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APPLICATION OF NEURAL NETWORKS TO MODAL SPLIT MODELLING

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Abstract: A transport system user's choice of one among alternative travel models is based on acquired experience and personal views concerning the availalable alternatives. Hence our assumption that it is possible to create a neural network which can be "fed" by real (collected) input data on user type, parameters relevant for decision making and information about user behaviour under specific conditions. This information is used to train the network (by employing some of the known algorithms) to simulate user behaviour. This paper briefly presents a special methodology we have used in performing research that permits filing the gap in the knowledge of user behaviour towards offered transport conditions. Based on this, a NEKOP (neural network and user behavior) model for user behaviour simulation has been developed. The results obtained by modal split simulation are compared with real data. The field of application and the constraints of the NEKOP model are described.

Keywords: Modal split, transportation planning, behaviour analysis, neural computing networks.

1. INTRODUCTION

In recent years, experts from various fields (social, natural, engineering science) have started focussing their research interests on so-called artificial neural networks. Advances in computer technologies have introduced computers into domains that have, until recently, belonged exclusively to human intelligence. Attempts are being made to create machines capable of learning, memorizing and inferring in a way that imitates human mental processes.

Artificial neural networks are inspired by biological networks, they "copy" the functioning of neurons. They can "copy" some human brain properties, for example they are capable of learning based on experience, making generalizations (from previous to new cases), and of distinguishing between significant and insignificant features.

A number of network learning algorithms have been developed in past years [5]. The basic learning principle is to give a set of input data (and sometimes even the expected output) to the network, while the mechanism by which the network establishes internal relations is not visible to the user. Once trained, the network is supposed to be insensitive, to a certain extent, to small input variations. The generalization capability results from the network structure itself. At present, the applicability of neural networks is limited, because they represent a relatively new research area and little practical experience has been gained.

As neural networks try to simulate the functioning of the human brain, we have made an attempt to use these networks to model the modal split in a way that simulates user views and behaviour.
As far as the author of this paper is informed, no papers analyzing the applicability of neural networks to modal split modelling have been published so far.

A transport system user's choice of one among the alternative travel modes is based on acquired experience and personal views concerning the availeble alternatives. Hence our assumption that it is possible to create a neural network which can be "fed" by real (collected) input data on user type, parameters relevant for decision making and information about user behaviour under specific conditions. This information is used to train the network (by employing some of the known algorithms) to simulate user behaviour.

Although the capabilities of neural networks are incomparably smaller than those of the human brain, the use of neural network theory can be very beneficial in many fields. Simulating the behaviour of intelligent beings who respond to information obtained from the environment, neural networks show considerable analogy with the potential behaviour of a transportation system user. So, it was only logical to try to apply neural networks to create models which are adequate descriptions of user behaviour by including appropriate self-learning rules. It is assumed that such a tool for user behaviour simulation can be suitable for use in a nonaggregate approach to modal split analysis.

2. WHAT IS THE MODAL SPLIT ?

The modal split in transportation planning represents an estimate of the possible volume of travel in a particular mode, i.e. the share of certain transport modes in total travel demands. The modal split is an element of the transport system development strategy for the area under consideration.

A large number of factors affect the modal split. Several different approaches to the modal split have been in use. The methods applied differ depending on research goals, level and character, on information availability, etc. About 300 different modal split methods were known as early as in 1970 [7]. The method used for modal split forecasting depends on the overall planning procedure, i.e. on whether this method precedes of follows the trip distribution determination. Depending on the calibration procedure, models can be classified into static and analytical models based on choice probability, on user behaviour, etc. Models can be aggregate or disaggregate, depending on whether the basic unit under consideration is a spatial unit or an individual user. Binary and multimodal models can be distinguished according to the number of travel modes.

A transport system user's choice of the mode of transport is neither a static or random process. This process is affected by several different factors [2] which can be classified into the following three groups.

- travel characteristic
- passenger characteristic
- transport system characteristic.

The main travel characteristic affecting a transport system user's choice of travel mode are: trip purpose, distance, duration, orientation in space, etc. For example, the modal split of work trips differs considerably from that of shopping trips. There exist radial-type trips directed towards a center, trips from one residential area to another, trips from residential to work zones or some special-purpose zones, etc.

The modal split is also affected by the socio-economic characteristics of an individual or household. These characteristics include: income, the number of cars, family size, the number of employed, age and education structure, etc. One of the most important factors of the modal split is the motorization degree, because it directly determines the size of the population having the choice between a car and mass transport in contrast to those who have no car and must use public transport. Population density is also one of the factors used in analyzing and forecasting the modal split. The percentage of trips by public transport decreases with decreasing population density. This is explained by the fact that low-density areas can hardly be served by public transport at an adequate service level which would simultaneously be economically acceptable.

The notion of service level includes many transport system characteristics that affect, often decisively, the distribution between individual and mass transport. Travel time and travel cost are the most widely used measures for comparing the efficiency or appropriateness of different means of transport (car/public transport); the results of these comparisons are expressed either as travel time or travel cost ratios or as their differences. The total travel time by public transport comprises the driving time, terminal (pedestrian) times at the trip source and destination points as well as delay and transfer times. Travel time by car is characterized, in addition to driving time, by a considerable portion of terminal time at trip destinations which depends on parking conditions.

Frequently, existing modal split models are not based on sufficient knowledge of people's lives and work reality. The models usually describe adequately the physical characteristics of a transport system, but they often describe incompletely the social conditions under which trips are made. For a better analysis and modelling of user behaviour, it is necessary to study different components simultaneously: economic, social, psychological as well as transport system components that affect user behaviour. Such a generalized approach should be obtained using diverse methods that allow user behaviour to be studied from an individual's standpoint. The explanations of user behaviour (such as the travel mode choice) must take into account both the real components faced by an individual and the characteristics of his lifestyle (household, employment) that affect how he organize his time and environment. The real characteristics of one's lifestyle and the importance attached to them provide a background for behaviour analysis [8].

3. WHAT IS A NONAGGREGATE APPROACH TO TRANSPORTATION PLANNING ?

The models based on aggregation at a transportation zone level explain interzonal differences but do not explain the differences among units within one zone [6]. Intrazonal behaviour is not homogenous in real-life conditions; moreover, the diversity in intrazonal behaviour can be considerably wider compared to the interzonal differences, especially if spatially large zones are considered. If a model is not applicable to different areas, its validity is questionable when the model is used in different zones of the same area. A significant difference occurs between the basic state and the values obtained by the model and this error is then introduced into the forecast.

As a separate forecast is made for each spatial zone, all data about the socio-economic characteristics and the transportation system be at a zone level, but these are difficult to estimate for a future state. It is characteristics of the aggregate approach to neglect intrazonal differences in behaviour, so a considerable amount of important information about families and their behaviour is lost through the aggregation procedure.

The aggregate approach to modelling does not take intrazonal trips into account. There are many transportation studies that treat very large zones in which the intrazonal flows are relatively large but are not included in the model. The spatial boundaries "created" by a planner are not known to a user whose actual behaviour is different from the planner's assumptions.

Aggregation-based models produce significant differences even for the behaviour of homogeneous groups whose features are included in the model. These models may be incorrect because they do not explain individual user behaviour well enough, on one hand, and do not use the available data about households that have been collected by surveys, on the other.

A nonaggregate approach to modelling is based on the parameters of individual behaviour - of either a household or an inhabitant. Such an approach permits the real behaviour of household members and their trips to be treated and the studied parameters to be utilized more efficiently. The richer the data considered, the better the model's chances to explain individual differences. Considering individual behaviour and trying to discover actual relationships, one has larger chances of developing a model that is applicable, with certain constraints, to different areas and different populations.

The shortcomings of the disaggregate approach are a considerably longer and more expensive data acquisition and processing procedure, a more complex graphical interpretation, and difficulties in forming the units at the required level. The definition of the model itself is not a problem in the nonaggregate approach, the main problem is the impossibility of estimating future variable parameters at the required level of detail. This applies especially to long-term transportation forecasts.

As far as short-term studies of the effects of some measures are concerned, the disaggregate approach is much more suitable than the aggregate one. It requires a smaller amount of data and the observed existing state provides a sufficiently reliable background for short-term forecasting purposes. Citizens' views and opinions can also be obtained in this way. This is why the disaggregate approach is a valuable tool used by decision makers in performing state evaluations and in analyzing the consequences of their decisions.

4. THE NEKOP MODEL

The formation of the NEKOP model represents our attempt to develop a tool to stimulate user behaviour in the modal split process using neural network properties. NEKOP is the Serbian acronym for neural networks and user behaviour. To generate the NEKOP model, we have employed the Boltzmann learning procedure [15] for neural networks. This procedure belongs to statistical training methods.

The statistical training methods (which we have applied to forming the modal split model) are used in both training a neural network and obtaining the output from a previously trained one. The training is performed by changing the values of weights in a pseudorandom manner and retaining any value that yields an improvement. Network training can be carried out using the following algorithm:

Step 1: A set of input values is given and the resulting output is calculated.

Step 2: The obtained output is compared with desired output values and the measure of their difference is calculated. This is usually done by a method that finds the difference between the real and desired output values for each element of a lerning pair, squares the differences and sums all these squares values. The objective of learning is to minimize this difference.

Step 3: A random weight is chosen and then adjusted for a small randomly chosen quantity. If this change helps, this value is retained; otherwise, the preceding weight value is retained.

Step 4: Steps 1 to 3 are repeated until the network is trained to a desired extent.

Artifical neural networks can be trained in an essentially identical manner by randomly adjusting the values of weights. At the beginning, large adjustments are made and only such changes in weight values are retained as decrease the objective function value. The average step size is then gradually decreased until a global minimum is eventually reached.

As this procedure is very similar to mental annealing, it is often referred to as "simulated annealing".

A learning algorithm [11] consisting of the following four steps has been defined for the NEKOP network:

Step 1: A variable (T), representing artifical temperature, is defined. The initial value (T) is large.

Step 2: A set of input data is given to the network. The output and the objective function value are calculated.

Step 3: The weight value is changed arbitrarily, and the network output is calculated again as well as the change in the objective function due to the changed weight.

Step 4: If the objective function value is decreased (which means improved), the change in the weight value is retained.

If the changed weight value increases the objective function value, the probability of this change being accepted is calculated from the Boltzmann distribution in the following way:

$$P(c) = \exp\left(-c / kT\right)$$

where:

$P(c)$ - the probability of change c in the objective function value
k - a constant analogous to the Boltzmann constant which must be chosen separately for each problem
T - artifical temperature.

A random number (r) uniformly distributed in the interval from zero to one is chosen. If $P(c)$ is larger than (r), the changed value is retained; otherwise, the preceding weight value is retained.
In this way the system is allowed to take an appropriate step in the direction which worsens the objective function, i.e., to skip the local minimum where any small step increases the objective function value.
To complete the Boltzmann learning strategy, steps 3 and 4 are repeated for every weight of the network by gradually decreasing the temperature (T) until an acceptably small objective function value is reached. After that, a different input vector is taken and the whole learning process is repeated. The network is trained for all vectors of the learning set, as many times as required for the objective function to assume an acceptable value for each vector.
The NEKOP model uses the following input data for each user [11]:

- travel time by passenger car
- travel time by public transport
- estimated public transport comfort
- travel mode.

All these data are based on the results of transportation system user behaviour studies.

Why have these parameters been chosen ?

Previous research and analyses, the author's personal experience in studying the parameters affecting travel mode choice decisions, and the results obtained under a pilot research project carried out in Belgrade in May 1991., have indicated that the following three basic parameters should be taken into consideration (the first two of which are subjective, while the third is relatively objective in nature):

- travel time
- travel comfort
- travel cost.

Thus, a user's choice of travel mode is affected by THE USER'S NOTION of time, cost and comfort. A user's subjective estimate of travel cost does not differ essentially from the actual amount of money spent on travel. In contrast to this, a user's travel time estimate deviates considerably from the actual travel time [2].

A user's personal judgement of the comfort offered by some travel mode can be included in the modal split analysis as one among the variables (most often as an additional variable) together with engineering (quantitative) and socio-economic parameters. For this analysis, the user's notion of comfort must be transformed into a clearly defined set of characteristics that are appropriate to analyze user behaviour in modal split modelling.

The modelling output includes the expected travel mode for each user for the appropriate values of travel time (for public and car transport) and comfort index.

A graphical presentation of the two-layer neural network we have used in forming the NEKOP model is given in Fig. 1.

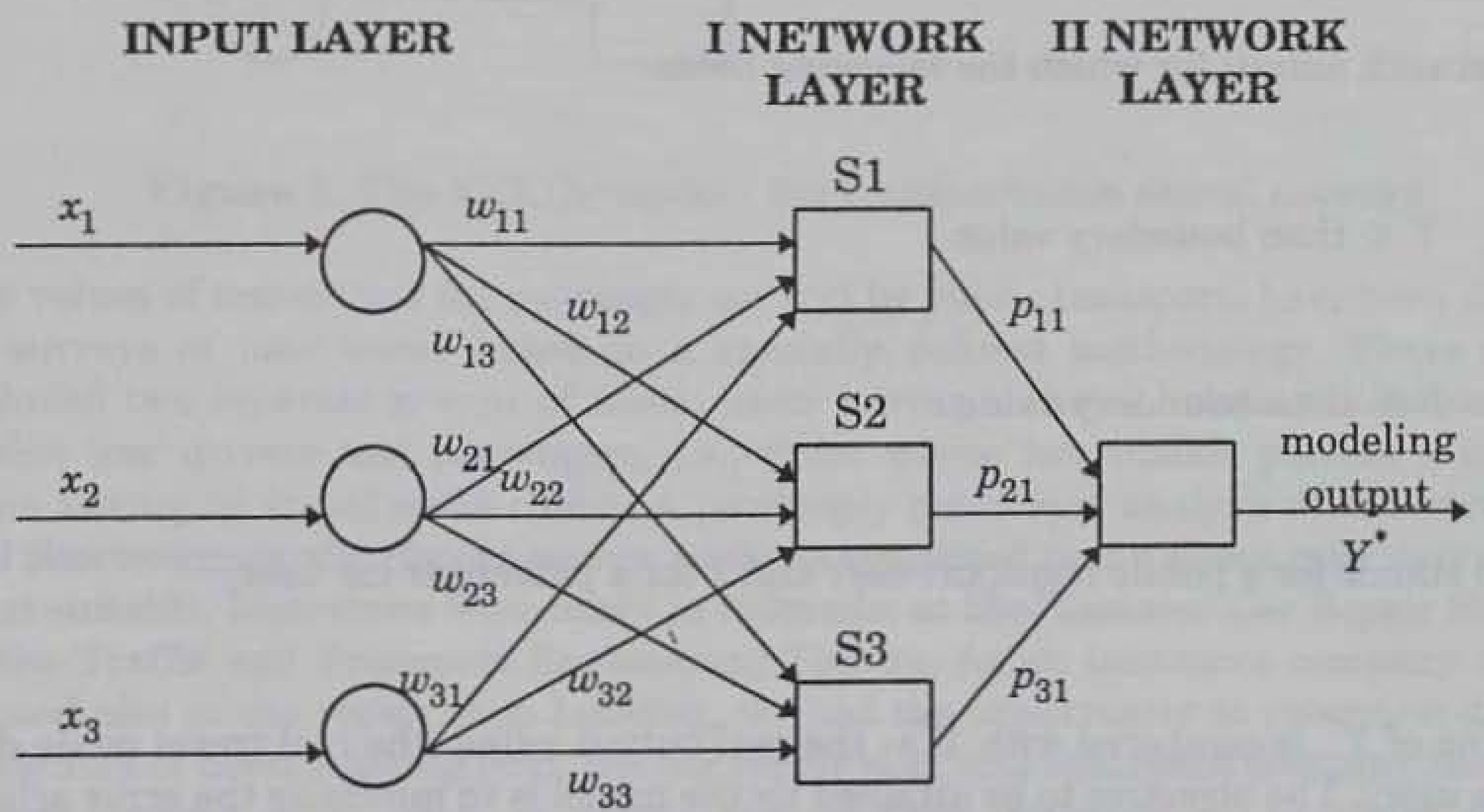

Figure 1: A neural network - theoretical foundation of the NEKOP model

Symbols used in the Fig. 1 have the following meaning:

x_1, x_2, x_3 - input parameters

$\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix}$ - the matrix of first layer weight cofficients

$\begin{bmatrix} p_{11} \\ p_{21} \\ p_{31} \end{bmatrix}$ - the matrix of second layer weight coefficients

$$S_j = \sum_{j=1}^{3} x_i w_{ij} \quad j = 1,2,3$$ - the first network layer

$$Y = \sum_{j=1}^{3} S_j p_{ij} \quad j = 1,2,3$$ - the second network layer

The neural network has been transformed into a transportation neural network - the NEKOP model. The model input data for each transportation system user are: travel time by passenger car (*Tpc*), travel time by public transport (*Tpt*), and a comfort index (*IK*). The NEKOP transportation neural network is illustrated in Fig. 2 where, apart from the input parameters, the following symbols are used:

Y^* – network output for which the following holds:

$$Y^* = \begin{cases} 0, & Y \leq \text{ than boundary value} \\ 1, & Y > \text{ than boundary value} \end{cases}$$

where 0 stands for a public transport user and 1 for a passenger car user.

The value of Y^* is compared with Y^*s - the real output value (the real travel mode data for each user). The objective to be attained by the model is to minimize the error arising with a given set of weights, for a particular set of input data, i.e.

$$F = \sum_{k=1}^{n} \left| Y_k^* - Y_{sk}^* \right| \rightarrow \text{min.}$$

where:

Y_k^* - modelling output result for the k-th user

Y_{sk}^* - real output result for the k-th user

n - the number of users.

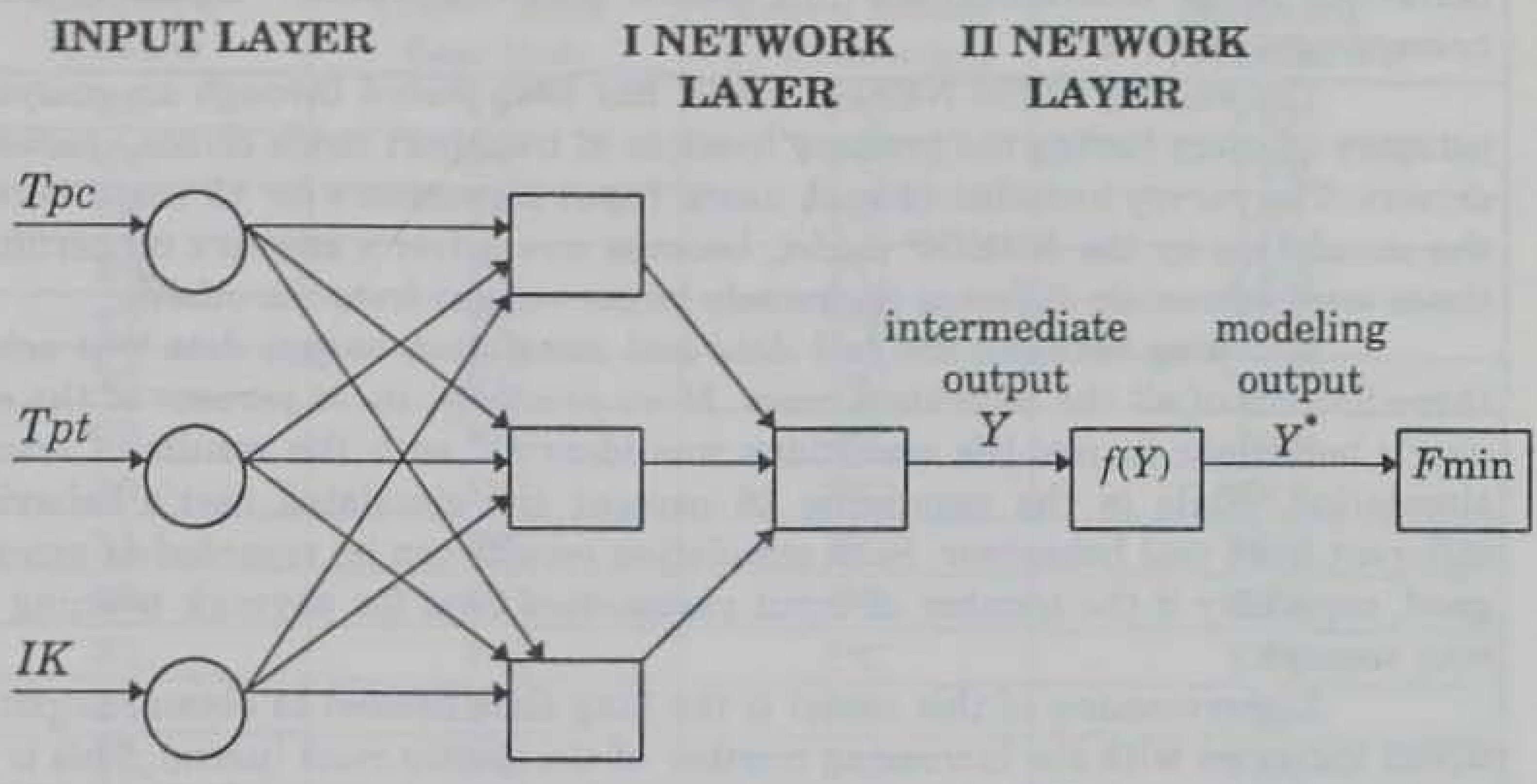

Figure 2: The NEKOP model - the transportation neural network

The values of travel time (by passenger car and by public transport) have been obtained by surveys of user views based on a specially defined methodology. These surveys included two separate groups of users: users having a choice between different travel modes (car drivers and passengers, i.e., those whose households possess a car) and users having no travel mode choice. A previously performed analysis of the advantages and shortcomings of different survey methods suggested that a direct interview was the most suitable. Interviews were made in Belgrade, at the "Zastava" Car Repair Shop and at the Traffic and Transport Engineering Faculty. As an insurance company office is located also in the repair shop building, we had the opportunity to interview different categories of users ranging from the car repair staff and insurance company employees to car owners who come to have their vehicles repaired or to claim damage. Predominantly nonteaching personnel was selected for interviews at the Faculty to eliminate, or reduce, the influence of the professional attitudes of university employees.

5. ANALYSIS OF THE NEKOP MODEL

As has been stated, the NEKOP model is based on neural network training and its learning input parameters are the values of the travel time by passenger car and by public transport and of the estimated public transport comfort. The data for network training, for each interviewed user, have been obtained by traffic surveys. Using these collected data, the model tries to simulate transportation system user behaviour. Simulation output includes the expected travel mode for appropriate travel time and comfort values.

The choice of such an approach to modelling is based on transportation system user behaviour. A user chooses one among the alternative travel modes on the basis of acquired experience and personal judgements concerning the possible alternatives. The basic statements used in forming the model indicate that this model simulates the behaviour of an individual, and this means that the NEKOP model is based on a nonaggregate approach.

The validity of the NEKOP model has been tested through an analysis of the category of users having the greatest freedom of transport mode choice - passenger car drivers. The survey included 44 such users. Input parameters for 43 users were used in the simulation by the NEKOP model, because one driver's answers concerning travel times were extremely different (extremely larger values) from the others.

Matching between the real data and simulation output data was achieved in three-fourths of all the individual cases. More precisely, in 74 percent of the cases the user's behaviour in real-life conditions was identical with the results of travel mode simulation, while in the remaining 26 percent the simulated user's behaviour was different from real behaviour. Such simulation results can be regarded as exceptionally good, especially if the number of input parameters used for network training is taken into account.

A shortcoming of this model is the long time needed to obtain output results, which increases with the increasing number of simulation runs (users). This is why the model is, at present, rather impractical for large sets of users.

The input data for the training of the NEKOP transportation neural network are given in Table 1, and a comparison of simulation results with real data is presented in Table 2.

Table 1: Comparative analysis of NEKOP simulation results and real data

Interview Number	Travel Mode-Real Data	Travel Mode-by Simulation	Matching Yes/No
1.	PT	PT	YES
2.	PT	PT	YES
3.	PT	PC	NO
4.	PT	PT	YES
5.	PC	PC	YES
6.	PC	PC	YES
7.	PC	PC	YES
8.	PT	PT	YES
9.	PT	PC	NO
10.	PC	PC	YES
11.	PC	PC	YES
12.	PC	PC	YES
13.	PC	PC	YES
14.	PC	PC	YES
15.	PT	PT	YES
16.	PT	PC	NO
17.	PT	PC	NO
18.	PT	PC	NO
19.	PT	PC	NO
20.	PC	PC	YES
21.	PC	PC	YES
22.	PC	PC	YES

Interview Number	Travel Mode-Real Data	Travel Mode-by Simulation	Matching Yes/No
23.	PC	PC	YES
24.	PC	PC	YES
25.	PT	PC	NO
26.	PC	PC	YES
27.	PC	PT	NO
28.	PC	PC	YES
29.	PC	PT	NO
30.	PC	PC	YES
31.	PC	PC	YES
32.	PC	PC	YES
33.	PC	PC	YES
34.	PC	PC	YES
35.	PC	PC	YES
36.	PC	PC	YES
37.	PT	PT	YES
38.	PT	PT	YES
39.	PC	PC	YES
40.	PT	PC	NO
41.	PT	PC	NO
42.	PC	PC	YES
43.	PC	PA	YES

Table 2: Input Data for Training the NEKOP Neural Network

Interview Number	Real Travel Time by Passenger car (min)	Real Travel Time by Public Transport (min)	Comfort (*IK* or *CI* - comfort index)	Real Travel Mode
1.	10	20	0.4	0
2.	5	10	0.4	0
3.	15	40	0.4	0
4.	20	30	0.6	0
5.	10	30	0.5	1
6.	10	50	0.3	1
7.	20	55	0.2	1
8.	10	10	0.1	0
9.	10	40	0.1	0
10.	20	70	0.4	1
11.	60	90	0.3	1
12.	15	30	0.5	1
13.	25	45	0.1	1
14.	15	30	0.3	1
15.	15	25	0.4	0

Interview Number	Real Travel Time by Passenger car (min)	Real Travel Time by Public Transport (min)	Comfort (*IK* or *CI* - comfort index)	Real Travel Mode
16.	15	3	0.4	0
17.	15	30	0.1	0
18.	30	60	0.1	0
19.	20	40	0.1	0
20.	25	35	0.1	1
21.	30	50	0.2	1
22.	30	45	0.4	1
23.	25	45	0.3	1
24.	15	30	0.2	1
25.	30	50	0.1	0
26.	30	60	0.2	1
27.	20	30	0.3	1
28.	25	45	0.7	1
29.	10	10	0.4	1
30.	15	35	0.2	1
31.	15	45	0.4	1
32.	25	45	0.2	1
33.	25	45	0.1	1
34.	10	25	0.1	1
35.	10	30	0.1	1
36.	15	30	0.2	1
37.	15	30	0.6	0
38.	15	15	0.5	0
39.	2	45	0.4	1
40.	15	30	0.3	0
41.	15	30	0.1	0
42.	10	25	0.1	1
43.	10	25	0.1	1

6. APPLICABILITY AND CONSTRAINTS OF THE NEKOP MODEL

Bearing in mind the employed methodology, the results obtained by this model have, for the time being, a limited application for the following reasons:

1. The applied procedure is based on the results of surveys which are used to calibrate the NEKOP model. Thus, for practical applications, surveys with a representative sample should be made. This has not been done in the work reported in this paper. As a standard planning procedure includes household surveys with a representative sample, on such an occasion the method proposed here can be used to collect the input data

needed for calibrating the NEKOP model. The results obtained in this way can be incorporated into standard planning procedures and spatial trip matrices by travel modes.

2. The results presented and quantified here are not directly usable because they are only representative of the population treated for purposes of this paper.

3. The NEKOP model can be universally applied, but, needless to say perhaps, reasonable and competent usage is expected. If needed, the author's advice can be obtained.

It wll be useful to continue performing studies in other areas and with representative spatial samples in order to widen the limits of application of the proposed procedure. It would be particularly beneficial to find out whether individual users have the same views and judgements at travel source and destination points. Surveys carried out under the BETRAS study have indicated that one person can have different views and judgements of travel time and comfort requirements at different source points.

Although travel cost has been studied in detail in many papers (and is not discussed in this paper), further research should be extended to include the so-called "generalized cost" by applying neural network theory. This has not been done so far, although there are some indications that the use of neural networks could facilitate and clarify a user's decision making procedure.

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