EUROPEAN FREIGHT TRANSPORT ANALYSIS USING NEURAL NETWORKS AND LOGIT MODELS

Aura Reggiani*, Peter Nijkamp** and Wai Fai Tsang**

* Department of Economics, Università di Bologna, Piazza Scaravilli, 2
40126 Bologna, Italy - e-mail: areggiani@ecn01.economia.unibo.it

** Department of Regional Economics, Free University, De Boelelaan 1105
1081 HV - Amsterdam, The Netherlands - e-mail: pnijkamp@econ.vu.nl

Abstract

The present paper aims to analyse interregional freight transport movements in Europe in order to forecast spatio-temporal patterns of new transport economic scenarios.

In view of the high dimension of our data-base on transport flows, two different approaches are compared, viz. the logit model and the neural network model. Logit models are well-known in the literature; however, applications of logit analysis to large samples are more rare. Neural networks are nowadays receiving a considerable attention as a new approach that is able to capture major patterns of flows, on the basis of fuzzy and incomplete information. In this context an assessment of this method on the basis of a large amount of data is an interesting research endeavour.

The paper will essentially deal with a research experiment, oriented towards both calibration/learning procedures and spatial forecasting, in order to compare the two above methodologies as well as to investigate the potential/limitations of the two above mentioned different, but related assessment methods. The first results in this framework highlight the fact that the two models adopted, although methodologically different, are both able to provide a reasonable spatial mapping of the interregional transport flows under consideration.

1. Changes in the European Freight Transport Scene

After the completion of the European market and with the widening of Europe towards easterly direction, mobility in general has shown a steady increase in Europe. In particular, cross-border transport has been at a rising edge with annual growth rates exceeding 10 percent, a process reinforced by the current globalisation trends. The integration of former segmented markets -and the related liberalisation in the European space- has led to drastic changes in both goods and passenger transport.

The European Commission has recognised this restructuring phenomenon already several years ago, an observation which can also be found in the Maastricht Treaty. European networks are seen as the backbone of integration forces, while changes in the morphology of the networks are expected to generate system-wide impacts. Clearly, the emphasis on the potential of these networks for competitiveness and cohesion provokes various questions on the relative efficiency and substitutability of the different modes of this network. This issue is particularly important, as the competition between different modes and the social acceptability of modal choices are not only determined by the direct operational costs, but also by environmental externalities.

As a result, there is an increasing interest in the issue of intermodal competition and complementarity. For surface transport in Europe, especially the competitive position of rail vis-à-vis road is at stake. This holds increasingly also for commodity transport. It needs to be added however, that the analysis of freight transport in Europe is fraught with many difficulties, as freight is not a homogeneous commodity, but is composed of an extremely diversified set of goods with specific haulage requirements and logistic needs. This means that a commodity -specific approach is necessary to analyse in depth implications of changes in network configurations. This approach will also be adopted in the present paper.

The aim of the present paper is to investigate freight flow patterns in Europe from a multiregional perspective, by looking into the modal choice for these goods from the viewpoint of freight costs and transport time. In this paper, two competing models, viz. a discrete choice model and a neural network model, wil be employed to map out the spatial flow patterns in an explanatory context. This offers also a possibility to compare the relative performance of those models. A selection of Dutch regions and Italian regions will be used to test the predictive power of the models concerned. Next, a sensitivity analysis will be carried out in order to investigate the expected consequences of a rise in transport costs, e.g. as a consequence of a European environmental tax on freight costs.

2. The Models Used

The present paper aims to analyse interregional freight transport movements in Europe as well as to forecast resulting spatio-temporal flow patterns on the basis of new transport economic scenarios. For this purpose, a modal split analysis will be carried out by means of two statistical models, namely the logit model and the neural network model. A binary logit model will be discussed in Section 2.1, while a feedforward neural network model will be presented in Section 2.2.

2.1 The Logit Approach

A widely adopted approach for modal split analysis is the logit model (see e.g. Ben-Akiva and Lerman, 1985). Recent experiments using logit models / spatial interaction models in order to map out the freight transport in Europe have been carried out by Tavasszy(1996), who showed the suitability of logit models also for the goods transport sector (where data are more ‘fuzzy’ and incomplete compared to the passenger sector). Logit models are discrete choice models, which are used for modeling a choice from a set of mutually exclusive and exhaustive alternatives. It is assumed that the decision-maker chooses the alternative with the highest utility among the set of alternatives. The utility of an alternative is determined by a utility function, which consists of independent attributes of the alternative concerned and the relevant parameters. In a logit approach the concept of random utility is adopted, which means that the true utilities of the alternatives are considered to be random variables, i.e.,

$$U_{in} = f\,(X_{i,m}) + \varepsilon_{in} \tag{1}$$

where

U_{in} = the utility of alternative i for individual n

$f\,(X_{i,m})$ = a function of attributes m related to alternative i

ε_{in} = a random disturbance term.

By maximizing then the stochastic utility (1), the probability that an alternative is chosen is defined as the probability that it has the highest utility among all relevant alternatives (see e.g. Ben-Akiva and Lerman, 1985, Cramer, 1991 and McFadden, 1977).

Since in our case two discrete choices -rail (t) and road (c)- will be considered, a binary logit model is adopted. Then the following assumption is made concerning the random term:

$$F(\varepsilon_n) = \frac{1}{1+e^{-\mu\varepsilon_n}}, \qquad \mu > 0, \; -\infty < \varepsilon_n < \infty, \tag{2}$$

$$f(\varepsilon_n) = \frac{\mu e^{-\mu\varepsilon_n}}{(1+e^{-\mu\varepsilon_n})^2} \tag{3}$$

For the sake of convenience, also the following assumption is made: $\mu = 1$. Thus the logit model for modal split choice of the train versus the car between two regions i and j has the following formulation:

$$P_{ij}^{t} = \frac{\exp^{(U_{ij}^{t})}}{\exp^{(U_{ij}^{t})} + \exp^{(U_{ij}^{c})}} \tag{4}$$

where

$$U_{ij}^{t} = \beta_1 * X_{1,ij}^{t} + \beta_2 * X_{2,ij}^{t} \tag{5}$$

and

$$U_{ij}^{c} = \beta_3 * X_{1,ij}^{c} + \beta_4 * X_{2,ij}^{c} \tag{6}$$

and where:

P_{ij}^{t} = the probability of choosing the train from region i to region j (i $\neq$ j);

U_{ij}^{t} = the utility connected with the rail mode (t) on the link ij;

U_{ij}^{c} = the utility related to the road mode (c) on the link ij;

$X_{1,ij}^{m}$ = the attribute ‘time’ for mode *m* in the utility function for the link ij;

$X_{2,ij}^{m}$ = the attribute ‘cost’ for mode *m* in the utility function for the link ij;

β_1, β_2 = the parameters related to the attributes time and cost, respectively, for the mode train;

β_3, β_4 = the parameters related to the attributes time and cost, respectively, for the mode road.

The binary logit model has become in the meantime a standard analytical tool in discrete choice modelling. The results of this logit model for an empirical case on European freight transport will be given in Section 3.

2.2 The Neural Network Approach

Neural network (NN) analysis has in recent years become a popular analysis tool (see for reviews Himanen et al., 1997). NNs replicates human brain functions and are thus considered as ‘intelligent’, since they learn and generalize by examples (see e.g. Reggiani et al., 1997). NNs have been widely applied to the area of transport engineering, in particular in relation to traffic control problems and accidents (see Himanen et al., 1997). However, only a few experiments exists in the field of transport economics or transport route / mode / destination choice (see e.g. Nijkamp et al., 1996 and Schintler and Olurotimi, 1997). Our experiments aim to explore also this novel research direction.

Following the majority of applications on NNs, in this study a two-layer feedforward, totally connected NN will be used in order to analyse the freight transport modal split problem. The methodological structure of the main steps related to the application of a feedforward NN is described in Reggiani and Tritapepe (1997) (see also Figure 1). Concisely, it consists of three stages: a) definition of network architecture; b) learning phase; c) forecasting phase. It is necessary to define the right architecture of the network, i.e. the number of units on the relevant levels. Usually, the input and output units depend on the number of input and output variables which define the problem. In our application one possible NN architecture contains 4 input units which correspond to the attributes time and cost related to each transport mode (rail and road) and one output unit corresponding to the probability of choosing one mode[1] (e.g., the rail mode). In the past years we have witnessed an increasing acceptance of NN models in social science research, including transportation science. Section 3 will offer empirical results obtained by applying an NN model to European freight flow data.

[1] The choice probability of the other mode is just the complement.

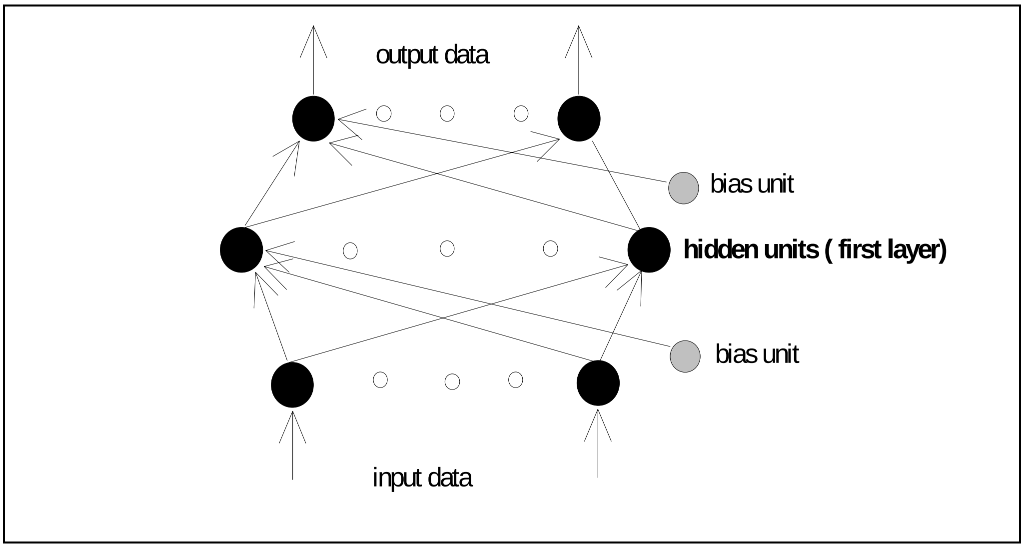

Figure 1 Feedforward Neural Network architecture

3. Empirical Application

In this section the experiments with the logit and the neural network approach (see Subsection 2.1 and 2.2) will be presented and discussed. In Subsection 3.1 a concise description of the data set will be given. The experiments carried out by means of the logit approach and the neural network approach are presented in Subsections 3.2 and 3.3, respectively. Then the two approaches will be mutually compared in Subsection 3.4.

3.1 The Data

The data set[2] contains the freight flows and the attributes related to each link between 108 European regions[3] for the year 1986. The attributes considered are '*time*' and '*cost*' between each link (ij) with reference to each transport mode. In particular, each observation of the data set pertains to variables related to each link (ij). Furthermore, the flow distribution in the matrices concerned refers to one particular kind of goods, viz. food.

Since 108 areas have been considered, the data set should ideally contain 11664 observations (according to the previous remarks on our observations). However, our data set contains finally

[2] The data set has been kindly provided by NEA Transport Research and Training, Rijswijk.
[3] See Table 11 and Figure 2.

4409 observations because of the following considerations (by analysing the data set):

- the intra-area freight flows are zero;
- for each link, only the transport movements towards one direction $i \rightarrow j$ have been considered;
- only the links where the flows and the attributes (of both road and rail) are different from zero have been considered (i.e., empty cells are excluded).

The data set has been randomly subdivided into three sub-sets:

- a *training set* containing 2992 observations, i.e. about 68% of the data-set;
- a *cross-validation set* containing 447 observations, i.e. about 10% of the data-set;
- a *test set* containing 970 observations, i.e. about 22% of the data-set.

3.2 Experiments by means of a logit approach

As mentioned before, a binary logit model has been used in order to analyse a modal split problem between road and rail in relation to the interregional food transport between 108 regions in Europe. In Subsection 3.2.1, the calibration results and an evaluation of the logit model will be presented. Then the spatial forecasting of the calibrated logit model will be performed and evaluated in Subsection 3.2.2.

3.2.1 Calibrating the binary logit model

First, the logit model has been calibrated in order to estimate the unknown parameters in the utility function. For this purpose, a data set, which is the learning set combined with the cross-validation set, has been used. Concerning the logit model structure, two cases are considered; in Case A, the two competing transport modes rail and road are supposed to have the same parameter for a given attribute (i.e. $\beta_1 = \beta_3$, $\beta_2 = \beta_4$), while in Case B each transport mode has different parameters for a given attribute. The logit model has been calibrated by using the LIMDEP software. The estimated parameters resulting from the calibration stage are presented in Tables 1 and 2 for Case A and Case B, respectively.

Next, the goodness-of-fit of the model has been evaluated using two statistical indicators: the likelihood-ratio (ρ^2)[4] and the t-test. The related results are also presented in Tables 1 and 2.

Variables	coefficient		std error	t - ratio
time	β_1	-0.00952	0.3514^E-05	-2707.83
cost	β_2	-0.06493	0.1535^E-04	-4229.71
Log likelihood	= -0.2750E+08			
χ^2 (2)	= 0.1348E+09			
ρ^2	= 0.71023			

Table 1. The Results related to Case A

variables	coefficient		std error	t - ratio
time	β_1	-0.00806	0.4825^E-05	-1670.67
	β_3	-0.00802	0.5258^E-05	-1525.31
cost	β_2	-0.06208	0.2303^E-04	-2696.35
	β_4	-0.05567	0.6843^E-04	-813.498
log likelihood	= -0.2739^E+08			
χ^2 (2)	= 0.1350^E+09			
ρ^2	= 0.71138			

Table 2. The Results related to Case B

The t-test indicates that the two parameters are significantly different from zero in both cases (see Table 1 and Table 2). Also the value of ρ^2 indicates that the calibrated logit models are performing reasonably well for the two cases. Table 2 also indicates that β_1 has almost the same value as β_3. This is also the case for β_2 and β_4. However, the calculated ρ^2 for Case B is slightly better than for Case A, which suggests that Case B performs slightly better than Case A.

[4] The definition of the statistical indicator $\rho^2 = 1 - (\lambda_{(0)} / \lambda_{(\beta)})$, where $\lambda_{(0)}$ = the value of the log likelihood function when all weights are zero and $\lambda_{(\beta)}$ = the value of the log likelihood function at its maximum (see Ben-Akiva and Lerman, 1985).

3.2.2 Spatial forecasting performance of the binary logit model

The binary logit model, as calibrated in the previous subsection, can be used to make spatial forecasts on the basis of various transport economic scenarios. For this predictive purpose, both the data set used in the calibration stage and the test set which is not used in the calibration stage, are employed.

In order to analyse the spatial forecasting performance of the binary logit model, the statistical indicators R^2 and ARV[5] will be used. The coefficient of determination R^2 is usually adopted in the calibration procedure for logit models, while the Average Relative Variance (ARV) is more commonly used for neural network models (see e.g. Fischer and Gopal, 1994). However, we will consider here the indicator ARV also for our logit model in order to carry out a comparison with the NN approach. Both the R^2 and the ARV indicators have been calculated for the two cases, as well as for the test set. Especially the test set shows significant results. It will be also used subsequently to explore the NN's performance. The probabilities of train and car are used in calculating the statistical indicators. The results are presented in Table 3 and Table 4 for case A and B successively.

size of data set	**3439 observations**	**970 observations**
ARV	0.302	0.203
R^2	0.816	0.835

Table 3. The Results related to Case A

size of data set	**3439 observations**	**970 observations**
ARV	0.267	0.185
R^2	0.865	0.887

Table 4. The Results related to Case B

[5] The definition of the statistical indicator $ARV = \frac{\sum (y-\hat{y})^2}{\sum (y-\bar{y})^2}$ and the statistical indicator $R^2 = \frac{\sum (\bar{y}-\bar{\hat{y}})^2}{\sum (y-\bar{y})^2}$, where y = the observed transport flow using car, $\hat{y}$ = the transport flow using car, predicted by the adopted model and $\bar{y}$ = the average of the observed transport flow using car (see Fischer and Gopal, 1994).

It should be noted that the ARV measure should ideally approach zero, while the R^2 measure should approach one, if the estimates tend to be accurate. Concerning the general results presented in Table 3 and Table 4, the binary logit model appears to have a good predictive ability; in particular, Case B turns out to perform better than Case A for different numbers of observations. Therefore, only the results of Case B will be illustrated in Subsection 3.4 and in Section 4 where the logit model will be compared with the NN model.

3.3 Experiments by means of a neural network approach

As mentioned in Subsection 3.2, the modal split problem will also be analysed by means of a more recently developed statistical model, viz the feedforward neural network model (see Subsection 2.2).

It has already been mentioned that the whole data set contains 4409 observations (examples or patterns). The following general considerations apply to the experiment undertaken here:

· The training for the neural net model (and the calibration for the logit model) has been carried out by using the *training set*.

· The performance measure has been evaluated by using the *test set* (spatial forecasting).

· The attributes (time and cost denoted by V_j) have been transformed (in a value range between [0-1]) by means of the following functions:

$$V_j^f = \exp(-0.002 * V_j) \tag{7}$$

The variables are defined as follows:

TC_{ij}^f : transformed rail cost for link (ij);

TT_{ij}^f : transformed rail time for link (ij);

RC_{ij}^f : transformed road cost for link (ij);

RT_{ij}^f : transformed road time for link (ij);

T_{ij} : total freight flow related to link (ij);

T_{ij}^{train} : total rail flow related to link (ij);

p_{ij}^{train} : rail mode probability for link (ij), in relation to the following relationship:

$$T_{ij}^{train} = p_{ij}^{train} * T_{ij}. \qquad (8)$$

Concerning the number of hidden units, they have empirically been defined by taking into account the number of observations in the data set as well as by carrying out a large number of experiments. In regard to the parameters defining the neural architecture, they have been determined after several empirical experiments. Finally, the parameters of the NNs are set as follows:

- number of hidden units: 8
- learning rate a = 0.9
- momentum factor l = 0.05
- epoch size: 1
- initial weight values: randomly between [-0.1;0.1]

It should be noted that by using a feedforward NN it is necessary to cope with the overfitting problem. Consequently, in the experiments the cross-validating technique (by using the cross-validation subset) has been used in order to avoid such a problem (for details on the overfitting problem and the cross-validating technique, see e.g. Fischer and Gopal, 1994, Reggiani and Tritapepe, 1997).

The results related to the above mentioned experiment will now be presented. In general, by using a statistical model for forecasting, the first step is to evaluate the predictive quality of the model, i.e. to determine how well the model learned to approximate the unknown input-output function for arbitrary values of input units, while the final aim of our work is to evaluate the freight transport movements in Europe in order to forecast spatio-temporal patterns on the basis of new transport economic scenarios. The present section will particularly analyse this first research stage, i.e. the spatial forecasting of the model adopted. The predictive quality will be evaluated - by means of a performance measure - by using the test set which had been set apart and not yet used for the calibration (learning) phase, as mentioned above.

The predictive performance of an NN can be judged by means of the statistical indicator ARV (see Nijkamp et al., 1996a and Subsection 3.2.2); the result of the test statistic is the following:

$$ARV_{NN} = 0.176$$

It is then evident that the above ARV indicator, emerging from NN, gives a better result than the ARV indicator emerging from the logit analysis. Tables 3 and 4 present also the values of ARV = 0.203 and ARV = 0.185 -both greater than 0.176- and show thus a better performance of the NN approach. This result is rather promising and gives sufficient confidence in the validity of the NN approach for spatial analysis.

3.4 Comparison of the Logit and Neural Network Approach

In this subsection, the spatial forecasting performance of the two alternative approaches adopted will be compared and evaluated.

By using the test set, which was not used for the calibration procedure, in our procedure both the binary logit and the neural network model have been employed to predict the freight flows for link (ij). This performance has been evaluated using the statistical indicator ARV.

In light of the enormous number of commodity flows we will not present the estimates for all interregional flows in Europe, but only for three illustrative types of flows, viz. from Dutch regions to Europe as a whole and vice versa, and from Europe to Italian regions. Tables 5, 6 and 7 illustrate the predictions made by the two distinct approaches.

	Food Transport Flows			rel. prediction error	
Regions	**LOGIT**	**real**	**NN**	**LOGIT**	**NN**
Breda	170981	181032	176781	-5,6%	-2,3%
Eindhoven	904321	968534	945732	-6,6%	-2,4%
Maastricht	252429	264424	255930	-4,5%	-3,2%
Total	1327732	1413990	1378442	-6,1%	-2,5%

Table 5 Food Transport Flows from Dutch regions to Europe

	Food Transport Flows			rel. prediction error	
Regions	**LOGIT**	**real**	**NN**	**LOGIT**	**NN**
Breda	15837	15922	15634	-0,5%	-1,8%
Eindhoven	121918	119772	122434	1,8%	2,2%
Maastricht	59550	59880	60010	-0,6%	0,2%
Total	197304	195574	198077	0,9%	1,3%

Table 6 Food Transport Flows from Europe to Dutch regions

Regions	Food Transport Flows LOGIT	real	NN	rel. prediction error LOGIT	NN
Ancona	898	921	888	-2,5%	-3,6%
Bari	16722	16925	16040	-1,2%	-5,2%
Bologna	71272	68916	72920	3,4%	5,8%
Cagliari	4072	4019	4010	1,3%	-0,2%
Florence	27052	27488	26756	-1,6%	-2,7%
Milan	60781	59977	59482	1,3%	-0,8%
Naples	55916	54720	57807	2,2%	5,6%
Palermo	29344	29221	29018	0,4%	-0,7%
Pescara	8939	8895	8471	0,5%	-4,8%
Reggio di Calabria	1384	1375	1324	0,6%	-3,7%
Rome	13879	14504	13756	-4,3%	-5,2%
Turin	106438	105414	108563	1,0%	3,0%
Venice	8776	9280	9155	-5,4%	-1,4%
Total	405472	401655	408189	1,3%	-0,2%

Table 7 Food Transport Flows from Europe to Italian regions

Table 5 presents the predictions for the export flows of foodstuff from three regions in the Netherlands (Breda, Eindhoven and Maastricht). Both approaches predict a slightly smaller transport flow than the observed flow; however the predictions made by the logit model are less accurate than those predicted by the NN model.

Analogously, the predicted import flows from Europe to the same three regions in the Netherlands are presented in Table 6. This table indicates that the logit results are slightly more accurate than the NN results. In the case of Maastricht the logit prediction is slightly smaller than the observed value, while the neural network prediction is slightly higher.

Next, we have focused our attention on the import flows from Europe to Italian regions. The predicted import flows to thirteen Italian regions are shown in Table 7. The NN model again appears to make on average slightly more accurate predictions than the binary logit model, although at the individual (regional) level the logit model also gives a good approximation.

Finally, Table 8 shows the ARV indicators, which have been calculated for both the logit and the NN approach (see also the previous sections).

	ARV
NN	0.176
Logit	0.185

Table 8. Comparison of Logit and NN performance

According to the ARV indicator, the NN approach for forecasting spatial flows performs overall slightly better than the logit approach.

4. Policy Scenario Experiments

As mentioned above, freight transport causes high social costs, which might be charged to the transportation sector. We will now investigate the consequences of varying the transportation costs for freight flows. A sensitivity analysis of the previous results based on some economic scenarios will now be carried out in this section by using again both the binary logit model and the NN model. Two policy scenarios based on different external costs assignments will be used; they will concisely be discussed here. Later on, we will present the results related to the sensitivity analysis for the logit and the neural network approach.

At present, because of severe problems on the road transport network (for example, congestion), governments are trying to reduce the road usage by imposing policy measures that serve to increase the cost of road usage (see Verhoef, 1996). An example of a Pigouvian policy for coping with environmental externalities is the recently increased tax on fuel in the Netherlands. In so doing, the usage of the road transport network is made less attractive than other transport networks. In the light of these recent developments, two scenarios have been developed and considered for an sensitivity analysis; these are based on the observations in the test set. In Scenario 1 we assume that a uniform European tax policy for freight transport is adopted and that the cost attribute related to the road mode is increased by 25 % for all links (ij). Scenario 2 assumes only a national environmental policy, which means that same cost increase is made exclusively for links (ij) which start or end in Dutch regions.

The conditional predictions for the three Dutch regions are presented in Tables 9 and 10 for the binary logit and the neural network model, respectively. The relative prediction error (see Tables 9 and 10) is defined as the difference between the predicted flow and the real flow as a percentage of the real flow. These tables indicate that the binary logit model is relatively more sensitive to changes in the cost attribute than the NN model. Table 9 also shows that the binary logit model gives the same predictions in the two scenarios, which is caused by the independence of irrelevant alternatives feature (IIA) of this discrete choice model. The NN model estimates appear to give the lowest prediction error.

It is interesting to note that in the neural network case, and particularly in the case of inflows from Europe to the Netherlands, the model shows -in the mean value- a slight increase of flows, despite the cost increase. This result may be plausible by taking into account the increasing amount of interaction among regional flows as a result of increased efficiency. It would certainly be relevant to compare these results with more updated data in order to better evaluate the ‘forecasting’ analysis of the two models, since we have used -as a starting point- a test set related to the year 1986.

However, the above results may be considered valid, in the absence of updated data that would be able to test our hypothesis of a 25% increase in the costs, given the good performance of the calibration / test phase. Moreover, these results may offer a ‘range of values’ to policy actors aiming to evaluate the impact of cost changes on flows, given the intrinsic limits of both adopted models.

On the one hand, the large amount of data at an aggregate level, hampers a behavioural perspective inherent in logit models. On the other hand, the type of architecture adopted in NN models seems critical for the validity of the results. Consequently, the results of our model may be used as a benchmark for the results of other models, by offering a more ‘flexible’output to policy actors.

	Food Transport Flows				**Relative Prediction Error**		
From NL to Europe **Regions**	*real flow*	*pred. flow* **a) test set**	**b) scen. 1**	**c) scen. 2**	**a)**	**b)**	**c)**
Breda	181032	170981	161327	161327	-5,6%	-10,9%	-10,9%
Eindhoven	968534	904321	861082	861082	-6,6%	-11,1%	-11,1%
Maastricht	264424	252429	245336	245336	-4,5%	-7,2%	-7,2%
TOTAL	1413990	1327732	1267745	1267745	-6,1%	-10,3%	-10,3%
From Europe to NL **Regions**	*real flow*	*pred. flow* **a) test set**	**b) scen. 1**	**c) scen. 2**	**a)**	**b)**	**c)**
Breda	15922	15837	15599	15599	-0,5%	-2,0%	-2,0%
Eindhoven	119772	121918	119056	119056	1,8%	-0,6%	-0,6%
Maastricht	59880	59550	58363	58363	-0,6%	-2,5%	-2,5%
TOTAL	195574	197304	193018	193019	0,9%	-1,3%	-1,3%

Table 9 Results of the sensitivity analysis for the binary logit model (columns b and c)

	Food Transport Flows				Relative Prediction Error		
From NL to Europe **Regions**	*real flow*	*pred. flow* **a) test set**	**b) scen. 1**	**c) scen. 2**	**a)**	**b)**	**c)**
Breda	181032	176781	175783	171600	-2,3%	-2,9%	-5,2%
Eindhoven	968534	945732	941847	930447	-2,4%	-2,8%	-3,9%
Maastricht	264424	255930	255261	254181	-3,2%	-3,5%	-3,9%
TOTAL	1413990	1378442	1372891	1356228	-2,5%	-2,9%	-4,1%
From Europe to NL **Regions**	*real flow*	*pred. flow* **a) test set**	**b) scen. 1**	**c) scen. 2**	**a)**	**b)**	**c)**
Breda	15922	15634	15598	15508	-1,8%	-2,0%	-2,6%
Eindhoven	119772	122434	122117	121270	2,2%	2,0%	1,3%
Maastricht	59880	60010	59832	59368	0,2%	-0,1%	-0,9%
TOTAL	195574	198077	197548	196146	1,3%	1,0%	0,3%

Table 10 Results of the sensitivity analysis for the neural network model (columns b and c)

5. Concluding Remarks

This paper has aimed to depict transport flows of commodities in an interregional European setting. Based on an extensive (NEA) data set, various estimates of the impacts of costs on transport movements have been made. The test results show that both the logit and the NN approach are giving fairly favourable results. In general, NN models seem to perform slightly better. After this exploratory comparative study of two modelling approaches, it is certainly opportune to investigate more thoroughly the differences in background of these two research paradigms. It is well known that the logit model is a particular spatial interaction model that has its roots in social behaviour of actors, however with the limit of assuming certain properties, like the well known IIA (Independence from Irrelevant Alternatives) assumption. The NN model is based on similarily of learning experiments and has certainly a behavioural adjustment potential, but is less easily interpretable from social science motives, even though recent results show a compatibility between feedforward NNs and binary logit models (see Schintler and Olurotimi, 1997), feedforward NNs and spatial interaction models (see Fischer and Gopal, 1994) and feedforward NNs and logistic regression models (see Schumacher et al., 1996). Given its predictive ability, more research is needed to better investigate the behavioural roots of NN models.

References

Ben-Akiva, M. and S. R. Lerman, **Discrete Choice Analysis: Theory and Application to Travel Demand**, MIT Press, Cambridge, Massachusetts, 1985.

Cramer, J. S., **The LOGIT Model: an Introduction for Economists**, Routledge, Chapman and Hall Inc., New York, 1991.

Fischer, M. M. and S. Gopal, Artificial Neural Networks: A New Approach to Modelling Interregional Telecommunication Flows, **Journal of Regional Science**, Vol. 34, N. 4, 1994, pp. 503-527.

Himanen, V., Nijkamp, P. and A. Reggiani (eds.), **Neural Networks in Transport**, Avebury, Aldershot, 1997 (forthcoming).

McFadden, D., Econometric Models of Probabilistic Choice, in Mansky, C. F. and D. McFadden (eds), **Structural Analysis of Discrete Data with Econometric Applications**, MIT Press, Cambridge, Massachusetts, 1977.

Nijkamp, P., Reggiani, A. and T. Tritapepe, Modelling Inter-Urban Transport Flows in Italy: A Comparison between Neural Network Approach and Logit Analysis, **Transportation Research C**, 1996 (forthcoming).

Schintler, L. A. and O. Olurotimi, Neural Networks as Adaptive Logit Models, in Himanen, V., Nijkamp, P. and A. Reggiani (eds.), **Neural Networks in Transport**, Avebury, Aldershot, 1997 (forthcoming).

Schumacher, M., Roßner, R. and W. Vach, Neural Networks and Logistic Regression, **Computational Statistics & Data Analysis**, Vol. 21, 1996, pp. 661-682.

Tavasszy, L. A., **Modelling European Freight Transport Flows**, Ph.D. Thesis, Delft University of Technology, Delft, 1996.

Verhoef, E. T., **The Economics of Regulating Road Transport**, Edward Elgar, Aldershot,1996.

Belgium	**The Netherlands**	98 Canary Islands

1	Antwerp
2	Bruxelles
3	Liege
4	Gent
	Danmark
5	Copenhagen
6	Odense
7	Aarhus
8	Fredericia
	France
9	Lille
10	Amiens
11	Rouen
12	Paris
13	Metz
14	Dijon
15	Lyon
16	Marseille
17	Montpellier
18	Toulouse
19	Bordeaux
20	Rennes
21	Tours
22	Clermont-Ferrand
23	Reims
	Greece
24	Thessaloniki
25	Athens
26	Patras
27	Heraklion
	Italy
28	Turin
29	Milan
30	Genoa
31	Venice
32	Bologna
33	Florence
34	Ancona
35	Pescara
36	Rome
37	Naples
38	Bari
39	Reggio di Calabria
40	Palermo
41	Cagliari
	Irland
42	Dublin
43	Rosslare
44	Cork
45	Galway
46	Athlone
	Luxemburg
47	Luxemburg
48	Groningen
49	Amsterdam
50	Almelo
51	Arnhem
52	Utrecht
53	Rotterdam
54	Eindhoven
55	Maastricht
56	Breda
	Germany (west)
57	Kiel
58	Hamburg
59	Hannover
60	Oldenburg
61	Bremen
62	Essen
63	Koln
64	Kassel
65	Frankfurt
66	Ludwigshafen
67	Stuttgart
68	Freiburg
69	Nurnberg
70	Regensburg
71	Munchen
72	Berlin
	United Kingdom
73	Carlisle
74	Newcastle
75	Leeds
76	Manchester
77	Nottingham
78	Birmingham
79	Cardiff
80	Holyhead
81	Bristol
82	Cambridge
83	London
84	Southampton
85	Glasgow
86	Aberdeen
87	Dumfries
88	Belfast
	Spain
89	Lugo
90	Bilbao
91	Zaragoza
92	Barcelona
93	Valencia
94	Sevilla
95	Madrid
96	Valladolid
97	Caceres
	Portugal
99	Porto
100	Coimbra
101	Lisbon
	Austria
102	Innsbruck
103	Linz
104	Vienna
105	Graz
	Switserland
106	Geneva
107	Bern
108	Zurich

Table 11 List of the 108 European Regions considered

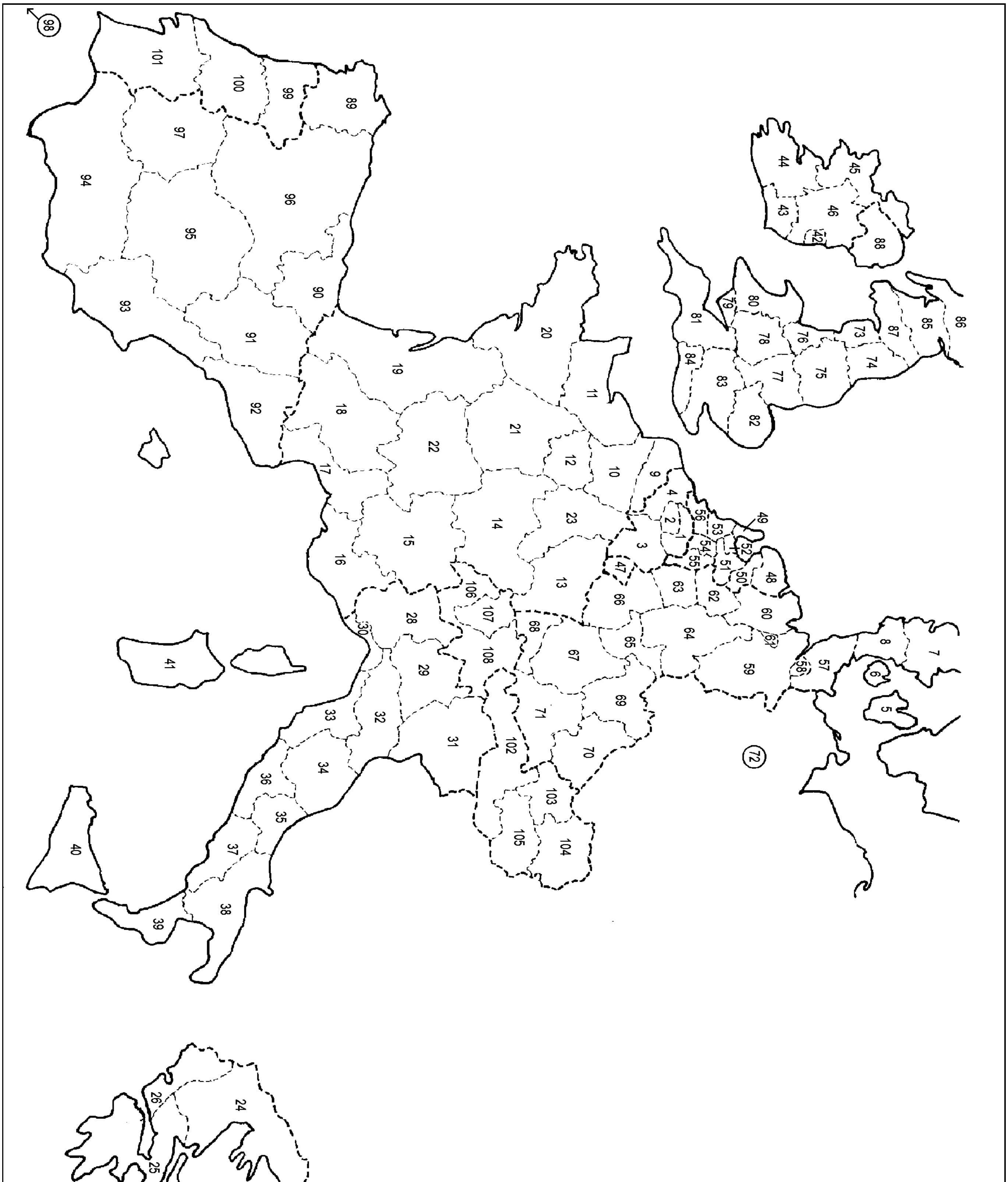

Figure 2 Map of the 108 European Regions considered