN model is the determination of its topology. Usually, the number of layers and the number of nodes in each layer are based on a previous examination of the data. But that is not all, because these values also vary with the complexity of the problem. In addition, once defined the initial topology, the most appropriate structure for the final model is usually obtained through successive refinements. The entire process can be significantly time-consuming, given the empirical component involved in it (Queiroz, 1999).

The objective of this adjustment process is to obtain the network topology that is not only able to produce estimates with high degree of accuracy for the training group data, but that also has good generalization capacity. However, the data sometimes contain errors resulting from the sampling processes. Consequently, the construction of Artificial Neural Network models shall seek for a structure that models the data without modeling the noise contained in them. That involves a structure that is not very rigid to the point of not modeling the data accurately, but that is not also excessively flexible to the point of also modeling the noise. The balance between the rigidity and the flexibility of the network is obtained through its size definition. Large structures have a large number of parameters asking for adjustment and, consequently, they have larger flexibility. However, when data are first presented to the ANN there is usually no previous knowledge of the problem complexity, what adds difficulty to the process of defining the best network structure.

This general description of the mathematical tool selected for the present study certainly helps to understand the options taken in the case study analysis, which is described in the sequence.

3. The case study

The main sources of information about the selected variables were: the *Sales Index Database* (Marktest, 2002), the *Atlas of Portuguese Cities* (INE, 2002), and the *Geographic Base of Information Reference* (INE, 2001). Not many variables that can influence the levels of energy consumption for transportation had their data available in Portugal at the time of this study. The variables to which data was found are listed in Tables 1 and 2. It is important to highlight the difficulties found for obtaining data aggregated at the city level, given that in Portugal the statistical information aggregated at this level was not long ago nearly null and it is still rare. Most of the statistical information available was aggregated at the level of the *Concelho* and also of the *Freguesia*, which are administrative subdivisions of the country. Alas, in the Portuguese case, the limits of those subdivisions do not necessarily correspond to the boundaries of the cities. In some cases, one single *Concelho*, for example, can encompass more than one urban area. In that case, the rest of the territory inside the *Concelho* has lower urban densities, quite different from those found in its urban portions (Costa, 2003). The first data sets aggregated at the level of statistical sections and subsections (i.e., smaller fractions of the territory) were only recently released, with the *Atlas of Portuguese Cities* (INE, 2002). Thus, the present study selected the available variables aggregated at the city level, which were taken from INE (2002), along with the variables aggregated at the level of the *Concelho* found in Marktest (2002).

Table 1 – Variables related to the total energy consumed per year in the *Concelhos*.

Input variables	Variable name
Index resulting from the division of the urbanized area by the smallest circle around it	UrbArea/CircArea
Shape Factor	SF
Proportion of the population of the *Concelho* living in the urban area	Prop_Pop
Population of the *Concelho*	Pop_conc
Length of the municipal road network	R_net
Total fleet of vehicles used in public transportation	PT_fleet
Total fleet of automobiles	Car_fleet
Average distance between the municipalities and the main municipality of the same *District*	Dist_MM
Total number of employed people in agricultural activities	ECAE1R2
Total number of employed people in extractive industry	ECAE2R2
Total number of employed people in transforming industry	ECAE3R2
Total number of employed people in production and distribution of electricity, gas and water	ECAE4R2
Total number of employed people in construction	ECAE5R2
Total number of employed people in retail activities	ECAE6R2
Total number of employed people in transportation, storage and communication	ECAE7R2
Total number of employed people in financial activities, services to other companies, and real estate	ECAE8R2
Total number of employed people in public administration, education, health, and others	ECAE9R2

Table 2 – Variables related to the energy consumed *per capita* per year in the *Concelhos*.

Input variables	Variable name
Index resulting from the division of the urbanized area by the smallest circle around it	UrbArea/CircArea
Shape Factor	SF
Proportion of the population of the *Concelho* living in the urban area	Prop_Pop
Population density in the urbanized area	Dens_UA
Population density in the *Concelho*	Dens_conc
Unemployment rate in the urbanized area	Unemp_rate
Average size of companies in the urbanized area	Comp
Average distance between the municipalities and the main municipality of the same *District*	Dist_MM

The variables aggregated at the level of the *Concelho* selected for this study were: population of the *Concelho* (in the year 2001), density of the *Concelho* (in the year 2001), total fleet of vehicles used in public transportation (in the year 1998), total fleet of automobiles (in the year 1998), average distance between the municipalities and the main municipality of the same *District* (in the year 1998), length of the municipal road network (in the year 1996), and measures of the most important economic activities in the *Concelho* (in the year 1998). In contrast, the following variables were aggregated at the city level: population of the urban area (in the year 2001), density of the urban area (in the year 2001), average size of the companies in the urban area (in the year 1999), proportion of the population of the *Concelho* living in the urban area (in the year 2001), shape factor (in the year 2002), and an index resulting from the division of the urban area by the smallest circle around it.

Most of the variables selected can be used to describe the socioeconomic aspects of the urban areas and of their respective *Concelhos*. A few of them can be seen as measures of accessibility, while the last two variables listed above reflect the spatial nature of the urban areas and therefore they can be used to characterize aspects of the overall form of these urban areas.

The index resulting from the division of the urban area by the smallest circle around it was obtained by first drawing around the boundaries of each urban area the smallest circle that can fully contain the irregular area of the city, as shown in Figure 1 for the case of the city of Braga. This variable was introduced in the analysis as a way to represent the proportion of unoccupied spaces in relation to the smallest involving circle. The closer of the unit becomes the index, the smaller the proportion of idle land. It is important to point out, however, that this index only refers to empty spaces that are external to the urbanized area and not to the land left vacant due to some sort of leapfrogging development. This is in fact a limitation of the chosen variable, considering the large proportion of vacant land found in many Portuguese cities. However, as we would not be able to find this data for most of the cities included in the study, we decided to keep the index as explained.

The other variable used to differentiate the forms of the urbanized areas was the Shape Factor (Eastman, 1997). If the area (AREA_UA) and the perimeter (PERIM_UA) of the urbanized area are both known, so the calculation of the Shape Factor (SF) is possible through Equation (1). The first part of the expression is divided by 3.545, which is the SF value of a circle, regardless its radius. As it does not happen with other geometric forms, one can assume that a SF close to one is always associated with a more compact form.

$$SF = \frac{\text{PERIM\_UA}}{\sqrt{AREA\_UA}} \times \frac{1}{3.545} \qquad (1)$$

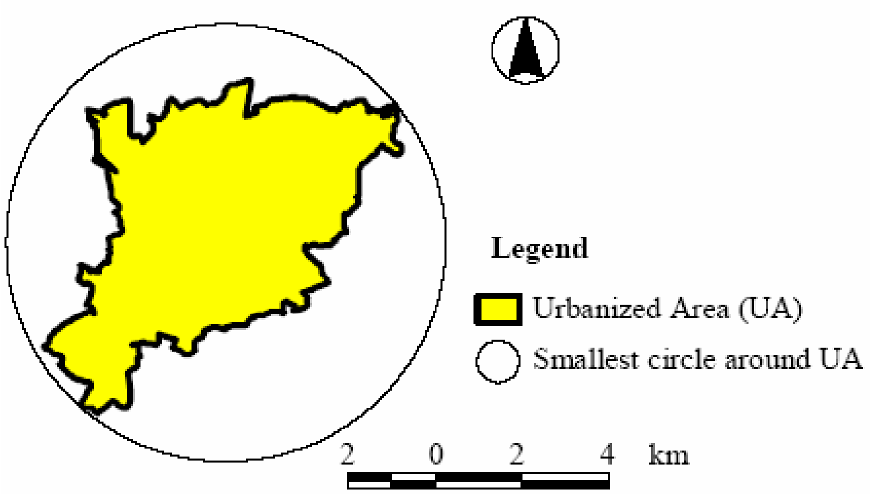

Figure 1 – Urbanized area of the city of Braga and the smallest circle around it.

After this brief description of the variables selected for the study, the procedures used for building the models are discussed in the sequence.

3.1. The ANN models

Data preprocessing began with the normalization of all values of the variables in the interval between zero and one. This was done to speed up the learning phase of the ANN model construction. Next, three different subsets of data were randomly generated for each one of the following outputs: Total Energy and Per capita Energy. These three subsets are then split to form three different Training, Validation, and Query groups for the same ANN model. The selection of the network characteristics, (i.e., topology, Learning rate (L), and Momentum (M)), was only made after all those procedures were completed. The selection of these parameters started by using the initial values suggested in the computer program. The parameters were subsequently changed in order to test the model performance under different combinations of network topologies, M and L values.

The network topologies tested for the Total Energy model were: 17-20-1, 17-10-16-1, and 17-20-10-1. The first value (i.e., seventeen) represents the number of neurons in the input layer, the last value (i.e., one) represents the number of neurons in the output layer, while the intermediate values, which may vary depending on the total number of layers in the model, are the number(s) of neurons in the hidden or intermediate layers. Similarly, the network topologies tested for the Per capita Energy model were: 8-20-1, 8-10-16-1, and 8-30-1.

In such a way, eighteen alternatives were built per group, what resulted in fifty-four networks trained for each one of the outputs (i.e., Total Energy and Per capita Energy), as shown in Tables 3 and 4. The selection of the best networks was based on the Mean Relative Error (MRE), which was used as the main performance measure of the ANN, observed in the validation subsets of data. The average values of the MRE found in the three subsets of data of each network tested were, along with the standard deviation, the basis for the selection of the best ANN models in both cases studied.

Table 3 – Error values of the Total Energy model for the validation data.

ANN Topology	Learning rate (L)	Momentum (M)	MRE			Average Error	Standard Deviation
			Group 1	Group 2	Group 3		
17-20-1	0.6	0.8	0.421	0.613	0.435	0.490	0.107
	0.8	0.6	0.433	0.683	0.435	0.517	0.144
	1.0	0.8	0.414	0.536	0.382	0.444	0.081
	0.6	0.6	0.440	0.696	0.470	0.536	0.140
	0.8	0.8	0.414	0.624	0.413	0.484	0.122
	1.0	0.6	0.428	0.658	0.403	0.496	0.141
17-10-16-1	0.6	0.8	0.409	0.652	0.418	0.493	0.138
	0.8	0.6	0.437	0.602	0.438	0.492	0.095
	1.0	0.8	0.445	0.745	0.368	0.519	0.199
	0.6	0.6	0.440	0.593	0.448	0.494	0.086
	0.8	0.8	0.444	0.664	0.401	0.503	0.141
	1.0	0.6	0.449	0.605	0.415	0.490	0.101
17-20-10-1	0.6	0.8	0.469	0.666	0.366	0.500	0.152
	0.8	0.6	0.487	0.621	0.348	0.485	0.136
	1.0	0.8	0.468	0.724	0.456	0.549	0.152
	0.6	0.6	0.501	0.610	0.456	0.522	0.079
	0.8	0.8	0.465	0.688	0.375	0.509	0.161
	1.0	0.6	0.480	0.621	0.333	0.478	0.144

Table 4 – Error values of the Per capita Energy model for the validation data.

ANN Topology	Learning rate (L)	Momentum (M)	MRE Group 1	MRE Group 2	MRE Group 3	Average Error	Standard Deviation
8-20-1	0.6	0.8	0.900	1.132	1.078	1.037	0.121
	0.8	0.6	0.769	0.865	1.044	0.893	0.140
	1.0	0.8	1.350	0.857	1.134	1.114	0.247
	0.6	0.6	0.908	1.190	1.076	1.058	0.142
	0.8	0.8	1.667	1.090	1.104	1.287	0.329
	1.0	0.6	0.952	1.090	1.039	1.027	0.070
8-10-16-1	0.6	0.8	0.983	0.689	0.848	0.840	0.147
	0.8	0.6	1.397	1.019	0.795	1.070	0.304
	1.0	0.8	1.065	0.610	1.071	0.915	0.264
	0.6	0.6	1.381	1.146	0.884	1.137	0.249
	0.8	0.8	1.458	0.718	0.935	1.037	0.380
	1.0	0.6	0.999	0.924	0.754	0.892	0.126
8-30-1	0.6	0.8	1.380	0.880	1.186	1.149	0.252
	0.8	0.6	0.980	0.908	1.144	1.011	0.121
	1.0	0.8	1.498	0.686	1.203	1.129	0.411
	0.6	0.6	0.961	0.898	1.167	1.009	0.141
	0.8	0.8	1.424	0.732	1.190	1.115	0.352
	1.0	0.6	1.087	0.849	1.129	1.022	0.151

In the case of the Total Energy model, the network with the best performance was the alternative with seventeen neurons in the input layer, twenty neurons in the intermediate layer and one neuron in the output layer, with L = 1.0 and M = 0.8. That network presented an average MRE of 0.444 with a standard deviation of 0.081 for the three data subsets evaluated. In the case of the Per capita Energy model, two alternatives had nearly the same performance. The first one, which had the parameters 8-10-16-1, L = 1.0, and M = 0.6, resulted in an average ERM of 0.892 with a standard deviation of 0.126. The second one, which resulted in an ERM of 0.893 with a standard deviation of 0.140, was the alternative 8-20-1, with L = 0.8 and M = 0.6. Although the average ERM was not exactly the same in both cases, the values were very close. Thus, an analysis of the average ERM values together with the respective standard deviations could indicate the selection of any one of the two models. However, once the method used for the calculation of the relevance of the variables is indicated for networks with only one hidden layer (Garson, 1991), the alternative selected for the Per capita Energy model was the one with eight neurons in the input layer, twenty neurons in the intermediate layer and one neuron in the output layer.

At this point, it was already possible to carry out a first evaluation of the results found with the best models obtained. In summary, in the case of the Total Energy model the best performance was an average MRE of 0.444 and a standard deviation of 0.081 for the three data subsets evaluated. In contrast, in the case of the Per capita Energy model, the values obtained were higher than those found in the previous model: the average MRE was 0.893 and the standard deviation was 0.140.

After the selection of the best ANN models, the following step was the calculation of the relevance of the input variables for each of the two models proposed. The relative importance of the variables was obtained using Garson's method (1991) and the results are presented in Figures 2 and 3.

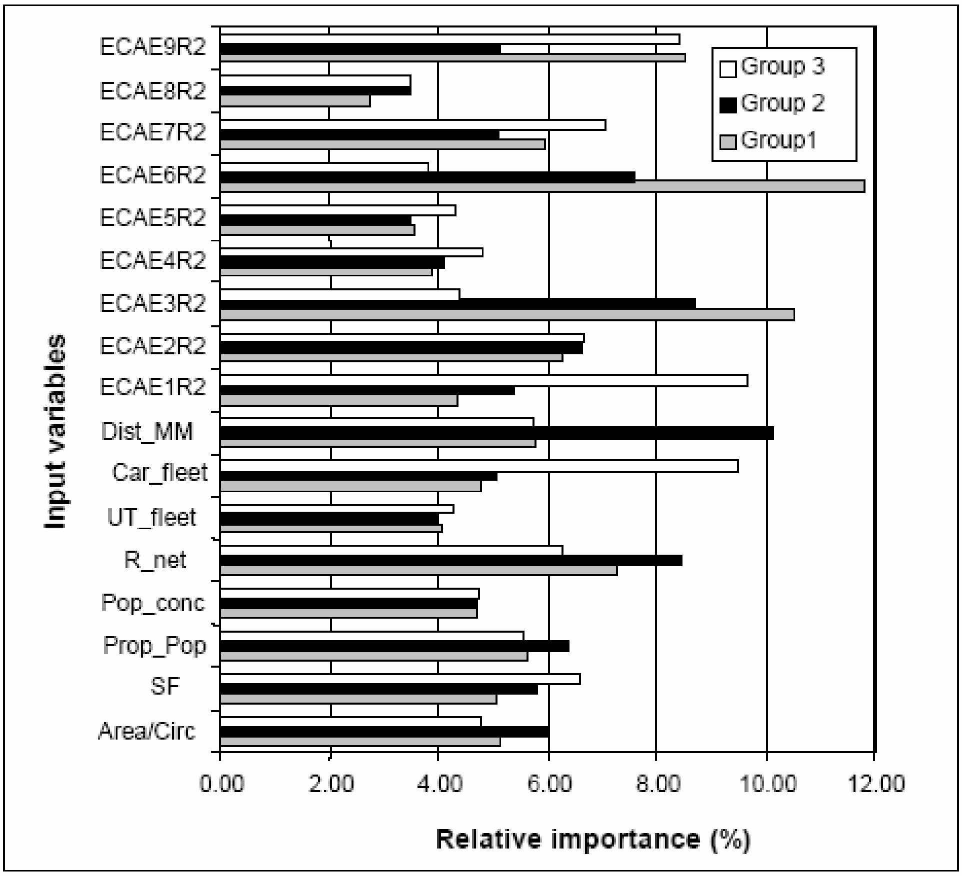

Figure 2 – Relative importance of the input variables for the Total Energy ANN model with the best performance (17-20-1; L = 1.0; M = 0.8).

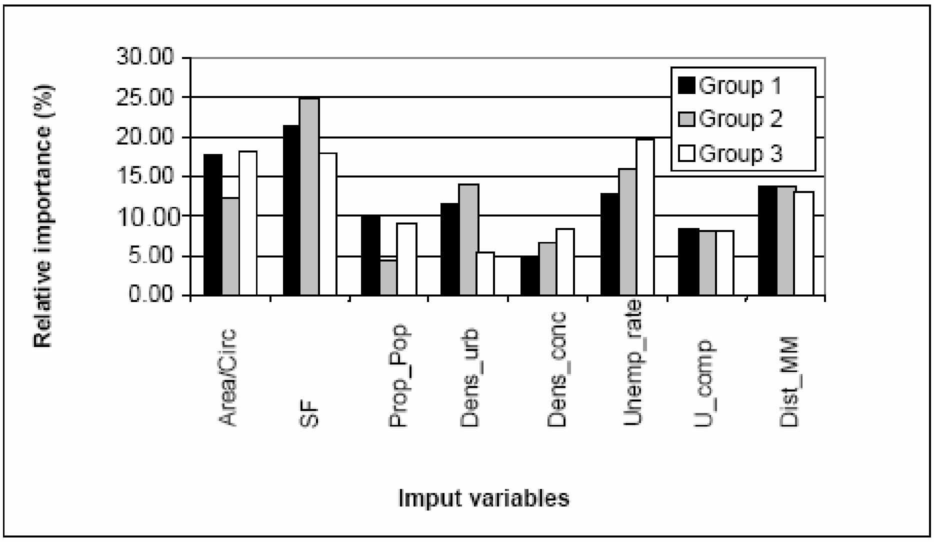

Figure 3 – Relative importance of the input variables for the Per capita Energy ANN model with the best performance (8-20-1; L = 0.8; M = 0.6).

3.2. Variables with low relative importance

A few changes had to be implemented with the aim of improving the performance of the Total Energy model. A first attempt was based on the analysis of the results shown in Figure 2. The idea was to eliminate the variables that presented the lowest relative importance values. That was the case of the following input variables: ECAE8R2, ECAE5R2, ECAE4R2, and PT_fleet (see Table 1 for a full description of the variables). As they have relative importance values equal to or smaller than 4 %, a new model was built without them in order to see if there was any improvement in the model performance. After several tests with different combinations of L and M values, and also distinct topologies, the alternative with the best performance was a 13-10-1 configuration, Learning Rate equal to 1.0 and Momentum equal to 0.8.

The performance of the new model was once again computed for the validation data. At this point we added another performance measure in the evaluation process, which was the R^2 coefficient. That measure is commonly used in regression analysis. Along with the average and standard deviation values of ERM for the three data subsets, it gives a good picture of the quality of the model estimates. The results of these measures calculated for the validation values of the three data subsets are shown in Table 5. The analysis of the values in Table 5 did not show, except for data group 2, any significant improvement of the model performance when compared to the previous model results shown in Table 3. The relative importance values of the input variables of the new model are shown in Figure 4.

The elimination of input variables was not even tried in the case of the Per capita Energy model because of its poor performance in the first phase of the analysis.

Table 5 – Performance measures applied to validation data and the Total Energy model after the elimination of input variables with low relative importance.

Group	R^2	MRE	
		Average	Standard Deviation
1	0.29	0.44	0.28
2	0.00	0.80	1.07
3	0.71	0.41	0.39

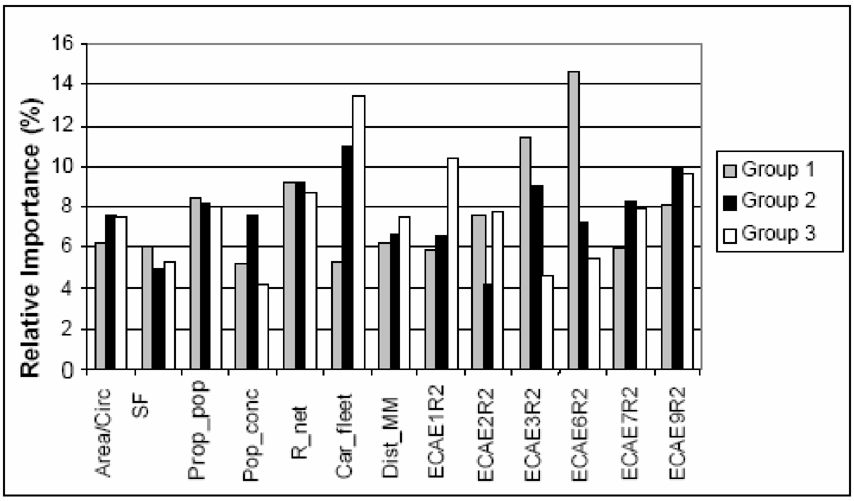

Figure 4 – Relative importance of the input variables in the Total Energy model after the elimination of input variables with low relative importance.

3.3. Insertion of a classificatory variable

As the simple exclusion of the input variables with low relevance did not significantly affect the model performance, the next alternative explored for improving it was to look for patterns in the spatial distribution of the estimation errors. Maps were then generated to display the estimation errors for validation and query values for all subsets of data.

The relative errors found for query data were always higher than those found for validation data. This was expected, since the actual values used as references in the query process were totally new for the ANN. Consequently, they could be used to demonstrate the model generalization capability. The observation of the map with the error values in the case of query data made possible the identification of the areas in the country that have the highest values of relative errors. That was the case of the southern Portuguese regions of Alentejo and Algarve. The existence of a clear pattern of errors distribution was taken as an indication that the model could be improved with the introduction of a classificatory variable representing the distinct country regions. In this case, the regions boundaries matched the limits of the NUTs II, which is one of the territorial divisions used for statistical purposes by the European Community. The ANN model generated after the inclusion of the new input variable was an 18-10-1 network, with L = 0.6 and M = 0.8). The calculation of the new mean relative errors for validation and query data showed an error reduction in all but two cases, as can be seen in Tables 6 and 7.

Table 6 – Performance measures applied to validation data and the Total Energy model after the insertion of a classificatory variable.

Group	R^2	MRE	
		Average	Standard Deviation
1	0.77	0.24	0.18
2	0.78	0.41	0.32
3	0.44	0.40	0.50

Table 7 – Performance measures applied to query data and the Total Energy model after the insertion of a classificatory variable.

Group	R^2	MRE	
		Average	Standard Deviation
1	0.57	0.82	0.96
2	0.45	0.68	0.82
3	0.50	0.55	0.50

The analysis of the performance measures in the case of the validation data (Table 6) suggested an improvement of the model after the inclusion of the classificatory variable. Hence, we assumed that the model was finally ready to satisfactorily characterize the problem for the objective aimed in this work, which was the evaluation of the relative importance of the input variables on the energy consumption for transportation. The relative importance values that were calculated once again according to Garson's (1991) for the new set of variables are presented in Figure 5.

In order to facilitate the interpretation of the results and the organization of the information available in Figure 5, the input variables were grouped according to common characteristics, as follows:

- Characteristics of urban form and population distribution
- Road network and accessibility
- Total fleet
- Economic activities

Table 8 somehow summarizes the entire process by displaying: a list of all input variables, the groups in which they were classified, and the relative importance values obtained for the three data subsets analyzed. The relative importance values per classificatory group are also presented in the same table. These can also be graphically visualized in Figure 6.

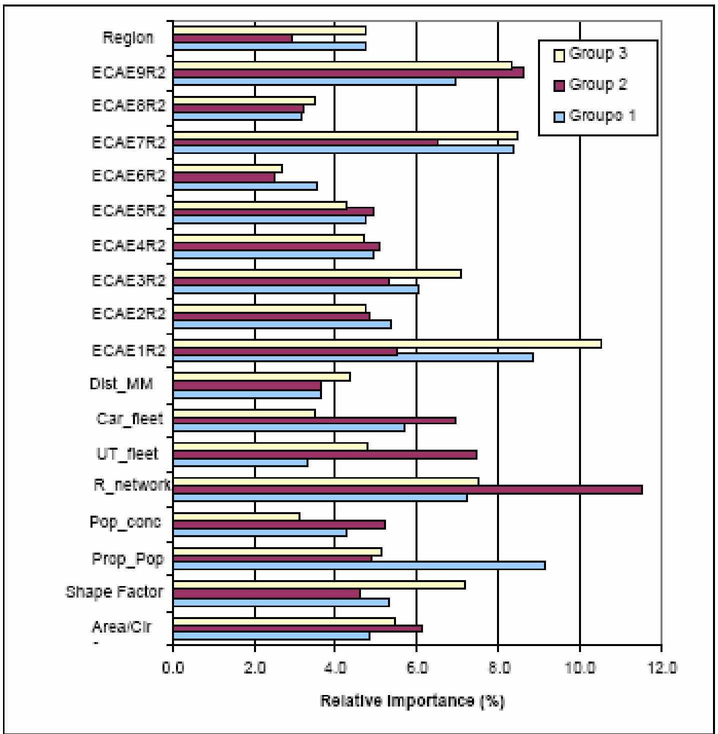

Figure 5 – Relative importance of the input variables in the Total Energy model after the insertion of the classificatory variable.

In contrast with the results found with the initial networks obtained, there was no significant difference among the relative importance values of the classificatory groups found in the three data subsets shown in Table 8. This seems to be an indication that the model was able to make a reasonable representation of the situation meet in the three groups of data. Given the apparent stability of these values we calculated the average relative importance values for each classificatory group, as displayed in the right column of Table 8. These values were also used to build the graph of Figure 7. The analysis of the values in Table 8 and in Figures 6 and 7 suggests that the group *Economic Activities* (of the *Concelho*) has the larger share of influence on the energy consumption for transportation, with a total relative importance value close to 51 %. The group *Population Distribution and Urban Form Characteristics* comes next in terms of relative importance, with a value of 25 %, followed by the groups *Road Network and Accessibility*, with 13 %, and *Total Fleet*, with 11 %.

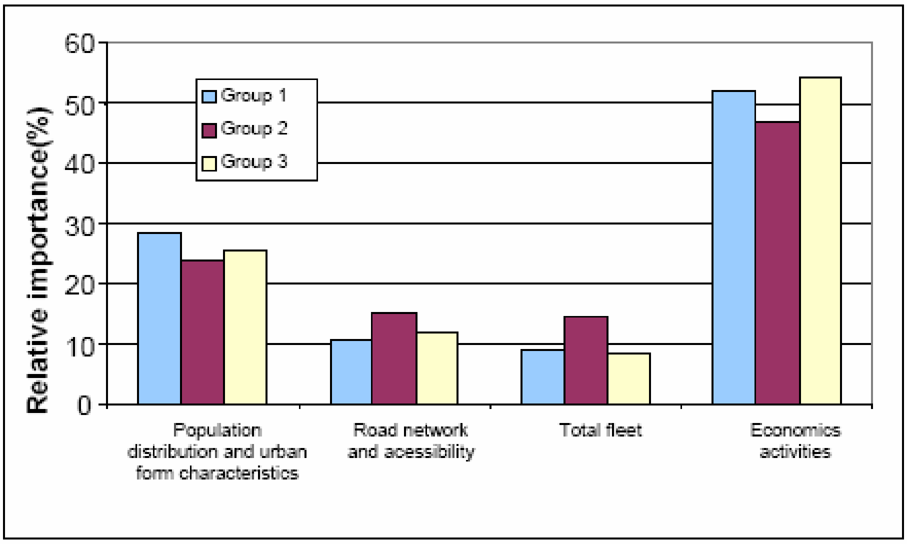

Figure 6 – Relative importance values of the classificatory groups.

Table 8 – Relative importance of the input variables and of the respective classificatory groups.

	Variable	Group 1 (%)	Group 2 (%)	Group 3 (%)	Average (%)
Population Distribution and Urban Form Characteristics	Area_circ	4.84	6.15	5.43	**25.88**
	SF	5.31	4.59	7.18	
	Prop_Pop	9.13	4.91	5.11	
	Pop_conc	4.26	5.23	3.12	
	Region	4.73	2.91	4.73	
	Group Total	**28.26**	**23.80**	**25.58**	
Road Network and Accessibility	R_network	7.24	11.51	7.51	**12.63**
	Dist_MM	3.62	3.67	4.34	
	Group Total	**10.86**	**15.18**	**11.85**	
Total Fleet	PT_fleet	3.30	7.48	4.79	**10.58**
	Car_fleet	5.69	6.95	3.53	
	Group Total	**8.98**	**14.43**	**8.31**	
Economic Activities	ECAE1R2	8.84	5.54	10.54	**50.91**
	ECAE2R2	5.34	4.83	4.72	
	ECAE3R2	6.03	5.30	7.11	
	ECAE4R2	4.95	5.09	4.67	
	ECAE5R2	4.72	4.95	4.23	
	ECAE6R2	3.56	2.48	2.68	
	ECAE7R2	8.36	6.53	8.47	
	ECAE8R2	3.17	3.22	3.53	
	ECAE9R2	6.94	8.64	8.31	
	Group Total	**51.89**	**46.59**	**54.26**	

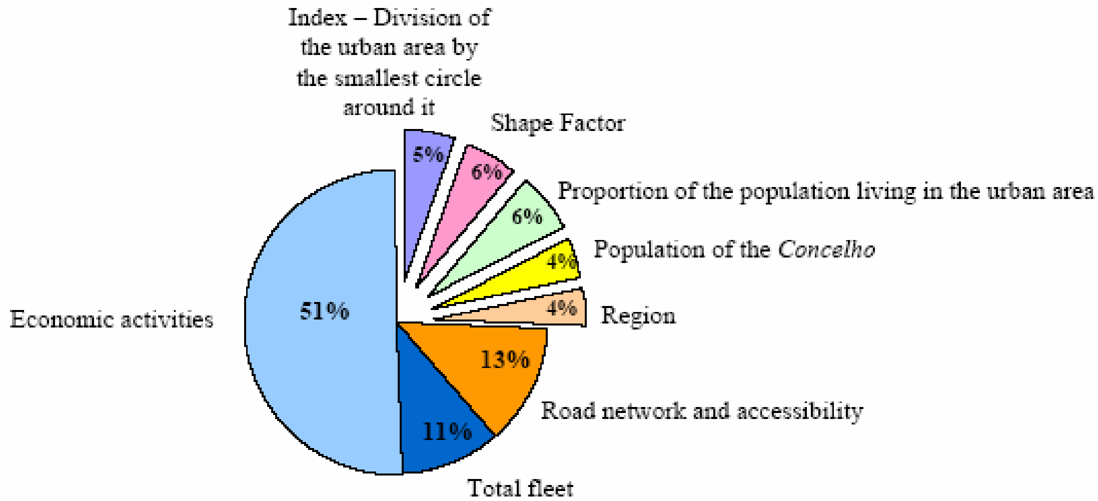

Figure 7 – Relative importance of the classificatory groups with the input variables of the group *Population Distribution and Urban Form Characteristics* highlighted.

4. Conclusions

The starting point of this work was the analysis of several studies developed in different parts of the world, which tried to look for evidences of a relationship between urban form characteristics and energy consumption for transportation. Some of these studies based the analyses on comparisons among cities of different countries; some considered cities of only one country; and some studied one or a few particular regions. A common finding of most of these studies based on empirical evidence is that sprawled cities would not be the most efficient arrangement when it concerns to energy consumption for transportation. Only a few researchers rejected this idea, with the argument that economic measures, such as the variation of fuel prices and the costs of ownership and use of the automobile, would be the most appropriate strategy and enough to reduce the consumption levels of energy used for transportation. Their arguments, however, do not have as much empirical evidence as the experience of several cities gathered in the numerous studies demonstrating that deficiencies in the physical planning of urban areas increasingly resulted in low-density sprawled cities, which in turn have produced high levels of energy consumption for transportation.

Given the empirical nature of that investigation trend, the main contribution of this work was to add more information for the analysis and discussion of the issue. The main focus here was the impact that physical and socioeconomic aspects of the main Portuguese urban areas, with the exception of Lisbon and Oporto, might have on energy consumption for transportation.

The selection of variables for the study was based on the existent literature about the topic. However, not all variables pointed out in those studies as the most important ones were used in the modeling process simply because they were not available in Portugal at the time of the data collection for the present study. As a matter of fact, the main difficulty was the acquisition of data aggregated at the city level. The available data in Portugal was most often aggregated at the level of the *Concelho*, and only sometimes, they were aggregated at the level of *Freguesia*. Only in the last decennial census (2001) the Portuguese Institute of Statistics distributed the population and household data aggregated at the level of statistical sections and subsections, which are spatial units smaller than the administrative division *Freguesia*.

The analysis based on Artificial Neural Networks required the determination of a set of parameters that can produce the best performance of the model. Thus, more than 110 different configurations were tested already in the initial phase of the study, varying the number of hidden layers, the number of neurons in each hidden layer, the Learning Rate, and the Momentum. From the several networks tested, the one that produced the smallest MRE was assumed as the best possible model at that point, given the variables used as input data. However, as the model performance was not satisfactory, further analyses were subsequently carried out in order to look for a different mix of input variables that could produce a better model.

The final results found in the current study confirmed the trend observed in several countries, in which the characteristics of urban form and population distribution played an important role influencing energy use for transportation. The number of people working in several economic activities was the most important group influencing energy use for transportation, but the characteristics of urban form and population distribution have also shown a high relative importance, even higher than the values found for the groups road network and accessibility and total fleet.

The results found for the group of selected Portuguese urban areas can indicate, similarly to what was observed in other countries, that the physical characteristics of the cities and the spatial distribution of the urban population have a strong influence on the consumption levels of energy used for transportation. These results somehow support the argument that, if the goal is to have a more efficient use of the energy for transportation, it is mandatory to have policies meant to drive the physical planning of the urban areas. As a result, further studies are required for determining with higher accuracy how the degree of dispersion of the Portuguese urban areas affects the energy consumption for transportation. One of the issues in this case is certainly the definition of the urban areas boundaries. Although the problem has been tackled in the present study, there is certainly room for improvement. Despite the huge contribution given by the Atlas of Portuguese Cities (INE, 2002) for solving the problem, the Atlas itself is not free of problems because of the different criteria used by the municipalities in the definition of their own limits.

Notwithstanding the clear need of further investigation, a better physical planning of the cities, which can include policies and measures for preventing extreme levels of urban sprawl, and other short and medium-term measures aiming to reduce the high level of energy consumption for transportation are important and opportune in Portugal. The latter certainly includes strategies to reduce the excessive automobile use and to produce a revitalization of public transportation. It can contribute thus for an improvement of important aspects of quality of life in urban areas, such as the reduction of traffic congestion and environmental impacts, a more appropriate use of the urban spaces, among others.

In conclusion, the present study could also be extended with the acquisition of more accurate socioeconomic data and also data regarding energy consumption for transportation, all preferably aggregated at the city level. In that aspect, the contribution of the Portuguese Institute of Statistics is fundamental, giving sequence to the excellent work started with the Atlas of Portuguese Cities.

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