Genetic algorithms application to EVA mode choice model parameters estimation

Irena Strnad, Marijan Žura

***Abstract*—**This paper presents parameters estimation of EVA (EVA – German abbreviation for Erzeugung, Verteilung and Aufteilung meaning Production, Distribution, and Mode Choice) mode choice model of city of Ljubljana, Slovenia by using genetic algorithms software. First we present design of stated preference survey, then we briefly review EVA mode choice model, present different types of utility functions, Maximum likelihood method as the estimation method and application of genetic algorithms software. Probabilities of choosing each of four considered modes (private car, public transport, bike, walking) can be calculated by using estimated mode choice model parameters. A practical example of mode choice probabilities for an actual trip is shown at the end. Final log-likelihood enables comparison among different types of utility functions. Results show that absolute differences in final log-likelihood among most types of utility functions are not high in spite of differences in function shapes, which implies that different functions may best describe different variables. Log-likelihood function for most utility function types by using standard optimization tool only convergated to local maximum, what clearly states the need to use genetic algorithms software to find the best solution.

***Keywords*—** Genetic algorithms, Maximum likelihood method, Mode choice model, Stated preference survey, Utility function.

I. Introduction

TRADITIONAL four-step transportation forecasting model consists of trip generation, trip distribution, mode choice and network assignment. An up-to-date disaggregated four-step traffic model for passenger transport of Ljubljana region had already been developed. However, the existent traffic model contains only utility functions of travel time and not of all mode choice affecting trip factors, what indicates the need to upgrade the model. Four modes are included in the traffic model, namely private car, public transport, bike and walking.

First step was to perform a stated preference survey in order to obtain the necessary data. Many directions for designing a stated preference survey are described in [1] and [2].

Stated preference survey was performed with portable computers on several locations all over Ljubljana. Several locations were needed to ensure a representative sample and the required sample size for all investigated trip purposes (work, education, shopping, leisure and other).

In stated preference survey 75 to 100 questionnaires per segment are needed, so the sample size has to be about 1000 survey respondents as utility functions are to be estimated for ten origin-destination purposes. However, as mode choice does not usually change for trips back from the destination, five trip purposes were used. Thus, the sample size of 500 survey respondents would be sufficient. In order to ensure stable Maximum likelihood estimation solution, 1276 surveys were made, to achieve sample size 150 per segment [3]. Number of surveys made for each purpose is shown on Fig. 1. References [4] and [5] were taken into consideration when defining relevant trip purposes.

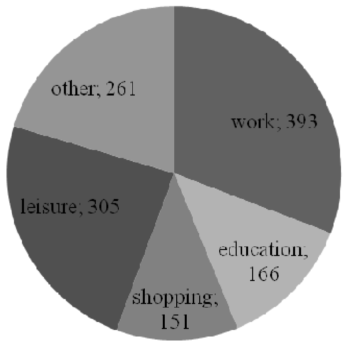

Fig. 1 Number of surveys made for each purpose

The survey includes questions about the usage of different modes in different situations. The questionary consists of ten hypothetical situations in which values of trip factors change. In each situation each traveler was asked to choose the most suitable mode for him if the situation actually occurred.

The second step was to estimate nine types of utility functions for each generalized cost parameter. These were estimated with Maximum likelihood method, by using genetic algorithms software.

The last step was to calculate probabilities of choosing each mode for an example trip by using estimated EVA 2 utility functions.

II. Stated Preference Survey

Stated preference data are convenient for estimating mode choice model parameters, since an alternative as a whole is described as a constituent of different factors as the analysis of stated preference survey data derives the relative importance

Manuscript received December 30, 2010.

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of different factors. Since SP derives relative importance of factors, their nature can be also described with the term generalized cost parameters.

In stated preference survey travelers were first asked about some factors of current trip, e.g. duration, costs, and about available alternatives. If there were other alternatives available, travelers were asked about similar information for them as well. Each interviewee was then asked to choose the most suitable mode in ten hypothetical situations with different values of trip factors. The questionary design, and the generation of the situations will be briefly explained bellow.

A. Questionary Design

In stated preference survey, four modes were taken into account, namely private car, public transport, bike and walking.

The following factors were included for trips made by private car: travel time in minutes, walking time from parking to destination in minutes, parking price in euro. Factors for public transport were: travel time in minutes, comfort, price of public transport in euro, frequency in minutes between two succession arrivals and walking time from origin to start station and from final station to destination in minutes. For trips made by bike and on foot, travelers were only asked about travel time.

TABLE I
FACTORS WITH THEIR LEVELS

Mode	Factor	Levels
Car	Parking price	actual
		+50%
		−50%
	Travel time	actual
		+20%
		−20%
	Walking	actual
		+20%
		−20%
Public transport	Public transport price	actual
		−25%
		−50%
	Walking	actual
		−20%
		−40%
	Frequency	actual
		−20%
		−40%
	Travel time	actual
		−25%
		−50%
	Comfort	actual
		better

Fractional factorial design was used to design hypothetical situations needed. Fractional factorial designs are experimental designs consisting of a carefully chosen fraction of the experimental runs of a full factorial design. Fractional designs are expressed with the notation l^{k-p}, where l is the number of levels of each factor investigated, k is the number of factors investigated, and p is the number of generators, i.e. assignments as to which effects or interactions are confounded (cannot be estimated independently of each other).

The study contains seven factors on three levels and one factor on two levels, as shown in Table I.

From Table I we can see that factors for car change up and down, whereas factors for public transport only changes for the better. The reason is a transport policy goal to enlarge the share of public transport users in comparison to private car users. That means that only changes for the better in public transport are needed. Some helpful tips for choosing relevant trip factors and their levels were adopted from [6] and [7].

Table I shows that parking price variability was in percentage. Since some free parking lots in Ljubljana are available, the price would not change in situations, which would mean less realistic results of the parking price affecting the mode choice. In case of free parking, a new parking price was set to generate situations. For purposes work and education that price was 5€ and for other purposes it was 2€. The prices were chosen on basis of parking duration for different purposes and an average price of parking in Ljubljana. Prices, set like described, than change in hypothetical situations.

According to number of factors and their levels a Mixed – Level $L_{18} – 2×3^{7-5}$ Fractional Factorial Design as in [8], should be built and is presented in Table II. Generation of eighteen hypothetical situations would therefore be needed. In each of those eighteen situations factors would be on a different level and the traveler would have to choose the most appropriate mode.

TABLE II
L18 — 2 X 37-5 FRACTIONAL FACTORIAL (MIXED-LEVEL) DESIGN

Run	X1	X2	X3	X4	X5	X6	X7	X8
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

Generating eighteen hypothetical situations would mean a huge practical barrier, since it would mean a long questionary which causes problems in travelers' concentration and possible choices different to choices made, if the situation actually occurred. We decided to split eighteen designed situations between two interviewed persons, each answering nine situations. Our choice included one control situation, in which factors are the same as given for the actual trip. This situation was a control, if the traveler choice process was in compliance with his actual mode choice.

We conducted the Stated Preference survey with portable computers in different locations around Ljubljana. Different locations were needed to ensure a representative sample and the required sample size for investigation purposes. The survey forms were made in Microsoft Access program.

Survey was performed in two steps. First step was entering requested data of current trip e.g. travel time, costs etc. and listing available alternatives. If there were other alternatives available, entering similar information for alternatives was needed too. On this basis, generation of ten hypothetical situations was made and choosing of most appropriate mode among available in each situation was requested as second step. An example of choice process in one situation is shown on Fig. 2. Modes offered to choose in hypothetical situations are the same as those available for the traveler. If the person surveyed does not mark one alternative as available, choosing the same will not be possible and parameters of this alternative do not appear to prevent choosing alternatives without given factor values.

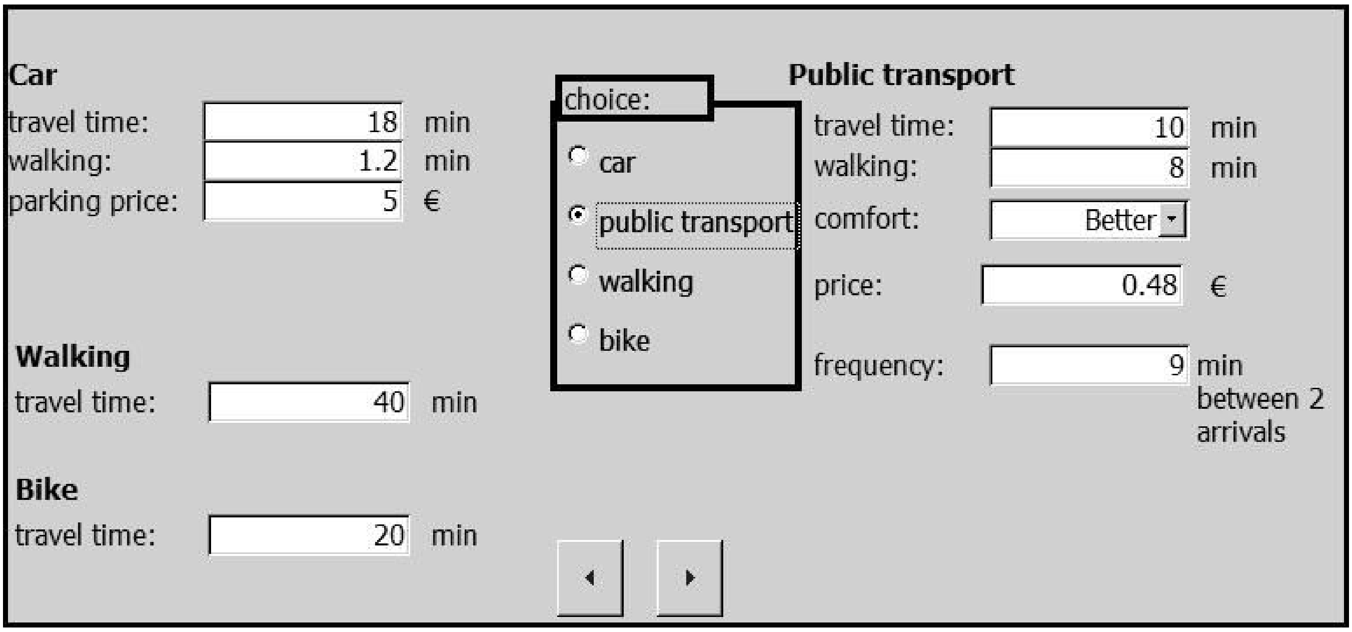

Fig. 2 Example of a hypothetical situation

III. EVA TRIP DISTRIBUTION AND MODE CHOICE MODEL

In this chapter we briefly review EVA trip distribution and mode choice model, described in [9], present types of utility functions tested, model for calculating mode choice probability and parameter estimation method described in [10].

EVA model generalizes simultaneous trip distribution and mode choice to trilinear model described by (1).

$$T_{ijk} = W_{ijk} \cdot o_i \cdot d_j \cdot m_k \, (i = 1,...n;\, j = 1,..., n;\, k = 1,..., p). \quad (1)$$

In (1) notation T_{ijk} presents trips from zone i to zone j by mode k, o_i, d_j, and m_k are the balancing factors used to keep marginal sums of productions, attractions, and mode trips, and W_{ijk} are weighted utilities of making trip from zone i to zone j by mode k. Weighted utilities are calculated as a product of accessibility of mode k in zone i and product of all utilities of making trip from zone i to zone j by mode k considering each generalized cost parameter for mode k (e.g. time, parking cost, fare,…).

To keep marginal sums of productions and attractions balancing factors o_i, d_j, and m_k must be determined so, that the following constraints are satisfied:

$$\sum_{j=1}^{n} \sum_{k=1}^{p} W_{ijk} \cdot o_i \cdot d_j \cdot m_k = \sum_{j=1}^{n} \sum_{k=1}^{p} T_{ijk} = P_i \, , \quad (2)$$

$$\sum_{i=1}^{n} \sum_{k=1}^{p} W_{ijk} \cdot o_i \cdot d_j \cdot m_k = \sum_{i=1}^{n} \sum_{k=1}^{p} T_{ijk} = A_j \, , \quad (3)$$

$$\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ijk} \cdot o_i \cdot d_j \cdot m_k = \sum_{i=1}^{n} \sum_{j=1}^{n} T_{ijk} = M_k \, . \quad (4)$$

A. Utility functions

The main task of the study was to evaluate different utility function types on data from the stated preference survey, in order to decide which type of utility function should be used in EVA mode choice model. Parameters of nine different types of utility functions must therefore be estimated.

In (5) – (13) x is a generalized cost parameter, $f(x)$ is utility function, describing one generalized cost parameter, and a, b, and c are parameters of the utility function. The following nine types of utility functions have been studied:

EVA 1

$$f(x) = (1+x)^{-\varphi(x)}, \text{ where } \varphi(x) = \frac{a}{1+e^{b-cx}}, \tag{5}$$

EVA 2

$$f(x) = \left[1+\left(\frac{x}{c}\right)^{b}\right]^{-a}, \tag{6}$$

Schiller

$$f(x) = \frac{1}{1+\left(\frac{x}{b}\right)^{a}}, \tag{7}$$

Logit

$$f(x) = e^{cx}, \tag{8}$$

Kirchhoff

$$f(x) = x^{c}, \tag{9}$$

BoxCox

$$f(x) = e^{\left(c\frac{x^{b}-1}{b}\right)}, \tag{10}$$

Box-Tukey

$$f(x) = e^{\left(cx^{\alpha}\right)}, \text{ where } \alpha = \begin{cases} \dfrac{((x+1)^{b}-1)}{b}, b>0, \\ \ln(x+1), b=0, \end{cases} \tag{11}$$

Combined

$$f(x) = ax^{b}e^{cx}, \tag{12}$$

Code

$$f(x) = \frac{1}{x^{b}+cx^{a}}. \tag{13}$$

B. Maximum likelihood method

Probability that trips between zone i and zone j will be made by mode k can be calculated from

$$P_{ijk} = \frac{W_{ijk}}{\sum_{A_l \in A(ij)} W_{ijl}}, \tag{14}$$

where $A(ij)$ is set of available alternatives between zone i and zone j.

Model parameters a, b, and c have been estimated by using Maximum likelihood method, described in [1].

Likelihood function, which shows the model probability that each individual chooses the option they actually selected is

$$L = \prod_{q=1}^{Q} \prod_{A_j \in A(q)} P_{jq}^{g_{jq}}. \tag{15}$$

Expression g_{jq} appears in likelihood function, which is defined by (16). In both expressions Q stands for a set of all situations conducted in experiment, $A(q)$ alternatives available in situation q and A_j the alternative chosen in situation q.

$$g_{jq} = \begin{cases} 1, \text{if } A_j \text{ is chosen in } q, \\ 0, \text{otherwise.} \end{cases} \tag{16}$$

As it is more convenient to use natural logarithm of L, model parameters can be estimated by finding such parameters a, b, and c where l in (17) has maximum.

$$l = lnL = \sum_{q=1}^{Q} \sum_{A_j \in A(q)} g_{jq} lnP_{jq} \tag{17}$$

IV. Application of Genetic Algorithms

A major limitation appears when estimating parameters with standard optimization tools, since the mathematical properties of these utility functions do not guarantee convergence to a global maximum likelihood estimate. The solution obtained by a nonlinear programming optimizer may critically depend on the location of the starting parameters values and convergating to a local maximum likelihood if starting values are not close enough to lead to a global maximum.

Genetic algorithms are very suitable for searching discrete, noisy, multimodal and complex spaces, since their application leads to a solution, that is not necessary the exact global maximum, but is in a neighborhood of the optimal solution.

Genetic algorithms are a special technique of artificial intelligence. They use random search procedures inspired by biological evolution, and cross-breeding trial, and allow only the fittest solutions to survive and propagate to successive generations. When using genetic algorithms to solve an optimization problem, the decision variables (utility functions parameters) are commonly encoded as short substrings of genetic representations. Each substring is composed of a series of genes. These substrings are concatenated to form longer strings representing a solution. The entire population of such strings represents a generation. A new set of strings (children or offspring) is created every generation using parts or pieces of the fittest strings (parents) of the previous generation. [11]-[16].

An example of limitation in searching maximum likelihood by using standard optimization tools is shown with tables III and IV and Fig. 3.

Parameters *a*, *b*, and *c* of EVA 2 utility function for purpose work, using Microsoft Excel optimization tool Solver (Newton method) are shown in Table III, when starting values of all parameters are set to 1. Log-likelihood function convergated to a final log-likelihood –601.412.

TABLE III
EVA 2 UTILITY FUNCTION PARAMETERS FOR PURPOSE WORK – SOLVER

Factor	unit	Parameter a	parameter b	parameter c
Travel time – private car	min	0.925	0.542	0.159
parking price	€	1.896	0.953	0.272
Travel time – public transport	min	1.999	0.801	1.189
Walking time - public transport	min	0.221	1.498	2.081
Public transport ticket price	€	0.331	1.575	1.629
Travel time - bike	min	1.864	1.317	1.524
Travel time - walking	min	1.579	2.048	3.028

Table IV shows estimated values of parameters *a*, *b*, and *c* of EVA 2 utility function for purpose work by using genetic algorithms optimization software Evolver included in Palisade DecisionTools Suite 5.5, which integrates into program Microsoft Office Excel.

TABLE IV
EVA 2 UTILITY FUNCTION PARAMETERS FOR PURPOSE WORK – EVOLVER 5.5

Factor	unit	Parameter a	parameter b	parameter c
Travel time – private car	min	3.409	1.771	52.666
parking price	€	40.253	0.493	203.578
Travel time – public transport	min	51.010	0.563	2637.739
Walking time - public transport	min	3597.371	2.185	1238.828
Public transport ticket price	€	2420.575	1.982	216.720
Travel time - bike	min	1616.083	0.960	12020.827
Travel time - walking	min	3.068	1.712	14.025

A higher maximum log-likelihood value (–595.849) provided by Evolver 5.5 obviously implies better optimization when genetic algorithms are used. Obviously, when using optimization tool Solver, log-likelihood function only convergated to a local maximum likelihood value, despite strict convergation limits. However, the global maximum of log-likelihood was find by using Solver, when starting value of parameter *a* was set to zero, what states that optimization algorithm is obviously critically depended on location of starting values.

Although the relatively small difference in final log-likelihood does not seem important at first sight, a quick look on Fig. 3 shows that the shape of EVA 2 utility function with estimated parameters by using each optimizer is quite different.

Shape of EVA 2 utility function is more believable, when parameters are estimated by using Evolver 5.5. Although the height of utility function may not be such important since the probability of using each mode is calculated by dividing utilities, function values changing slower for lower transport ticket prices when using Evolver 5.5 in contrast to almost-convex shape when using Solver, clearly states that using genetic algorithms leads to better results.

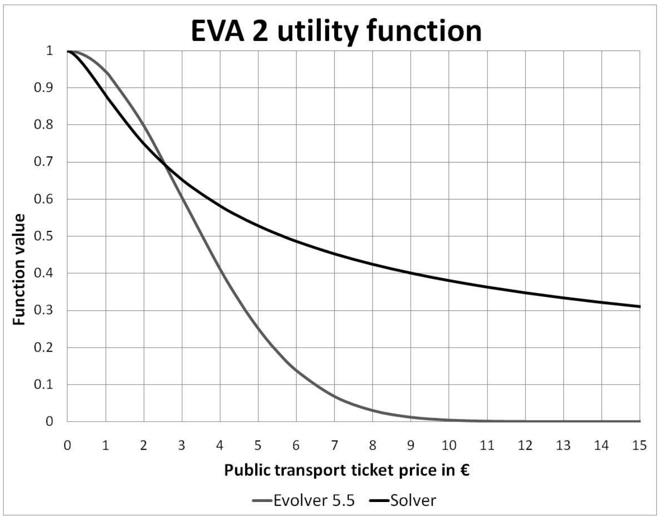

Fig. 3: Probability of choosing each mode

TABLE V
UTILITY FUNCTIONS PARAMETERS AND THEIR FINAL LOG-LIKELIHOOD

Utility function type	parameter *a*	parameter *b*	parameter *c*	Final log-likelihood
EVA 1	1.425	4.733	0.834	-598.126
EVA 2	2420.575	1.982	216.720	-595.849
Schiller	5.987	4.441	/	-679.460
Logit	/	/	-0.306	-601.329
Kirchhoff	/	/	-0.543	-618.590
Boxcox	/	1.728	-0.043	-590.741
Combined	0.720	-0.069	-0.454	-586.905
Code	3.356	0.106	0.010	-626.364
Box - tukey	/	0.512	-0.056	-581.579

When using some other types of utility functions, the estimated parameters were the same when using Solver and

Evolver. A good example are less complex utility functions Logit and Kirchoff, which do not require genetic logarithm optimizer, however, their simplicity results in convex and therefore less flexible function shape.

Table V shows estimated values of parameters *a*, *b*, and *c* for nine different types of utility functions for purpose work for only one generalized cost parameter – public transport ticket price by using Maximum likelihood method. All parameters were estimated by using optimization tool Evolver to avoid local maximums, since most types of utility functions were too complex to ensure finding best solution with a standard optimization tool. Final log-likelihood in Table V was estimated for trip purpose work, with estimated parameters for all generalized cost parameters.

With estimated utility functions parameters values, graphs of nine types of utility functions for each generalized cost parameter can be drawn for each purpose. Graphs of utility functions for generalized cost parameter public transport ticket price for purpose work are shown on Fig. 4.

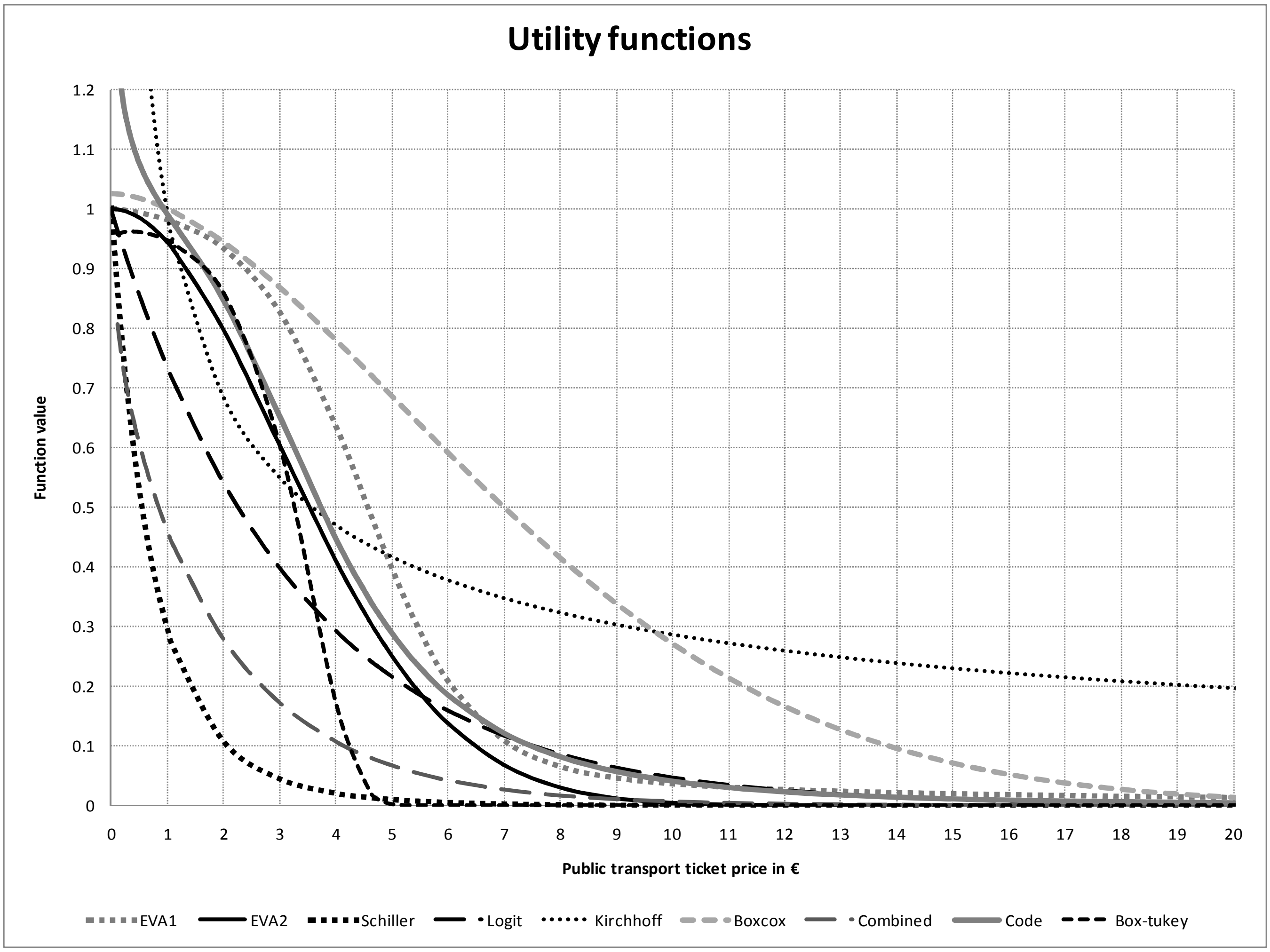

Fig. 4: Utility Functions graphs

One can observe that model which gives us the highest final log-likelihood is model with Box-tukey utility function, followed by Combined and others. Although final log-likelihood does not differ much among most utility functions, graph shows different shapes among them. Whereas some of utility functions are monotonously falling and are convex (Schiller, Logit, Combined, Kirchhoff), others show more believable results.

Shape of Kirchoff utility function is unbelievable at first sight, since its values are high (not close to zero) even when higher public transport ticket prices are high. But since the probability of using each mode is quotient between weighted utility of that mode and the sum of weighted utilities of all available modes, the height of function graphs is not important.

Lower values of final log-likelihood for three out of four convex functions (Schiller, Logit, Kirchhoff) are not surprising, but Combined utility function with high final log-likelihood is surprisingly convex, which may propose that Combined utility function is not the best fit for this particular generalized cost parameter.

Final log-likelihood is the lowest, when Schiller utility function is used. Graph shows that Schiller utility function is the lowest of them and using of this utility function for our mode choice model is less appropriate. Log-likelihood among other functions does not differ much, except Code and Kirchhoff utility functions give lower values. Whereas Kirchhoff utility function has the highest values when ticket price is very low or very high, the shape of Code utility function when ticket price is low is not as expected and is therefore questionable.

We decided to use EVA 2 utility functions in final mode choice model, even though final log-likelihood for some utility functions is higher for the particular trip purpose. The reason for choosing this type of utility function is that no outstanding results for different generalized cost parameters and different purposes (which give us different values of final log-likelihood) were found, preventing poorly described generalized cost parameters.

In general, different types of utility functions for different generalized cost parameters would fit best, differently from purpose to purpose. Due to the Fundamental Counting Principle, number of possibilities when choosing one of nine different utility functions independently for each ten generalized cost parameters for each purpose is

$$N_{possibilities} = 9^{10} = 3486784401. \quad (19)$$

The total number of 3,486,784,401 possibilities for each purpose would be impossible to explore. Trying to evaluate different combinations of utility functions for generalized cost parameters would be unreasonable, since final log-likelihood is estimated for all generalized cost parameters together and does not show which parameter is described well with the chosen type of utility function, and which is described rather poorly.

Table VI shows factors of an example trip (an actual trip from data of the survey), whereas table VII shows probabilities of choosing each mode calculated for trip with factors in table VI.

To be able to compare probabilities of choosing each of four modes, the selected trip was such that all four modes were available. If one alternative was not available, mode choice model would split the total probability – 1 among other three available alternatives.

TABLE VI
EXAMPLE TRIP FACTORS

Factor	unit	Factor value
Travel time – private car	min	15
Parking price	€	1.6
Travel time – public transport	min	30
Walking time needed- public transport	min	2
Public transport ticket price	€	0.8
Travel time - bike	min	25
Travel time- walking	min	45

TABLE VII
PROBABILITIES OF CHOOSING EACH MODE FOR EXAMPLE TRIP

Mode	Probability
Private car	0.3788
Public transport	0.3434
Bike	0.2505
Walking	0.0273

We can see that for a trip with factors in table VI travelers would find private car most preferable mode for the trip, since the probability of choosing it is the highest. Public transport is second most preferable, followed by bike, whereas travelers would find walking least attractive, since probability of choosing it is far lower than for all other modes. However, probabilities of choosing private car and public transport do not differ much.

Since probabilities of choosing each mode for trips between zones i and j can be understood as shares of mode trips, the mode choice model calculates mode shares for trips between two zones, with given factors of trips between the two zones. EVA model calculates trip distribution and mode choice simultaneously, providing number of trips between each two zones with each mode. Effects of changes in factor values (e.g. building new roads and/or new bus lanes, faster buses, higher/lower ticket and/or parking price, etc.) on the traffic network in the studied area can be therefore be evaluated with the traffic model.

On Fig. 5 graphs of probabilities of choosing each mode are shown for an example trip with factors in Table VI, where public transport ticket price changes. On Fig. 5 all the factors in table VI remain constant, but the public transport ticket price changes, to show how the price affects the probability of choosing each mode.

Fig. 5 shows that the most preferable mode for the example trip is private car, as the probability of choosing it is the highest for all public transport ticket prices. Relative difference in probability of choosing private car in comparison to public transport is higher when public transport ticket price is higher.

For low ticket prices usage of public transport is preferable to bike and walking, whereas for higher public ticket prices usage of bike and even walking is preferable.

Probability of choosing public transport is the highest when public transport ticket price is zero, and it is falling with increasing public ticket price, whereas probability of choosing other modes increases when increasing public transport ticket price, which is the expected result.

Choosing utility function type that does not necessarily result in convex shape reflects in the shape of changing probabilities; probability of choosing public transport is falling slowly for low public transport ticket prices, faster for higher ticket prices, and slowly falling to zero for high public transport ticket prices.

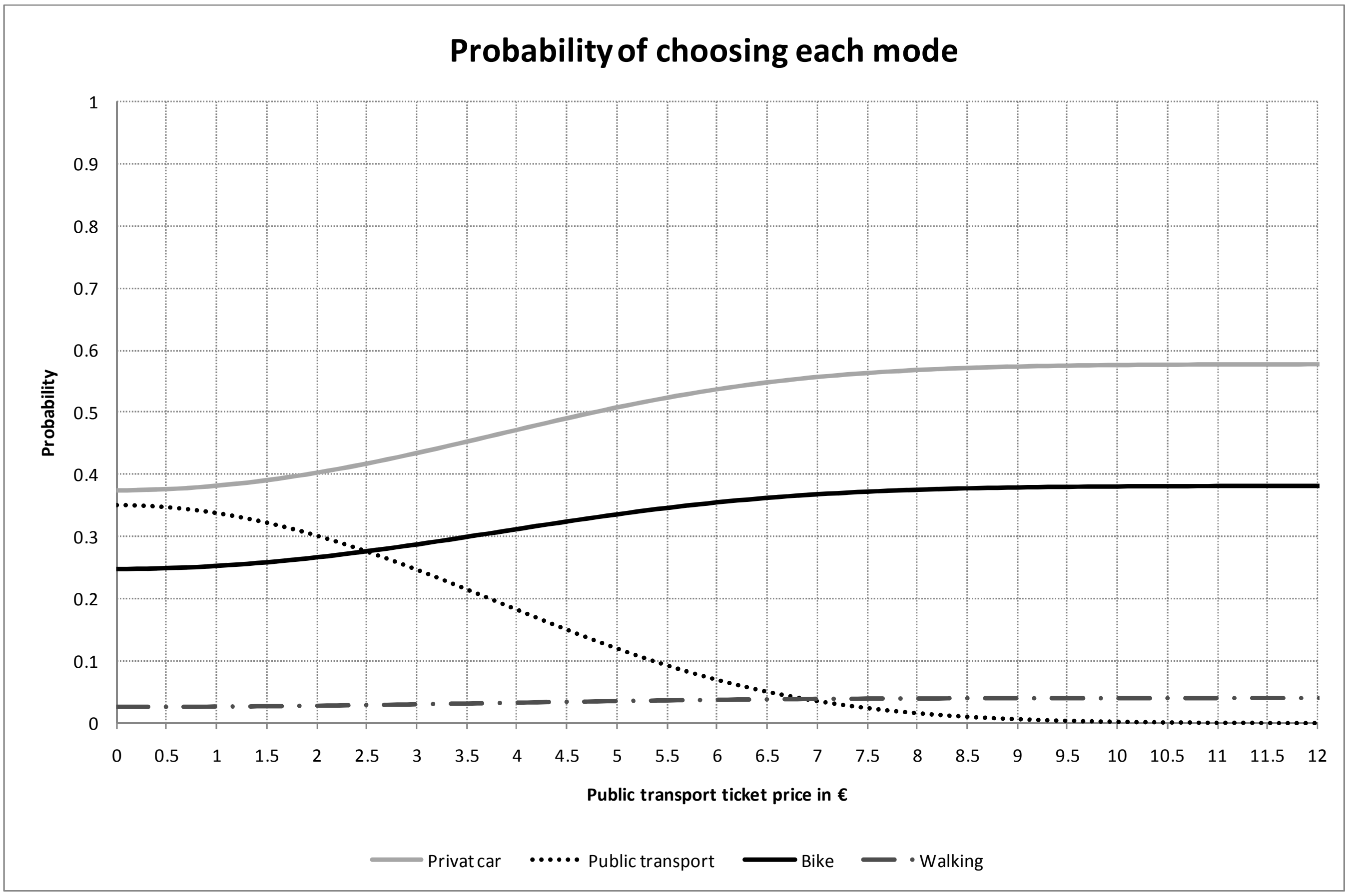

Fig. 5: Probability of choosing each mode

V. Conclusion

In order to estimate utility functions parameters Maximum likelihood method was used, which enables comparison among nine types of utility functions according to final log-likelihood. In order to find global maximum likelihood, genetic algorithms software was used. For the best fit, usage of different types of utility functions for each generalized cost parameter would be needed, which would mean a much too high number of combinations. For final EVA mode choice model EVA 2 utility functions were chosen, even though final log-likelihood for some utility functions for trip purpose work is higher. The reason is that no outstanding results for different generalized cost parameters and different purposes (which give different values of final log-likelihood) were found.

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