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Michal CINGEL^{1*}, Marek DRLICIAK², Jan CELKO³, Katarína ZABOVSKA⁴

MODAL SPLIT ANALYSIS BY BEST-WORST METHOD AND MULTINOMIAL LOGIT MODEL

Summary. The behavioral features of the population are addressed in transport models by different levels of territorial disaggregation and the creation of demand strata in a territory. The need for input data grows exponentially with the demand for a detailed zonal system of the territory. The basic source is the mobility survey. This article deals with the comparison of the calculation of the probability of choosing a transport mode for trips using the classic multinomial logit model and the best-worst method. We used data from a mobility survey in the Žilina region as a basic sample. The analysis covered 11 districts and their gravity areas. The individual transport relations are evaluated in detail in the analysis. The results confirm the high degree of accuracy of the best-worst method in the calculation of mode choice on a regional scale. Despite the promising results of the agreement in the confrontation with the mobility survey, it is necessary to verify the modeled data with a more detailed area with disaggregation on-demand strata.

1. INTRODUCTION

Transport infrastructure is an integral part of any territory that ensures the satisfaction of transport needs and the movement of people, goods, and space for means of transport. Traffic requirements are often underestimated in land planning documentation. This creates disproportions between the planning of land use and the overall provision of transport services. Transport problems are linked not only to passenger transport but also to freight transport. Increasing demand significantly affects the travel time of private transport [1], while the effect itself increases the quality and safety of driving [2].

The present article is focused on the processing of modal split analysis in the third largest region of Slovakia, which has a population of 700,000. As part of the analysis, we processed a comparison of the modal split for trips between districts. Data from the mobility survey in 2017 were used as a source. In a previous article [3], the positive indicators of the direct approach method were confirmed. The results from the extensive mobility survey were compared with the values of the modeled modal split using the best-worst method (BWM) and the classic multinomial logit (MNL) model.

The BWM was introduced by Jafar Rezaei. The method is designed for multicriteria decision solving (MCDM) [4]. Multicriteria methods are able to evaluate the best of the selected alternatives. The goal is to compile their overall ranking [5], [6]. The result is the order of individual alternatives [7]. Overall, MCDM is designed to reduce the incidence and impact of bias on the part of decision-makers, relying on their inner feelings as well as group decision failures (e.g., group thinking), which almost inevitably

¹ University of Žilina; University Science Park; Univerzitná 8215/1, 010 26 Žilina, Slovakia; e-mail: michal.cingel@uniza.sk; orcid.org/0000-0002-4942-4192

² University of Žilina, Faculty of Civil and Environmental Engineering; Univerzitná 8215/1, 010 26 Žilina, Slovakia; e-mail: marek.drliciak@uniza.sk; orcid.org/0000-0003-2095-9334

³ University of Žilina, Faculty of Civil and Environmental Engineering; Univerzitná 8215/1, 010 26 Žilina, Slovakia; e-mail: jan.celko@uniza.sk; orcid.org/0000-0002-6919-5251

⁴ University of Žilina, University Science Park; Univerzitná 8215/1, 010 26 Žilina, Slovakia; e-mail: katarina.zabovska@uniza.sk; orcid.org/0000-0003-3866-0613

* Corresponding author. E-mail: michal.cingel@uniza.sk

affects intuitive approaches. By explicitly structuring the weights and associated trade-offs between the criteria, MCDM leads to more transparent and consistent decision-making [7]. In general, MCDM appears as a matrix:

$$A = \begin{matrix} & c_1 & \dots & c_n \\ a_1 & p_{11} & \dots & p_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ a_m & p_{m1} & \dots & p_{mn} \end{matrix} , \quad (1)$$

where:

a_1, a_2, \dots, a_m – a set of feasible alternatives (actions, incentives),

c_1, c_2, \dots, c_n – a set of criteria,

p_{ij} – a score of alternatives, i , with respect to the criterion j [4].

The goal is to select the best (e.g., the most desirable, most important) alternative—in other words, the alternative with the best overall value. The overall value of alternative i , V_i , can be obtained using various methods. In a general form, if we assign weight w_j ($w_j \geq 0, \sum w_j = 1$) to criterion j , then V_i can be obtained using a simple additive weighted value function, which is the underlying model for most MCDM methods, as follows [8]:

$$V_i = \sum_{j=1}^n w_j p_{ij} . \quad (2)$$

MCDM analyses are based on paired observations. In the case of BWM, the principle is also based on pairwise observation, but less comparative data is used than in other methods based on the same principle.

MNL regression is an attractive statistical approach for choosing a transport mode. MNL imposes the restrictive assumption that choices are independent across alternatives. MNL does not impose the independence assumption, and advances in computer technology make its estimation increasingly practical [9].

Transportsociological data from an observed territory are a basic component of calculating the probability of transport mode choice. The calculation in the analysis is based on the use of mobility data from an extensive mobility survey.

The following section gradually describes the characteristics of the area and the methods used to determine the modal split.

2. MATERIALS AND METHODS

The Žilina self-governing region (ŽSK) consists of eight regions and is located in the northwestern part of Slovakia. ŽSK is the third largest region in Slovakia. It borders two republics: the Czech Republic to the west and Poland to the north. The rest of the region's boundary borders three Slovak regions: Trenčín, Banská Bystrica, and Prešov. ŽSK includes five sub-areas (Horné Považie, Kysuce, Liptov, Orava, and Turiec) and 11 districts (Bytča, Čadca, Dolný Kubín, Kysucké Nové Mesto, Liptovský Mikuláš, Martin, Námestovo, Ružomberok, Turčianske Teplice, Tvrdošín, and Žilina) (10). The city of Žilina has the largest population of all cities in the region (81,608 as of February 28, 2022) and is a major regional city.

The geographical location of ŽSK within the Slovak Republic (left picture) is shown in Fig. 1. The right picture shows the individual districts located in ŽSK. From a geographical point of view, ŽSK consists of the so-called “transport crossroads,” which represents acceptable transport accessibility both within the Slovak Republic and abroad (Czech Republic, Poland).

2.1. Modal split

The transport models gradually evolved from simple observations, which were adjusted to the outlook by growth coefficients. These coefficients took into account, in a simplified form, the expected growth of the population and job opportunities, while the territory was not yet divided into traffic zones, nor were the purposes of trips differentiated. Gradually, separate models for individual and public

transport were developed, with a distinction being made between the origin (volume) of traffic, the direction of traffic flow, and the load on the network. However, the calculations were still done manually (i.e., without the use of computer technology), which significantly limited the range of districts and networks analyzed [9].

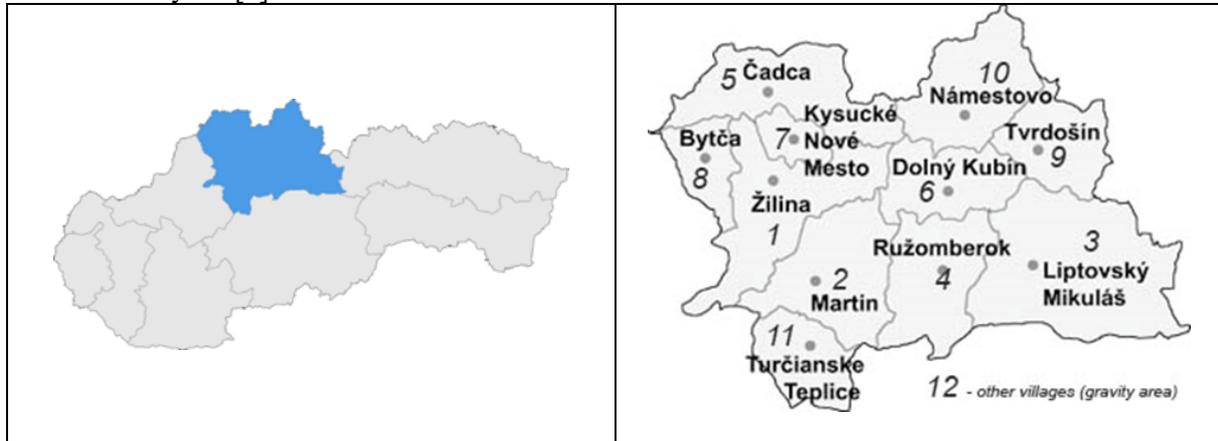


Fig. 1. Solved area (11 districts area, gravity area)

With the gradual development of the theory of traffic modeling, demands on computer technology increased. Although computer technology currently meets the technical requirements for modeling increasingly large areas, it is always necessary to take into account the complexity (especially the mathematical complexity) of the entire transport process [11].

The processing of the transport model consists of four [12] steps:

1. trip generation,
2. trip distribution,
3. modal split,
4. assignment.

The task of a modal split is to divide the transport stream into at least three parts to determine the shares of journeys made by pedestrians, individual means of transport, and public transport [11].

An important criterion in the processing of each transport model is its quality. From this, the term “quality” represents the nature of transport relations. The transport model must be credible. Setting and processing the traffic model requires much input data, which enter into the calculation.

Mode selection is characterized by the random selection of independent variables. In practice, random selection theory has a very wide application in various industries. Individual uses vary in their use and type of distribution function. The number of distribution functions is currently estimated to be in the thousands [13].

2.2. Best-worst method (BWM)

The BWM is a new method in the decision-making process. It was developed in 2015 by Dr. J. (Jafar) Razaei [4], [14]. The method is based entirely on pairwise comparisons. Through these pairwise comparisons, we can prove and express the direction and strength of an object and its properties (preferences) to others [4]. As stated in a previous article [4], problems do not occur when showing direction but when learning, as defined by the strength of a given preference over others. The article [4] also provides a basic explanation of the pairwise comparison. It presents pairwise comparisons as comparisons between the heights of fifth trees. The above pairwise comparison led to the conclusion that the pairwise comparison can be divided into two basic categories:

1. Reference comparisons: comparison a_{ij} , is defined as a reference comparison if i is the best element and/or j is the worst element [4].
2. Secondary comparisons: comparison a_{ij} , is defined as a secondary comparison if neither i nor j is the best or the worst element and $a_{ij} \geq 1$ [4].

The analysis of pairwise comparisons concludes that secondary comparisons are difficult to make, inaccurate, and generally redundant [4].

In the following section, the simplification procedure for determining weights based on reference comparisons will be presented. The BWM procedure consists of five steps [4]:

Step: Determine a set of decision criteria.

In this step, criteria are defined (in the matrix: c_1, c_2, \dots, c_n). These criteria represent the basic criteria needed for decision-making. The previous article [4] used an example of buying a car. In this case, the decision criteria can be quality, price, comfort, safety, and style.

The analysis presented in the article includes the individual criteria and the individual transport modes. Individual vehicle types are used daily, either for the transport of persons or goods. Seven transport modes of the vehicle were taken into account for this purpose: namely, bus region, bicycle, public transport, car driver, car passenger, foot and public transport – train.

1. Step: Determine the best (most desirable) and worst (least desirable) criteria.

In this second step, it is necessary to determine the best and worst criteria in general. According to the article [4], the best and worst criteria depend on the decision-maker. In the example, the best criterion is the price, and the worst criterion is style.

We proceeded to determine the worst and best criteria according to the number of trips made by each type of vehicle. For this reason, the transport relations between the individual transport zones in the Žilina region were separated. We achieved a total of 22 transport relationships, from which the best and worst criteria (transport modes) were subsequently determined.

2. Step: Determine the preference for the best criterion over all other criteria.

Criteria are ranked by employing numerical indicators 1 to 9, with 1 assigned to the best criterion and 9 assigned to the worst criterion. The resulting vector, called “best-to-others,” is:

$$A_b = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad , \quad (3)$$

where a_{Bj} indicates the preference for the best criterion B over criterion j . It is clear that $a_{BB} = 1$.

In the example according to [4], vector (3) shows the price preference and all other criteria. In this step, for our analysis, numerical indicators were identified as showing a preference for the best criteria over all others. Displaying the preference for the best criterion over all others has been determined for each shipping relationship separately.

3. Step: Determine the preference for all the criteria over the worst criterion.

This step is called “others to the worst” in the BWM. The assignment of values 1 through 9 is similar to step 3. The resulting vector from the others to the worst will be [4]:

$$A_w = (a_{1W}, a_{2W}, \dots, a_{nW})^T \quad , \quad (4)$$

where a_{jW} indicates the preference for criterion j over the worst criterion W . It is clear that $a_{WW} = 1$. In the example according to [4], vector (4) shows a preference for all other criteria over the worst criterion (style). As mentioned above, the numerical representation of the preference for all other criteria over the worst criterion was determined in our analysis. The numerical representation of the preference was determined for each shipping relationship separately.

4. Step: Find the optimal weights ($w_1^*, w_2^*, \dots, w_n^*$)

The optimal weight for a criterion is that for which each pair of w_B/w_j and w_j/w_W yields $w_B/w_j = a_{Bj}$ and $w_j/w_W = a_{jW}$. To satisfy these conditions for all j , we should find a solution where the maximum absolute differences $\left| \frac{w_B}{w_j} - a_{Bj} \right|$ and $\left| \frac{w_j}{w_W} - a_{jW} \right|$ are minimized for all j [4].

All obtained parameters must be validated for all calculations. In this case, the calculation itself, BWM, is realized through the consistency index, ξ , in the article [4]. The consistency index theory implies that the closer ξ is to zero, the more consistent the model is. In our case, this means that the given parameters represent the real state.

2.3. Multinomial logit (MNL) model

MNL is a discrete selection model used in conventional traffic modeling. Its advantage is that it allows us to choose from several independent quantities (means of transport) [11]. An important step in

the MNL calculation process is the parameterization of the utility function. The parameterization of the efficiency function was processed using the BIOGEME utility software environment. The BIOGEME program was created to calculate model parameters. Maximum likelihood estimation is designed for discrete models [15].

The prerequisite is the existence of an average individual decision-maker. This entity has average preferences regarding all possible attributes. The calculation maximizes the utility of the roads depending on the specific type of transport. The highest utility is the parameter based on which the decision-maker chooses an alternative. The probability model includes dependent parameters and estimated parameters. The estimations of the parameters are processed from the sample. The final value of the selection probability has the highest utility. The essence of the calculation, therefore, is the comparison and determination of the highest utility of all options from the selection [16], [17].

If we denote the chosen alternative with m , then it holds that [18]:

$$U_m = \max (U_j) \quad , \quad (5)$$

where V_i represents the average traveler's utility, and ε_i represents uncertainty. The individual utility function of traveler p is specified as:

$$U_{ip} = V_i + \varepsilon_{ip} \quad , \quad E[\varepsilon_{ip}] = 0 \quad . \quad (6)$$

The utility part V_i is a weighted sum of observable characteristics of the considered alternatives – for example, travel time components X_k [19]:

$$V_i = \sum_k \beta_k X_k \quad , \quad (7)$$

where the parameters β_k are assumed to be constant for all individuals but may vary across alternatives [20].

If we assume that ε_{ip} , $i = 1, 2, \dots$ are identically and independently distributed according to a Gumbel distribution with scale parameter μ , then it can be shown that [20]:

$$Prob[select(i)] = \frac{e^{\mu V_i}}{\sum_j e^{\mu V_j}} \quad , \quad (8)$$

where μ is the variance parameter. This parameter depends on the units in which the characteristics of alternatives are expressed, among other factors. This formula is generally known as the logit formula [19].

The logit choice model calculates the probability of use of the distinct alternatives depending on their differences in utility. The alternative with the highest observed utility will have the highest probability of use.

3. RESULTS

The first part of the previous section was devoted to a general description of the area. The second part described the mathematical calculation procedure using the new BWM. The third part was devoted to the selection of means of transport—specifically, using the MNL model – and its parameterization of the utility function using the BIOGEME software environment.

This section presents the results and their analyses. It is important to note that a total of 65 transport relationships were obtained from the overall mobility survey analysis. From them, a boundary condition was subsequently determined, which filtered out the transport relations with a total number of trips of less than 50. After this step, we obtained 22 transport relations for which the analysis was processed.

Due to the scope and size of the article, three specific transport relationships have been selected and are listed in the following section. The processing is solved as an analysis of the division of transport work between the mobility survey, MNL, and BWM.

The parameterization of the efficiency function was processed using the BIOGEME utility software environment. The definition of the utility function was processed for seven modes of transport (bicycle, regional bus, urban public transport, passenger car - driver, passenger car - passenger, foot, and public transport - train). The utility function for vehicle i has the following form:

$$U_i = ASC_i + \beta_{travel\ time} TT + \beta_{dis} * DIS + \beta_{cost} * COST + \beta_{accessibility} * ACCESSIBILIT \quad . \quad (9)$$

After the other steps in the BIOGEME program were defined, the resulting parameters of the performance function were calculated. The specific figures are given in Tab. 1.

Table 1

Estimated MNL parameters with the statistical report [2]

	Weight factor (β)	t-test	p-value
ASC Bike	-1.214490	-16.299741	0.000000
ASC BUSreg	0.510462	19.845553	0.000000
ASC PuT	-0.252029	-3.464431	0.000531
ASC Car-passanger	1.229627	19.869807	0.000000
ASC Car-driver	0.113790	4.291422	0.000018
ASC foot	-0.264066	-2.628405	0.008579
ASC Train	-0.123294	-2.133956	0.032846
β_{cost}	-0.021539	-1.921058	0.054724
β_{dis}	0.005215	0.836244	0.403018
β_{acces}	0.149797	27.075422	0.000000
$\beta_{travel\ time}$	-0.008710	-6.596001	0.000000
No of parameters:		11	
Sample size:		8201	
Excluded data:		0	
Init log likelihood:		-14,905.04	
Final log likelihood:		-1,1205.1	
Likelihood ratio test (init):		7399.888	
Rho square (init):		0.248	

Statistical data concerning the overall setting of the transport mode choice model are given at the bottom of Tab. 1. The most important statistical indicators that need to be monitored, whether within the individual search parameters or the overall setting of the modal split, are the t-test, p-value, and Rho square (init).

The t-test presents the infiltration statistics used to determine whether there is a significant difference between the averages of the two groups related to certain traits. The t-test focuses on t-statistics, t-distribution values, and degrees of freedom based on a pre-determined level of statistical significance [21]. The p-value determines the level of significance of the individual calculated parameters and their overall impact on the choice of means of transport. A parameter is evaluated as statistically significant at a p-value of less than 0.05, and a parameter is evaluated as statistically highly significant at a p-value of less than 0.01 [22]. From this point of view, we can say that the parameter distance, β_{dis} (0.403018), does not have a significant effect on the mode choice for the given model of division of transport work. Meanwhile, price and travel time have the most significant impact.

Rho square (init) represents the overall setting of the mode choice model. In the BIOGEME program, Rho square is expressed according to McFadden [23]. The numerical expression is in the range of 0-1. If a value is in the range of 0.2-0.4, the given model is set optimally.

The calculation and accuracy of the BWM were verified using the parameter ξ (consistency index). The following table shows the individual transport relationships and the corresponding values of ξ . The consistency index shows the compactness between individual pairwise comparisons. The closer the consistency index value is to zero, the better. In our pairwise comparison, the maximum value is 0.086957 (relationship 1-12). All consistency index values are very close to zero (Tab. 2); thus, they indicate high consistency.

Data from the mobility survey was used at a comparison level between the MNL and BWM models. From the analysis of the mobility survey, the distribution of modal split was obtained for individual transport relations between district cities and other villages.

Table 2

The final consistency index

Transport relationship	ξ	Transport relationship	ξ	Transport relationship	ξ
1-12	0.086957	12-8	0.035418	5-12	0.035418
12-1	0.067925	1-5	0.056118	6-12	0.056118
12-2	0.057052	1-7	0.039088	7-1	0.039088
12-3	0.052670	1-8	0.041155	7-12	0.041155
12-4	0.054054	2-12	0.085359	8-1	0.085359
12-5	0.063158	3-12	0.075314	8-12	0.075314
12-6	0.076954	4-12	0.050676		
12-7	0.083333	5-1	0.062230		

For simplicity, each town and village was assigned a numerical value from 1 to 12. Numbers 1 to 11 were assigned to district towns based on city size (Fig. 1 on the right), and number 12 was assigned to other villages located in the Žilina region. For example, the transport relationship 1-12 represents the transport relationship between Žilina and its gravity area (other villages).

Based on the individual recorded and executed routes, it was possible to perform the parameterization of the efficiency function for the MNL model. Based on the most and least preferred means of transport, we parameterized the calculation with BWM. The aggregated values of the utilization rate of transport modes from mobility survey, MNL, and BWM are shown in Fig. 2.

In the next part, we deal with the evaluation of the most important transport relations. Each city represents one traffic zone. Their gravity area is counted as another zone, which characterizes the source and destination transport of district towns. Only routes generated in the solved area (without long transit routes) were considered in the analysis.

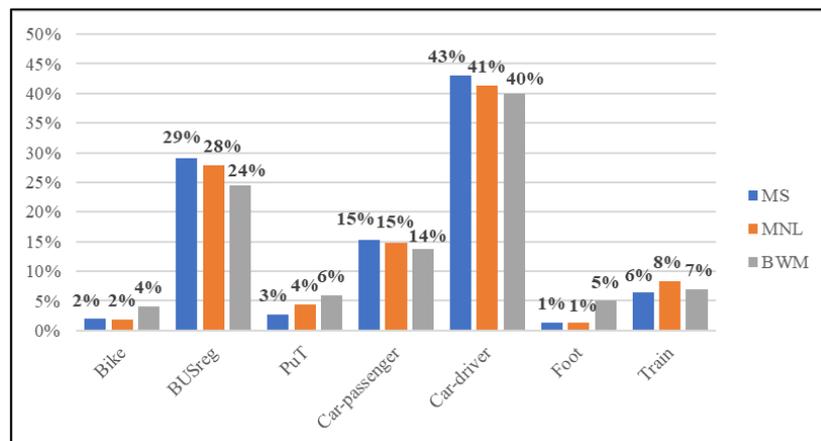


Fig. 2. Comparison of a modal split from mobility survey, MNL, and BWM

As mentioned, the analysis was processed for 22 transport relationships. Fig. 3 shows all transport relationships and their individual representation of the modal split based on the mobility survey. The largest representation is reflected by transport relations between district cities and gravity areas. District towns form the focus of transport in terms of territory and, thus, the needs of the population after relocation, especially for the purpose of travel to work [1-12]. The balance between origin and destination trips signals stable transport relations in the area [11].

The following section presents an analysis of the mode choice from the mobility survey, MNL model, and BWM of the three most important transport relations. The relationship between Žilina (zone 1) and the gravity area is described by 1157 trips. A significant share of these trips is represented by the means of transport of passenger car - driver, which represents 46%, 40%, and 43% of the total number of trips for a given transport relationship. The highest difference was recorded between data from mobility

survey and the MNL model (6%). In the comparison between mobility survey and BWM, the difference was 3%. The smallest share is represented by the pedestrian transport mode. In terms of mobility survey, it has a 1% share. The MNL model determined the same share, while the BWM determined a higher share of 5%. A similar distribution of attractiveness was found for the passenger car - passenger mode, with a 7% decrease in the BWM. The choice of the train was evaluated as more attractive in the MNL model (11%).

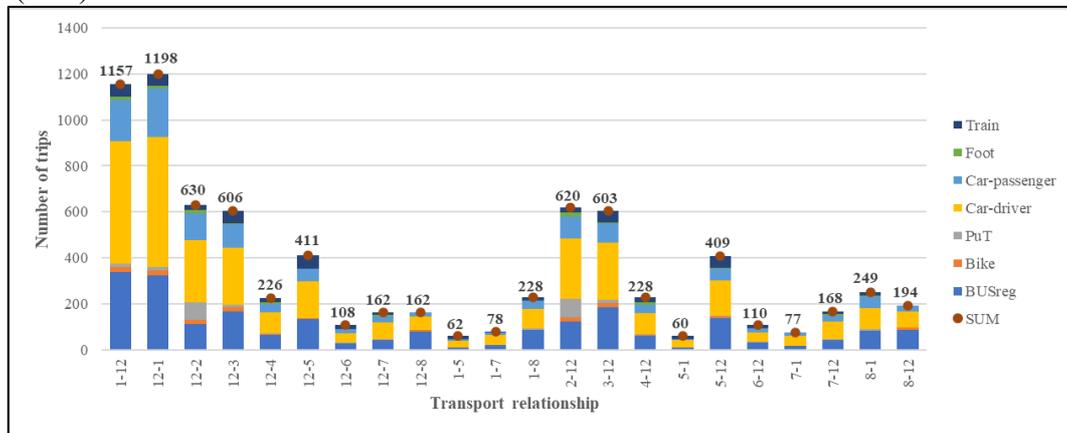


Fig. 3. Individual expression modal split for individual traffic relations

The relationship between the town of Martin (zone 2) and the gravity area is described by 620 trips. The largest percentage is represented by the means of passenger car - driver, which has an almost identical share between mobility survey (42%), the MNL model (43%), and BWM (41%). A significant difference in the modal split was evaluated for the BUSreg transport mode. The MNL model provided a 9% higher use. Counterbalancing this difference is the lower priority of urban public traffic. This difference is justified by the size of the city and the common use of regional and urban buses.

The relationship between the town of Ružomberok (zone 4) and the gravity area is described by 228 trips. The attractiveness of the passenger car - driver mode is the same in mobility survey and calculation methods. The highest difference between the calculation methods and mobility survey was for the bike transport mode, with a deviation of up to 4%. The described results are presented in Fig. 4.

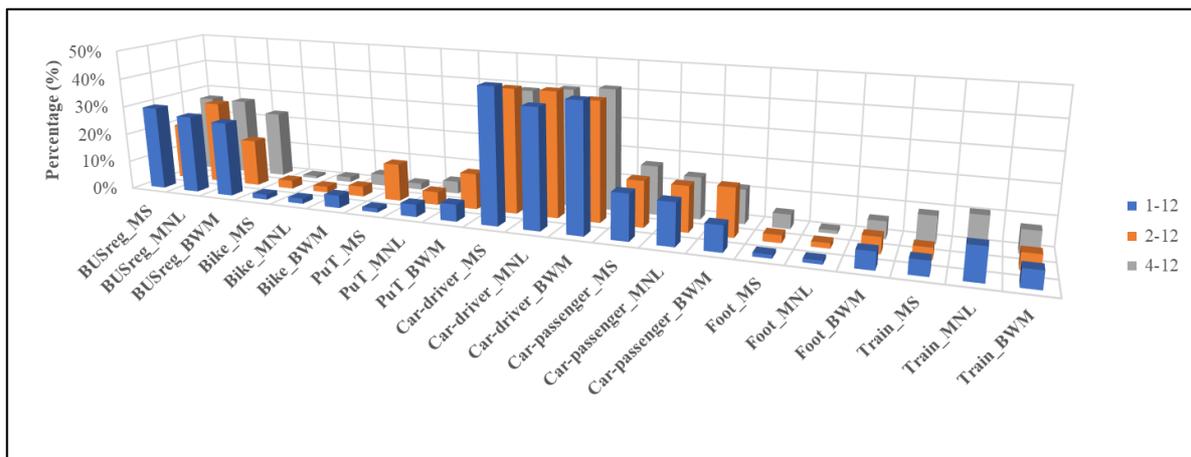


Fig. 4. Modal split for selected relations based on mobility survey, the MNL model, and BWM

4. DISCUSSION

Correctly evaluating the data is essential for territory analysis. This study described the possibility of using the results of the traffic-sociological survey in the process of determining the modal split. The

5. CONCLUSIONS

The choice model is a basic element of creating transport plans. It describes and models the traffic habits of a population depending on local conditions. The degree of detail, time factor, and availability of input data require individual settings. The BWM was applied in the model scenario of district roads. By analyzing the individual transport relations and their modal split, we evaluated the probabilities of the use of transport modes. The relatively successful application of the BWM for a modal split estimation was verified by mobility survey data. Data from the transport-sociological survey were used by employing the BWM. The input consistencies were acceptable. They were calculated for all compared traffic relations. Consistency shows the reliability of the answers. The BWM was validated. It is necessary to compare the effectiveness of the estimation over different periods, area scales, and survey types. The MNL model provides a much larger statistical output than the BWM. Despite the promising results of the agreement in the confrontation with the mobility survey, it is necessary to verify the modeled data with a more detailed area with disaggregation on-demand strata.

Determining the likelihood of mode choice for a particular trip in a given area requires a credible database of mobility survey data. The BWM offers the possibility to reduce the cost of a transport survey, which is fundamentally simpler than a conventional mobility survey. The BWM offers an interesting alternative in the process of modal split, which must include the character of the transport behavior of the population. Despite the relative simplicity of the probability calculation procedure, it is important to point out the necessity of using a proper approach to determine the utility of a particular trip. The use of the MNL model is desirable in detailed traffic analyses with a number of demand strata. Future research will focus on extending the analysis of the modal split calculation depending on the amount and character of the input data.

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References

1. Asmael, N.M. & Wazer, Z.A. Prediction origin-destination matrix of freight travel demand in Baghdad City. *Transport Problems*. 2022. Vol. 17. No. 3. P. 187-196.
2. Bučko, B. & Michálek, M. & Papierníková, K. & Záborská, K. Smart mobility and aspects of vehicle-to-infrastructure: A data viewpoint. *Applied Sciences*. 2021. Vol. 11(22).
3. Nikiforov, O. & Safronov, K. & Mochalin, S. & Koleber, Y. Survey method improvement of urban passenger transport works. *Transport Problems*. 2020. Vol. 15. No. 3. P. 127-138.
4. Rezaei, J. Best-worst multi-criteria decision-making method. *Omega*. 2015. Vol. 53. P. 49-57.
5. Decký, M. *Design of multicriteria decision-making methods and their application in the field of sports and games*. 2019. Available at: <https://opac.crzp.sk/?fn=docviewChild00009ADF>.
6. Krivda, V. & Petru, J. & Macha, D. & Plocova, K. & Fibich, D. An analysis of traffic conflicts as a tool for sustainable road transport. *Sustainability*. 2020. Vol. 12(17).
7. *What is MCDM / MCDA used for?* Available at: <https://www.1000minds.com/decision-making/what-is-mcdm-mcda>.

8. Keeney, R.L. & Raiffa, H. *Decisions with multiple objectives: preference and value tradeoffs*. Cambridge University Press, Cambridge & New York, 1993.
9. Dow, J.K. & Endersby, J.W. Multinomial probit and multinomial logit: a comparison of choice models for voting research. *Elect Stud*. 2004. Vol. 23(1). P. 107-122.
10. VÚC Žilina. Available at: <https://www.zilinskazupa.sk/sk/prave-menu/zilinsky-samospravny-kraj/zakladne-informacie/>
11. Celko, J. & et al. *Dopravné plánovanie*. Žilina: EDIS. 2015. [In Slovak: *Transportation Planning*].
12. Krsić, D. & Novačko, L. The impact of public transport network accessibility on trip generation model. *Promet - Traffic - Traffico*. 2015. Vol. 27(2). P. 165-172.
13. Kušnierová, J. & Hollarek, T. *Metódy modelovania a prognózovania prepravného a dopravného procesu*. Žilina: EDIS. 2000. [In Slovak: *Methodology of modeling and prognosis of the Transport process*].
14. Rezaei, J. Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega*. 2016. Vol. 64. P. 126-130.
15. Bierlaire, M. *PandasBiogeme: a short introduction*. Available at: <http://transp-or.epfl.ch/documents/technicalReports/Bier18.pdf>. 2018.
16. Novačko, L. & Babojelić, K. & God, N. & Babić, L. Estimation of modal split parameters-a case study. *Trans Motauto World*. 2020. Vol. 5(2). P. 51-53.
17. Ben-Akiva, M. & Bierlaire, M. Discrete Choice Methods and their Applications to Short Term Travel Decisions. In: *Handbook of Transportation Science*. Boston: Springer. 1999.
18. Oppenheim, N. *Urban Travel Demand Modeling: From Individual Choices to General Equilibrium*. Vol. 1. Wiley-Interscience. 1995.
19. Bovy, P.H.L. & Bliemer, M.C.J. & van Nes, R. *Course CT4801 Transportation Modeling*. 2006.
20. de Dios Ortuzar, J. & Willumsen, L.G. *Modelling Transport*. Vol. 4. United Kingdom: John Wiley & Sons, Ltd. 2011.
21. Chajdiak, J. & Komorník, J. & Komorníková, M. *Statistical methods*. Bratislava: STATIS. 1999.
22. *p-value*. Available at: <https://cit.vfu.cz/statpotr/POTR/Teorie/Predn3/hypotezy.htm>.
23. *Rho squared*. Available from: <https://thestatsgeek.com/2014/02/08/r-squared-in-logistic-regression/>.
24. Jandacka, D. & Durcanska, D. & Kovalova, D. Concentrations of traffic related pollutants in the vicinity of different types of urban crossroads. *Communications - Scientific Letters of the University of Zilina*. 2019. Vol. 21(1). P. 49-58.
25. Hrudkay, K. & Jaroš, J. Conceptual development of electromobility in conditions of Slovak municipalities. *Acta Logistica*. 2019. Vol. 6(4). P. 147-154.
26. Hudec, J. & Šarkan, B. & Czödöröová, R. & Caban, J. & Drożdziel, P. The impact of roadside technical inspections on transport and logistics systems in the Slovak Republic. *Transport Problems*. 2022. Vol. 17. No. 3. P. 61-73.
27. Kudela, P. & Fandáková, M. & Palcák, M. & Kordek, J. Utilization of modern methods for documentation of traffic accidents in road transport. In: *Transport Means - Proceedings of the International Conference*. 2021. P. 584-588.