DEVELOPMENT OF THE COMPOSITE INDICATOR CHARACTERISING THE URBAN PUBLIC TRANSPORT SYSTEM

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ABSTRACT

In this research the possibility of developing the composite indicator characterising the urban system of public transport (urban public transport quality index - UPTQI) is considered. The development of the composite indicator in terms of the initial data describing the urban public transport system (TS) currently operating in German cities (EUROSTAT) is presented with respect to two moments of time. Some variants of OECD algorithm realisation for developing the composite indicator have been applied. Special attention has been paid to the methods of changing missed data and their impact on the composite indicator value.
As a result, this work shows an alternative of constructing the composite indicator characterising urban public transport system, serving as a basis for drawing comparison between urban public transport system quality in various cities, and for assessing the influence of various characteristics and the selected methods of changing missed data on the overall estimate.

Keywords: public transport system, quality index, composite indicator, weights, imputation of missing data

INTRODUCTION

The composite indicators are applied in many fields of human activities – economy, sociology, psychology, technical area, logistics etc. Indicator is an integral performance index presenting a complex estimate of a process, system, or object. A multivariate set of sub-indicators forms a basis of developing the integral indicator which is transformed into a scalar in a certain way and used for benchmarking first of all.
The composite indicator is a function from sub-indicators and weights as follows:

$$CI_i^t = f(x_{i,1}^t, x_{i,2}^t, ..x_{i,m}^t, w_1, w_2, ..., w_m), \qquad (1)$$

where CI_i^t – value of composite indicator for object *i* (*i=1…n*) at time *t*;

$x_{i,j}^t$ - value of sub-indicator *j* (*j=1…m*) for object *i* at time *t*,

w_j - weight associated with sub-indicator *j* (*j=1…m*).

The most important advantages of composite indicator in the scalar form are a possibility of using it successfully for comparison and development analysis instead of a set of parameters. The European Plan of Research in Official Statistics (EPROS) for 2007-2013 singles out the continuation of work in the field of composite indicators and applying statistical methods in developing them as one of the top priorities. The Organization of Economic Cooperation and Development (OECD) proposes the ten-step algorithm described in Nardo M. "Handbook on Constructing Composite Indicators: Methodology and User Guide" (2005) for constructing the composite indicator.

At the Conference New Techniques and Technologies for Statistics (NTTS-2009) more than 160 examples of social indicators were mentioned – for instance, such as: Technology Achievement Index (TAI), Worldwide Governance Indicators, General Indicator of Science and Technology (NISTEP, Japan), Internal Market Index (European Commission), the Globalisation Index (G-Index) (World Markets Research Centre) etc. The World Bank experts have created Logistics Performance Indicator (LPI) based on analysis of principal components. LPI presents data of logistic development of countries in a scalar form based on 7 initial logistic development variables. It is convenient for taking corresponding political and economic decisions related to the development of this field.

A few authors have introduced some alternatives of composite indicators for transport systems, but the work in this direction is not finished yet. Coelho P. et al. (2008) determine Urban Mobility System and single out Indicator in Public Transports based on the following data group classes: Accessibility indicators, Reliability, Cost, Safety and Security, Environmental and other quality indicators. Authors presented the Objective Public Transport Assessment Methodology (OPTAM) to calculate the Multi criteria describing the quality of public transport system, which is calculated as a sum of criteria where a weight assigned by expert method corresponds to each criterion. Gitelman V. (2009) develops a composite indicator for road safety by using OECD algorithm and methods for Principal Component Analysis and Common Factor Analysis. Gertsbakh I. et al. (2008) describes some examples of the construction of logistics and transport indicators for EU countries using approach based on dynamic classification.

There is the attempt to construct a composite indicator of urban public transport quality index – UPTQ, provided for by urban public transport system (UPTS) in the work. The purpose of public transport is rendering safe, reliable, punctual, accessible, non-polluting and economically effective transport services to people. The standard "quality of service EN 13816" (approved in 2002) is based on the user needs and expectation and it provides the processes as well as a range of quality criteria that should be used and controlled. The elements within EN 13816 comprise: Availability, Accessibility, Information, Time, Customer care, Comfort, Security, Environmental impact.

It is accepted that the quality of service is usually a function of several particular quality factors (attributes). Murray A. (2001) denoted that the efficiency of public transport system has been reported in terms of operational indicators, engineering indicators, labour indicators, social indicators, resource indicators and financial indicators. Jabkowski P. (2005)

considered service quality of urban public transport as a part of life quality indicator. He uses the following characteristics of public transport for the analysis: Punctuality, Frequency of service, Ticket pricing, Cleanliness, Travel comfort. Seco A. & Gonçalve J. (2007) highlight 11 quality factors: Reliability/Punctuality, Commercial speed/Trip time, Comfort on the run, Service frequency/Regularity, Cleanness and maintenance, Safety, Trip price/Fare level, Security, Trip environment, Transfers necessity, Customers contact. These authors also determine ways of their calculation, as well as significance levels for users. Abreha D. (2007) provided a literature review of the field of service quality of urban public transport. Moreover, this author determines the performance indicator of public transport and states its main parameters.

Also over the last years, a few projects connected with this problem were developed: QUATTRO (1996-1998), Urban Audit (2003-…), (http://www.urbanaudit.org/). Together with experts from the European Committee for Standardisation (CEN TC 320 WG5), QUATTRO (Quality Approach in Tendering Urban Public Transport Operations Origin: European) developed a standardised set of quality indicators for Urban Public Transport (UPT) (Table 1). According to the developed in project QUATTRO approach the quality circuit includes the Expected Quality, the Targeted Quality, the Delivered Quality and the Perceived Quality.

Table 1 - The public transport quality matrix

1. Availability	1.1 Network 1.2 Timetable
2. Accessibility	2.1 External interface 2.2 Internal interface 2.3 Ticketing
3. Information	3.1 General information 3.2 Travel information – normal conditions 3.3 Travel information – abnormal conditions
4. Time	4.1 Journey time 4.2 Punctuality and reliability
5. Customer care	5.1 Commitment 5.2 Customer interface 5.3 Staff 5.4 Physical assistance 5.5 Ticketing options
6. Comfort	6.1 Ambient conditions 6.2 Facilities 6.3 Ergonomics 6.4 Ride comfort
7. Security	7.1 Safety from crime 7.2 Safety from accident 7.3 Perception of security
8. Environment	8.1 Pollution 8.2 Natural resources 8.3 Infrastructure

The Urban Audit pilot project was commenced in 2003 with the aim of testing the feasibility of collecting comparable indicators on the quality of life in European cities. The project and contains data for over 250 indicators across the different domains, including transport system (39 indicators in group Transport and Travel and 16 of them connected with public transport).

As mentioned before the most important advantage of the composite indicator is the convenience of service level benchmarking. However, service level benchmarking is a long term process which involves a number of successive steps. Some dedicated public programs performing such kind of analysis are available. For example: the question of service level benchmarks for Urban Transport of India is described in the Program of Ministry of Urban Development Government: Sustainable Urban Transport Project (SUTP),. The service level benchmarks for urban transport performance have been calculated there with respect to following areas: Public Transport in a city; pedestrian infrastructure facilities; non-motorized transport facilities; Integrated Transport System (ITS) operation facilities, travel speed along major corridors, road safety, availability of parking facilities, pollution level, land use transport integration, and financial sustainability of public transport. 4 levels of service in a city are spotlighted depending on the values of the following parameters describing the value of service of public transport: Availability of Organized Public Transport System in Urban Area, Extent of Supply / Availability of Public Transport, Service Coverage of Public Transport in the city (Bus route network density), Frequency of Public Transport Service, Level of Comfort in Public Transport, Percentage Fleet as per Urban Bus Specification. Each of these parameters is characterized by the respective indices.

Therefore, the purpose of the current research is developing the UPTQI (urban public transport quality index). The database EUROSTAT has been analysed about presence of the UPTS data for the European cities. The data from national sources has not been used, as they are not always calculated with use of one methodology. In Table 2 the list of the indicators from EUROSTAT database, characterising UPTS is presented. In the first column the components of the quality of UPTS (QUATTRO) service and in the second the corresponding indicators are specified.

Table 2 – UPTS characteristics (EUROSTAT).

Components	Indicators
Availability	Proportion of the area used for transport (road, rail, air, ports)
	Length of public transport network / land area
	Length of public transport network per inhabitant
	Number of buses (or bus equivalents) operating in the public transport per 1000 pop
Accessibility	Number of park and ride parking spaces per 1000 pop.
	Number of park and ride parking spaces per 1000 cars
	Number of stops of public transport per km2
	Number of stops of public transport per 1000 pop.
	Share of restrictred bus lanes from public transport network
	Number of stops per 1 km of public transport network
	Cost of a monthly ticket for public transport (for 5-10 km)
	Accessiblity by rail (EU27=100)
	Accessiblity by road (EU27=100)
	Multimodal accessibility (EU27=100)
Comfort	Average age of the bus (only buses) fleet
Environment	Length of public transport network on fixed infrastructure per 1000 pop
	Proportion of buses running on alternative fuels
	Proportion of public transport network on fixed infrastructure
	Length of restricted bus lanes per 1000 pop
	Length of public transport network on flexible routes per 1000 pop
	Proportion of public transport network on flexible routes

Unfortunately, the values of mentioned in Table 2 indicators in the database are missing for many cities. Therefore, in the given research the group of the cities (objects) with the most set of the indicators values has been used and special attention in the given work was attend to the quality of the composite indicator construction in case with the missing data.

RESEARCH METHODOLOGY

At the *first stage* Urban Public Transport Quality Index (UPTQI) without missing data was constructed. The sub-indicators for UPTQI development were selected according to:

- their relevance for monitoring service quality of UPTS;
- the availability of data important for the benchmarking process as expected to accompany the implementation of composite indicator.

To conduct the investigation, the data describing UPTS in German cities were used with respect to two moments of time: 1999-2002, denoted as t1, and 2003-2006, as - t2. The values of 8 indices shown in Table 3 were used in this investigation.

Table 3 – List of sub-indicators

№	Sub-indicators	Code
1	Proportion of journeys to work by public transport (rail, metro, bus, tram)	x1
2	Length of public transport network / land area	x2
3	Number of stops of public transport per km2	x3
4	Cost of a monthly ticket for public transport (for 5-10 km)	x4
5	Number of stops of public transport per 1000 pop.	x5
6	Number of stops per 1 km of public transport network	x6
7	Proportion of public transport network on fixed infrastructure /Proportion of public transport network on flexible routes	x7
8	Proportion of the area used for transport (road, rail, air, ports)	x8

Sub-indicators x2, x3, x5, x6 и x8 characterize the availability of UPTS, x4 – the economic component; x7 – the environmental impact (since the fixed-route transport uses alternative fuel (as electricity for example). x1 - may be attributed both to accessibility indicators and subjective indicators – i.e., the attitude towards the quality service as offered by the system: tenants tend to prefer the system more frequently if it provides a higher quality. Unfortunately, no data on other characteristics could be found – like, for example, indices that would characterize the safety of UPTS in these cities. Also let's notice that the data for second moment were without missing and with missing – for first time moment.

For constructing the composite indicator for the data without missing values (t2 time moment) it was used the following ten-step algorithm, which was developed the Organization of Economic Cooperation and Development (OECD):

1. Developing a theoretical framework;
2. Selecting initial variables;
3. Imputation of missing data;
4. Multivariate analysis;
5. Normalisation of data;

6. Weighting and aggregation;
7. Robustness and sensitivity;
8. Back to the details (indicators);
9. Association with other variables;
10. Presentation and dissemination.

The determining of each factor weight is the key moment of linear composite indicator constructing. The weights can be obtained by methods of two groups (Nardo M., 2005): based on statistical analysis (factor analysis, regression analysis etc) and based on the opinion of experts (Conjoint Analysis, Analytic Hierarchy Process etc). Many composite indicators are based on the sub-indicators (initial dated which were aggregated in subgroup) having equal weights – i.e., each group (if the data had been already grouped before), or the initial data in total (if each indicator is considered separately) equally contributes to the composite indicator. In our research for calculating weights and aggregating primary indices into the composite indicator methods based on Equal weighting approach, Principal Components and Factor analysis (PCA/FA) model and benefit of the doubt approach (BOD) were considered and compared.

The approach for *calculating the weights based on PCA/FA model* was developed by Nicoletti G., Scarpetta S., Boylaud O. (2000). The correlation structure of the data was checked. It is needed for preliminary analysis of the common factors existing. Then, according to standard approach to FA, identifying a certain number of latent factors smaller than the number of sub-indicators implies data representation and the factor structure rotation if necessary.

Let $a_{j,k}$ the k factor loading for j variable and $D[f_k]$ - variance explained by the k factor. In this case introduce the normalization of factor loading as

$$a_{j,knorm} = \frac{a_{j,k}}{D[f_k]}, \tag{2}$$

and the weight for j variable as maximum of factor loading multiplied the proportion of total variance for corresponding L factor

$$w_j = \max_k (a_{j,knorm}) \frac{D[f_k]}{\sum_{l=1}^{L} D[f_l]}, \tag{3}$$

The method of *weights estimation based on benefit of the doubt approach (BOD)* defines the composite indicator as the actual/benchmark performance ratio and the weights are city specific. The BOD approach endogenously determines country-specific weights that explicitly take account of a country's own choices and achievements across primitive dimensions of performance. Optimal weights are obtained by solving the constrained optimisation as linear programming problem (Nardo M., 2005):

$$CI_i^* = \arg\max_{w_{i,j}} \sum_{j=1}^{m} I_{i,j} w_{i,j}, \tag{4}$$

with following constraints: $\sum_{j=1}^{m} I_{z,j} w_{z,j} \leq 1; \;\; w_{z,j} \leq 0,$

for $\forall z = 1,...,n; \forall j = 1,...,m;$

where CI_i^* – value of composite indicator for object *i*,

$I_{i,j}$ – normalised value of sub-indicator *j* for object *i*,

$w_{i,j}$ – weight associated with sub-indicator *j* for object *i*,

n – number of objects and *m* – number of sub-indicators.

The values of UPTQI for 37 German cities' UPTS which constructed on both mentioned above approaches and with Equal weights were compared and ranks of cities' UPTS on the basis of these values (without missing data) are analysed.

The *second stage* was dedicated to investigating the influence of the selected method of missed data substitution upon the results of composite indicator calculation. First of all this stage of researches has been connected with one of the purposes of the composite indicator construction is its monitoring throughout some period of time and consequently, it was necessary to calculate and compare its values during other moments of time for the same cities. However, quite typical situation in this case is presence of the missing data at the same data set. As there are no universal recommendations for usage of this or that method of the imputation of the missing data and results of its usage depend on character of a solved problem, on a set of variables, and on model of skips. In order to choose the imputation method, first of all we will conduct the research by definition of the best method for our set of objects and variables.

The approaches to missing values imputation can be subdivided into two groups: Single imputation (Implicit modelling - Unconditional mean/median/mode imputation, Regression imputation, Expectation Maximisation (EM) imputation; Explicit modelling) and Multiple imputation.

For imputation of the missing data in considered data set the following methods were used:

- unconditional mean imputation;
- imputation by median;
- clustering-based imputation.

The method of *unconditional mean imputation* is the simplest one. It has been included into the investigation as the method most frequently used in statistical software. It implies estimation of missing values $x_{i,j}$ by the average value $\overline{x_j}$.

$$\overline{x_j} = \frac{1}{n_j}\sum_{i=1}^{n_j} x_{i,j} \, , \tag{5}$$

where $x_{i,j}$ – value of sub-indicator *j* for object *i*,

n_j – count of objects with fully observed sub-indicator *j.*

The *median* of the distribution could be calculated on the available sample and to substitute missing values.

Various approaches for missed data imputation, implying cluster analysis, are known. In this work, we consider the *clustering-base missing data imputation* based on next steps:

A. One of the methods of cluster analysis is applied to objects without missing data, - and *C* clusters are singled out.

B. The distance to the centres of all the *C* clusters is calculated with respect to each *i* object of observation having some missing data:

$$D_{i,c} = \sqrt{\sum_{j=1}^{m} (x_{i,j} - \overline{x_{j,c}})^2}\ , \tag{6}$$

where $D_{i,c}$ – distance between object *i* and cluster *c*,

$x_{i,j}$ – value of sub-indicator *j* (no missing) of object *i,*

$\overline{x_{j,c}}$ - mean value of sub-indicator *j* of *c*-cluster's objects.

Any variables where values are missing are not involved in the calculation of distance.

C. The nearest cluster is determined, with the minimal distance to it.

D. The skipped value of *i* object is substituted for the mean value of the corresponding variable pertaining to those observations that are attributed to the nearest cluster.

Therefore, the research on this stage included:

- Some values were deleted from the initial data. The first option of the missing scheme implied random deletion of 5% of all the sub-indicator values; in the second case, 10% of random values were deleted. For imputation of the missing data in this research the 3 above mentioned methods were used.

- The results of data imputation methods implying were analysed on the basis of consideration of ranks of cities with the full information.

At the *third stage* of the same set of objects – cities, but during other moment of time when in some of the variables are missing values were considered. The method which is chosen as the best for this problem during the previous research phase has been used to the missing data imputation.
Hence, for the chosen cities it has been calculated the composite indicator scores for two sequential moments of time that allows to analyse as stability of influence sub-indicators on the composite indicator (by the analysis weights values) and to trace the tendency of the indicators values changes.
So, the research was performed in three stages:

1. The development of Urban Public Transport Quality Index (UPTQI) for a determined set of objects (set of cities in fixed time moment) without missing data.

2. To investigate the influence of the missing data imputation methods on the value of UPTQI for a determined data set.

Take the same set of objects on other time moment with missing data and using method of imputation of the missing data chosen on the second stage in this research, the most suitable for analyzed data set to calculate UPTQI scores for set of cities in other moments of time and analyzing the time change of UPTQI values.

CONSTRUCTION OF URBAN PUBLIC TRANSPORT QUALITY INDEX

Let us consider as the object – the urban system of public transport, as composite indicator - urban public transport quality index - UPTQ and as the sub-indicators - the particular quality characteristics. To construct the index with respect to the complete set of data, we shall use the data describing 37 cities without missing data, for time moment 2003 – 2006 (denoted by t2).

Multivariate analysis and normalisation of data

The correlation analysis of data was fulfilled and the most of Pearson correlation values lie in [0.3;0.60] (Figure 1). The highest correlation (-0.60) between sub-indicators x2 (Length of public transport network / land area) and x6 (Number of stops per 1 km of public transport network). The same correlation value, but with positive sign (0.60) between sub-indicators x8 (Number of stops per 1 km of public transport network) and x5 (Number of stops of public transport per 1000 pop.). Also, high values of correlation: -0.58 for sub-indicators x8 and x1 (Proportion of journeys to work by public transport (rail, metro, bus, tram); 0.54 for sub-indicators x8 and x2 (Length of public transport network / land area). So, we can do preliminary conclusion about possibility to use PCA/FA for calculation of indicator' weights.

	X1	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**
X2	**0.40**						
X3	0.38	0.33					
X4	0.10	0.11	-0.02				
X5	**-0.44**	-0.25	0.33	-0.17			
X6	-0.09	**-0.60**	**0.47**	-0.03	**0.49**		
X7	0.18	-0.16	-0.17	0.03	-0.20	-0.02	
X8	**0.59**	**0.54**	**0.34**	**0.32**	**-0.60**	-0.26	-0.01

Figure 1 – Bottom triangle of Correlation matrix

The data was normalised through the Re-scaling normalising procedure and lies in (0;1). For one initial sub-indicator x4 (Cost of a monthly ticket for public transport) (for 5-10 km) the data was normalised through the Re-scaling procedure also, but the minimum value was reduced to 1 and the maximum value was reduced to 0. This is related to our assumption that the appeal of public transport is also connected with a low fare; therefore, we have made maximum transformation with respect to x4, to make the overall quality index dependence monotonous and positive with respect to all variables – i.e., making the overall quality index value rise with the growth of sub-indicator.

Weighting and Aggregation

All the calculations for the weights based on PCA/FA model were performed through using the package Statistica/Win5.5. The principal components were received and the first four components explain 85% of the total variance, while the eigenvalues for the first three components exceed 1 and that of the fourth component is close to 1. These 4 components have been considered for the subsequent analysis. A structure close to a simple one was obtained by the Biquartimax normalized rotation method. The weight values obtained with (3) are shown in Table 4. Moreover, weight values are presented with respect to the case of equal estimation.

Table 4 **–** Weights values for PCA/FA approach and equal weight approach

Methods	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**X8**
PCA	0.105	**0.140**	**0.135**	**0.148**	0.086	0.110	**0.155**	0.122
Equal	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125

To calculate weights through BOD method, the package MathCad14 was used where the linear programming problem was solved. In our calculations we imposed the requirement for each sub-indicator to weight at least 10% and no more than 15% of the total. The specific values of weights $w_{i,j}$ have been calculated for each city *c* and presented in Annex 1.

Composite indicator estimation

The next step is estimating a composite indicator scores. As aggregation method the Additive one was selected. Therefore, values three indicators: CI_{PCA}, CI_{BOD} and CI_{EW} have been obtained with respect to each city, with the weights were obtained through PCA and BOD methods; equal weights were used as well. The composite indicator values and the respective rating of a number of cities are presented in Table 5.

Table 5 **–** Composite indicators scores for set of cities at moment time t2

Cities	PCA			BOD			EW		
	CI	CI_{norm}	Rank	CI	CI_{norm}	Rank	CI	CI_{norm}	Rank
Düsseldorf	0.563	1.000	1	1.000	0.998	3	0.576	1.000	1
Halle an der Saale	0.527	0.896	2	0.990	0.980	4	0.531	0.873	4
Kiel	0.526	0.894	3	1.001	1.000	1	0.550	0.926	2
München	0.512	0.852	4	0.968	0.941	5	0.504	0.795	5
Berlin	0.511	0.850	5	1.000	0.998	2	0.539	0.896	3
Dresden	0.466	0.717	6	0.952	0.912	6	0.489	0.753	6
Leipzig	0.419	0.582	7	0.786	0.613	9	0.421	0.556	8
Nürnberg	0.409	0.554	8	0.776	0.595	10	0.407	0.518	10
Regensburg	0.400	0.527	9	0.763	0.571	11	0.399	0.493	11
Göttingen	0.394	0.510	10	0.809	0.654	8	0.413	0.535	9
…									
Weimar	0.234	0.045	33	0.558	0.201	31	0.277	0.145	31
Moers	0.234	0.044	34	0.482	0.065	36	0.237	0.030	36
Trier	0.228	0.027	35	0.492	0.083	35	0.252	0.073	33
Wiesbaden	0.225	0.018	36	0.495	0.087	34	0.247	0.060	34
Bielefeld	0.219	0.000	37	0.446	0.000	37	0.226	0.000	37

Analysing the results of calculating the indicator alternatives, we can point out that the same cities are ranking top 10 except for Augsburg that has fallen out of the top ten ratings according to the index CI_{PCA}; in terms of the other indices, however, the city remains at the 7th position. The CI_{PCA} values do not exceed 0.563, which corresponds to the city of Düsseldorf coming out to the top according to CI_{PCA}. At that, the value CI_{BOD} with respect to

the city assumes the magnitude which is little different from the maximum one - 1.00013, whereas its rank is the third one. The least value CI_{PCA} has been achieved by the city of Bielefeld and equals 0.219. At that, Bielefeld is ranking last also in terms of CI_{BOD} and CI_{EW}.
Also for correct comparison we can note that CI_{BOD} values are located within the interval (0.4;1.0), while CI_{PCA} does not exceed 0.6. For the sake of convenience, the indicator values can be normalized (to the interval 0;1) (see Figure 2). We can see that the largest difference in ranks pertains to the city of Frankfurt (Oder).

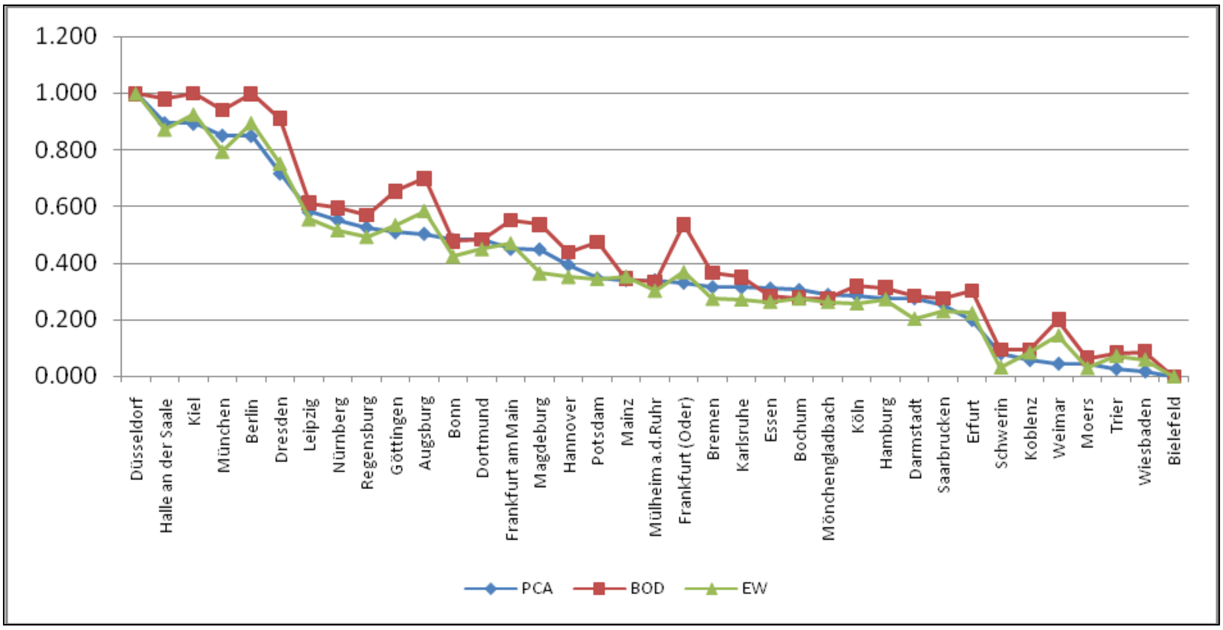

Figure 2 – Normalised CI scores of 37 Germany cities

ANALYSIS OF THE INFLUENCE OF MISSING DATA IMPUTATION METHOD ON COMPOSITE INDICATORS SCORES

To perform the second stage of the investigation, let's consider the same data describing 37 cities in 2003 – 2006 (t2) (without missing data) and the values of composite indicator with weights for variables estimated according to PCA method. Let's call the original CI.
To analyze the influence of missing data imputation method upon the results of estimation of composite indicator, the randomly was deleted:

- in the first case – 5% of all the values (15 values of variables out of 296);
- in the second case – 10% of all the values of variables (30 values).

With regard to all cases implying missing data, CI has been calculated by using the same weight calculation method as the one implying no missing data.
As mentioned before the following imputation methods were used: replacement by mean values, by median values and the method based on cluster analysis.
In all the cases, the composite indicator value was reduced to values lying within the interval [0;1]. CI values with respect to 37 cities without missing data and implying renewal by various methods in the case of 5% and 10% of missing data (case deleted) are presented in the Table 6 and Figure 3. The cities have been ranked in descending order of the original CI - from Dusseldorf (CI=1) to Bielefeld (CI=0) on the Figure 3.

Table 6 – Composite indicators scores for set of cities with different imputation methods

Cities	Original		5%						10%					
			Mean		Median		Cluster		Mean		Median		Cluster	
	CI_{norm}	Rank	CI_{norm}	Rank	CI_{norm}	Rank	CI_{norm}	Rank	CI_{norm}	Rank	CI_{norm}	Rank	CI_{norm}	Rank
Düsseldorf	1.000	1	0.667	6	0.659	8	0.791	6	0.693	4	0.662	5	0.518	7
Halle an der Saale	0.896	2	0.966	2	0.955	4	0.945	4	0.923	2	0.948	2	0.766	2
Kiel	0.894	3	1.000	1	0.963	2	0.972	3	0.531	7	0.562	7	0.560	5
München	0.852	4	0.958	3	1.000	1	1.000	1	0.912	3	0.898	3	0.732	3
Berlin	0.850	5	0.945	4	0.956	3	0.979	2	1.000	1	1.000	1	1.000	1
Dresden	0.717	6	0.818	5	0.794	5	0.848	5	0.601	6	0.620	6	0.553	6
Leipzig	0.582	7	0.646	7	0.659	7	0.662	8	0.663	5	0.684	4	0.634	4
Nürnberg	0.554	8	0.611	9	0.661	6	0.649	9	0.393	11	0.389	12	0.415	9
Regensburg	0.527	9	0.608	10	0.621	9	0.610	10	0.383	14	0.359	16	0.391	11
Göttingen	0.510	10	0.571	11	0.536	12	0.548	13	0.113	31	0.078	32	0.131	29
…														
Weimar	0.045	33	0.022	35	0.000	37	0.037	36	0.178	28	0.204	27	0.247	20
Moers	0.044	34	0.069	34	0.128	33	0.130	33	0.110	32	0.101	31	0.118	31
Trier	0.027	35	0.000	37	0.003	36	0.000	37	0.198	27	0.201	28	0.209	23
Wiesbaden	0.018	36	0.401	17	0.362	26	0.548	12	0.058	34	0.044	34	0.040	34
Bielefeld	0.000	37	0.015	36	0.064	35	0.072	35	0.009	36	0.000	37	0.000	37

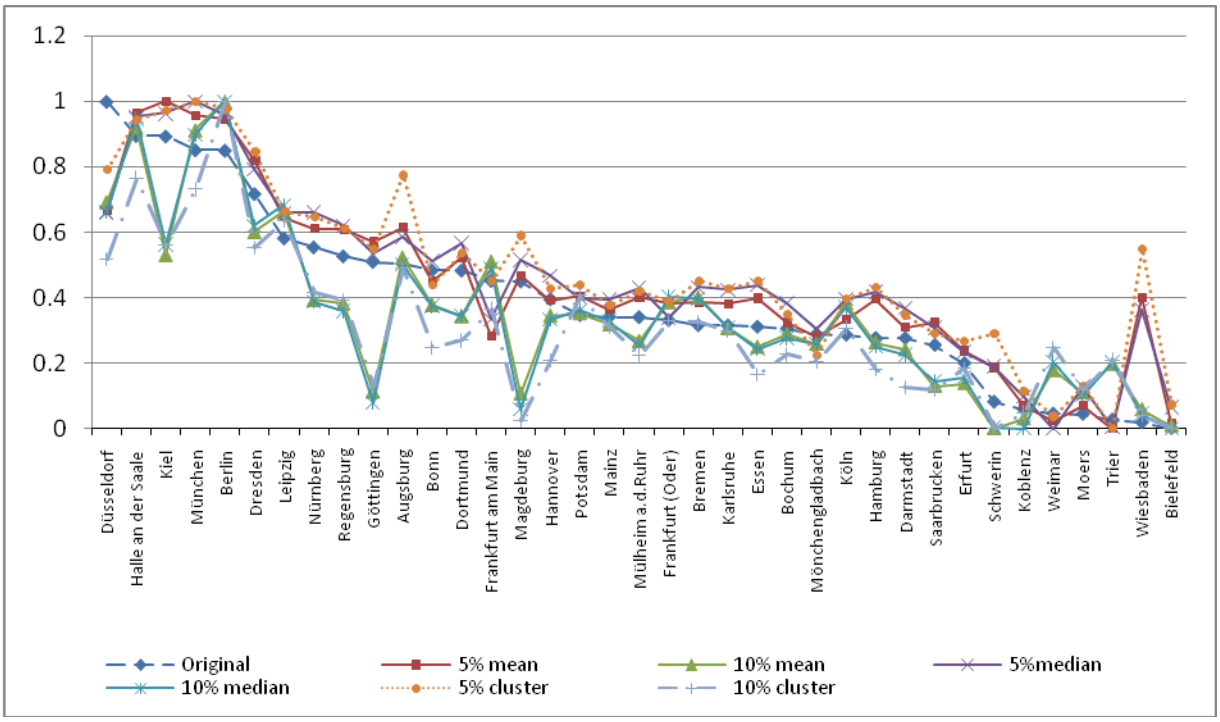

Figure 3 – CI scores with different imputation methods

The largest diversity from the original CI at 5% of blanks was observed in such cities as Dusseldorf (the missed values in the variables x1 and x3 and the imputation of missing data is performed by the cluster method), Augsburg (x2 – by the cluster method), Frankfurt am Main (x7 – by the mean-value method), Karlsruhe (no missing values), Essen (x4 – by the cluster method), Hamburg (x4 – by the cluster method), Wiesbaden (x2, x4, x5 – by the cluster method). At 10% of the variable values missing, the largest diversity from the original CI was recorded with the cities as follows: Dusseldorf (x3 and x5 – by the cluster method), Kiel (x3 – by the mean-value method), Gottingen (x5 and x6 - by the median-value method), Magdeburg (x7 – by the cluster method), Weimar (no missing data), Trier (x1 and x6 – by the cluster method).

It should be noted that lack of data describing some cities does exercise some influence on CI values describing even those cities that didn't have any missed values. Figure 4 shows CI values for some cities without missing data – neither in the first, nor in the second case. For example, the CI original value for Weimar equal to 0.045, while with the substitution of 10% of variables describing other cities for mean values of CI, the value for the same city is 0.233. Figure 5 shows CI values for the cities featuring missing data in two cases (5% and 10% missing data). The changes for these cities are more significant than the ones for the cities without missing data. This is most clearly seen with respect to the data with substitutions at 10% of blanks, and the indicator values are most frequently conservative.

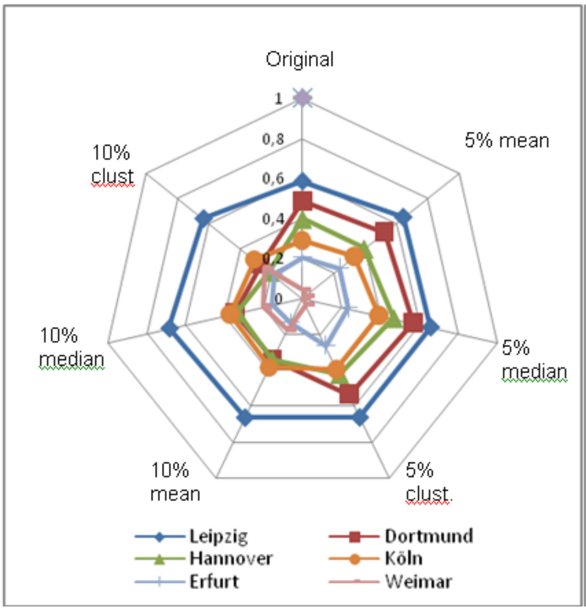

Figure 4 – CI scores for cities without missing data

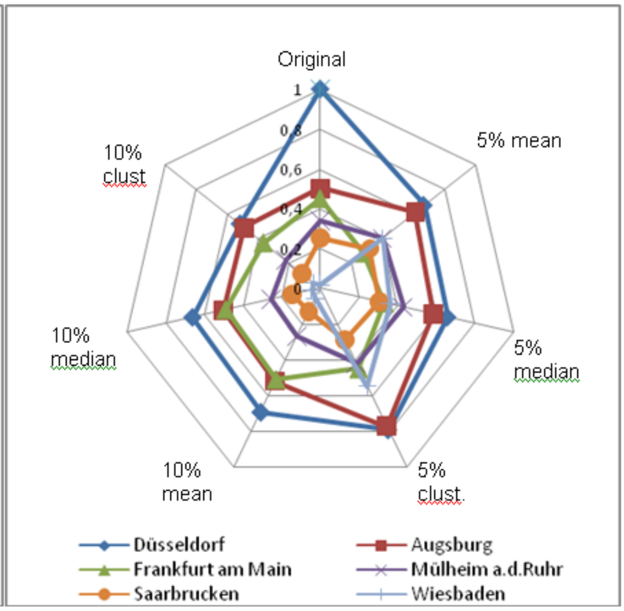

Figure 5 – CI scores for cities with missing data

We are interested to know which of the renewal methods yields the largest diversities of the composite indicator values with respect to the set of data investigated. For this purpose, the criterion - sum of squared deviations (SSD) of the index was used. SSD was calculated for the renewed missing data from the original CI value. The values of this criterion for CI calculated based on data with three investigated imputation methods are presented in Table 7.

Table 7 – Sum of squared deviations CI scores

	5% missing data			10% missing data		
methods	**mean**	**median**	**cluster**	**mean**	**median**	**cluster**
sum of squared deviations	0.011637	0.012974	0.018807	0.020091	0.022187	0.030459

As may be inferred from the results stated in the Table 6, the cluster method of substitution of missing data yields the maximum deviation both at 5% and 10% of missing data. The least deviation is obtained by the method of substitution by mean values.
The analysis of Pearson correlation between the original CI values and CI obtained through the use of these three methods (see Table 8) confirms the assumption that the method of substitution by mean values yields the closest result to CI original with respect to this set of data – as compared to other methods used.

Table 8 - Correlation coefficients' values between original CI and others

	5% missing data			**10% missing data**		
Imputation methods	**mean**	**median**	**cluster**	**mean**	**median**	**cluster**
correlation	**0.93**	0.93	0.91	**0.86**	0.85	0.82

Figure 6 shows the ranking of the cities implying the full set of data and using various methods of missing data substitution. Cities on the Figure ordered by their original CI position, ranking from 1 (for Dusseldorf) to 37 (for Bielefeld).

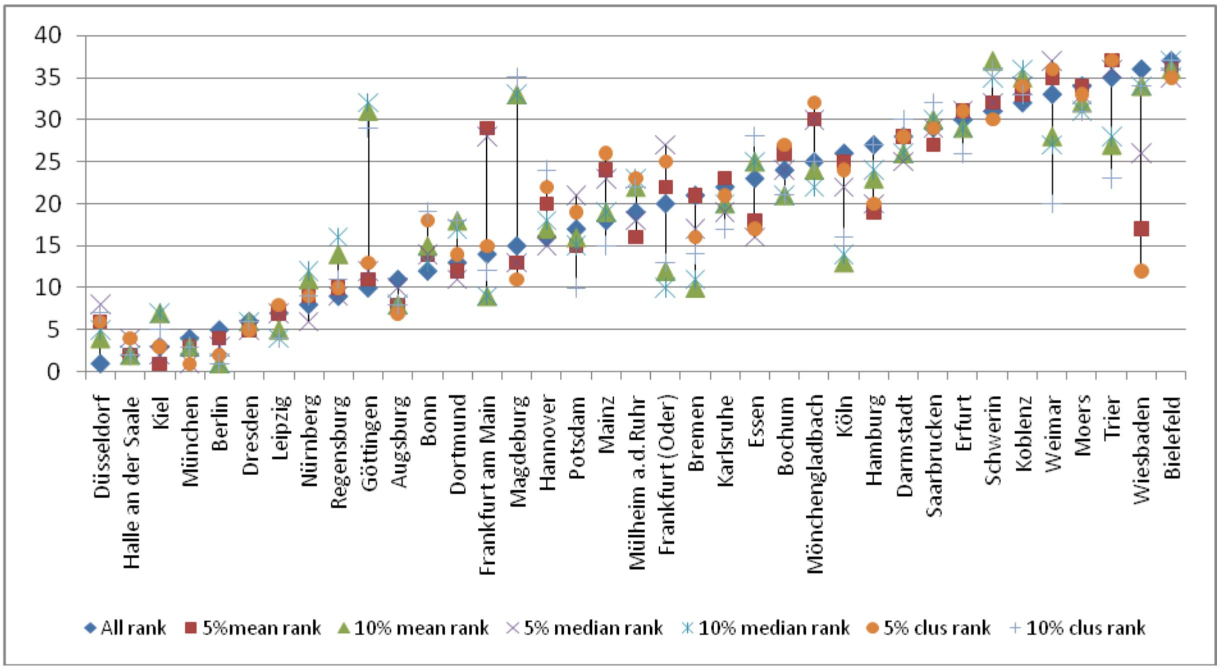

Figure 6 – Ranks of cities using various methods of missing data

THE ANALYSIS OF THE COMPOSITE INDICATORS SCORES CHANGE IN TIME

For the analysis of the composite indicators score changes in the time at the third stage we will calculate its values for 37 cities according to 1999-2002 (t1) and will compare with already calculated values for the data 2002-2006 (t2) (see Table 5).
In the data at t1 moment of time there are missing data for a set of variable 11 cities that makes about 7% from total sub-indicators values. For imputation of the missing data has been used unconditional mean method. For calculation of the weights values considered

methods also are used: PCA/FA, BOD and EW. The weights values calculated by method PCA/FA for two moments of time are presented in Table 9.

Table 9 – Weights values on the basis PCA/FA model for two time moments

Time	w1	w2	w3	w4	w5	w6	w7	w8
t1	0.118	0.154	0.104	0.150	0.114	0.136	0.144	0.079
t2	0.105	0.140	0.135	0.148	0.086	0.110	0.155	0.122

The greatest changes of the weights values for two moments of time are observed for variables x3 (Number of stops of public transport per km2), x5 (Number of stops of public transport per 1000 pop.) and x8 (Proportion of the area used for transport (road, rail, air, ports). It is obvious that the increase in weight for variables x3 and x8 is connected with increasing requirements of passengers to quality of services of public transport from the point of view of fuller covering network and approach of stops to attraction places. Also, it is important from the integrability of urban public transport point of view.
The specific values of weights $w_{i,j}$ at time moment t1 which have been calculated through BOD method have presented in Annex Table 2.
The normalised composite indicators scores and corresponding ranks for some cities for two moments of time are presented in Table 10.

Table 10 – Composite indicators scores for set of cities with different methods of weight estimation in two moments of time

Cities	**1999-2002**						**2003-2006**					
	PCA		**BOD**		**EW**		**PCA**		**BOD**		**EW**	
	CInorm	Rank	CInorm	Rank	CInorm	Rank	CInorm	Rank	CInorm	Rank	CInorm	Rank
Düsseldorf	1	1	1	1	1	1	1.00	1	1.00	3	1.00	1
Halle an der Saale	0.77	2	0.78	5	0.73	4	0.90	2	0.98	4	0.87	4
Kiel	0.77	3	0.97	2	0.84	2	0.89	3	1.00	1	0.93	2
Berlin	0.72	4	0.92	3	0.79	3	0.85	5	1.00	2	0.90	3
Dresden	0.7	5	0.8	4	0.67	5	0.72	6	0.91	6	0.75	6
München	0.6	6	0.71	6	0.61	6	0.85	4	0.94	5	0.80	5
Leipzig	0.55	7	0.56	10	0.52	7	0.58	7	0.61	9	0.56	8
Potsdam	0.48	8	0.58	9	0.47	10	0.35	17	0.47	17	0.35	19
Hannover	0.48	9	0.58	8	0.5	8	0.39	16	0.44	18	0.35	18
Augsburg	0.46	10	0.62	7	0.5	9	0.50	11	0.70	7	0.59	7
…												
Wiesbaden	0.03	33	0.11	33	0.06	33	0.02	36	0.09	34	0.06	34
Moers	0.03	34	0.09	34	0.05	34	0.04	34	0.07	36	0.03	36
Koblenz	0.02	35	0.07	35	0.04	35	0.06	32	0.10	32	0.08	32
Trier	0	36	0.04	36	0.02	36	0.03	35	0.08	35	0.07	33
Bielefeld	0	37	0	37	0	37	0.00	37	0.00	37	0.00	37

In Fig. 7 and 8 are presented CI_{PCA} scores and ranks for cities for two moments of time. Cities ordered by their CI_{PCA} (t1) position, ranking from 1 (for Dusseldorf) to 37 (for Bielefeld).

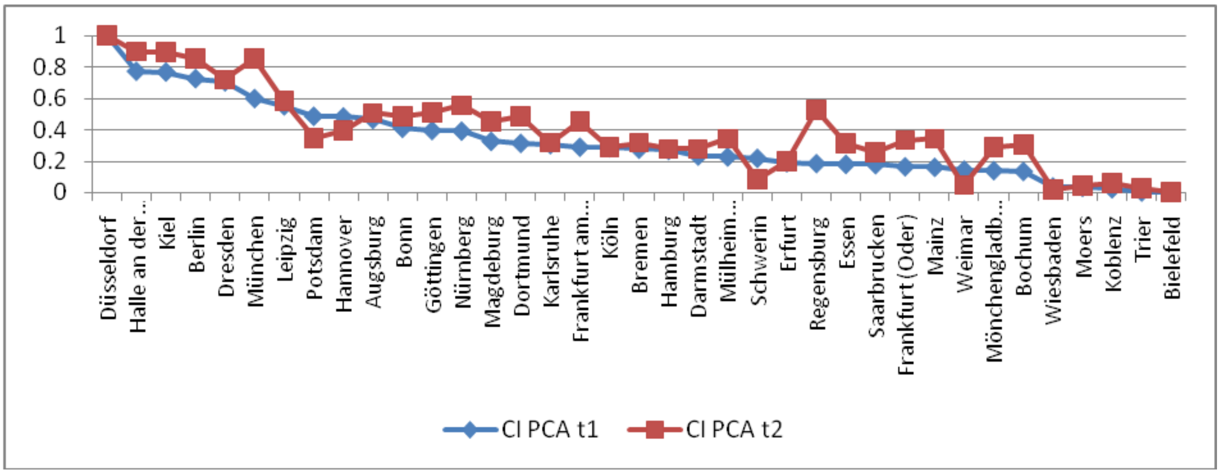

Figure 7 – Composite indicators normalized scores (PCA-methods for weights estimation)

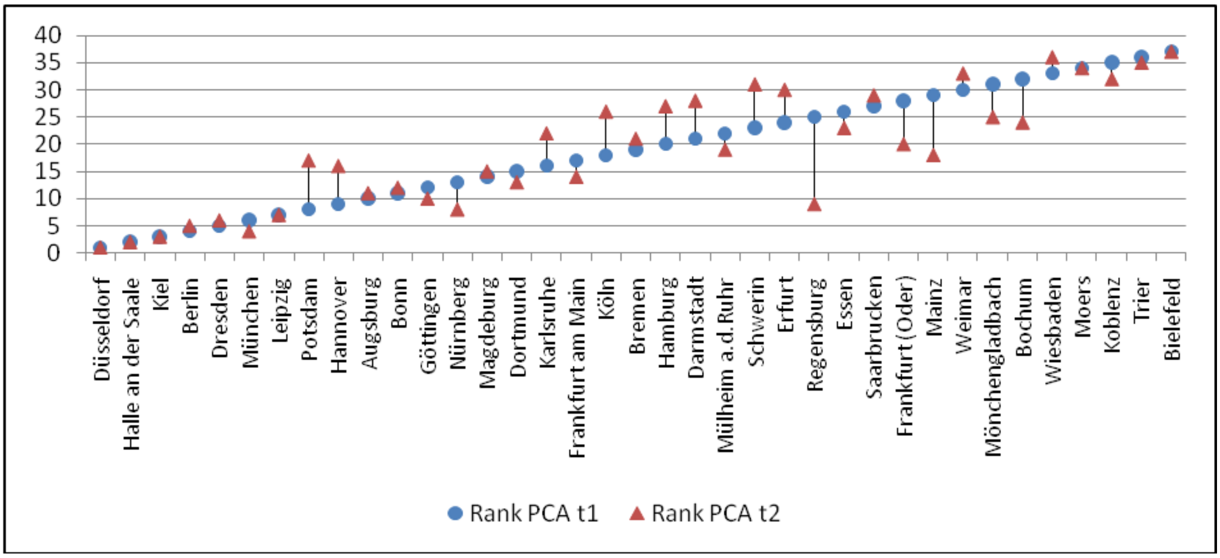

Figure 8 – Cities ranks (PCA-methods for weights estimation)

For cities, like Potsdam (has missed data for a moment t1 on a variable x8), Hannover (has missed data for a moment t1 on variables x3, x5, and x6), Schwerin (there are no missing data) – composite indicator score has considerably decreased from t1 to t2. For cities München (there is no value of a variable x4 at the moment of time t1), Regensburg (has missed data for a moment t1 on variables x3, x4, x5, and x6), Frankfurt (Oder) (there is no value of a variable x5 at the moment of time t1) CI – has considerably increased.

It is better to use for time tendency analysis the visualisation in polar coordinates (Fig. 9 and 10). There are examples of visualisation composite indicators scores for two cities Weimar (with missing dates) and Schwerin (there are no missing data) in polar coordinates. For city Weimar (has missed data for a moment t1 on variables x3, x4, x5, and x6) – CI scores based on method PCA decreased from t1 to t2 and increased for methods based on BOD and equal weights. For city Schwerin (without missing data) the tendency is more robust – the CI scores are increased to t2 for all methods of weights estimation.

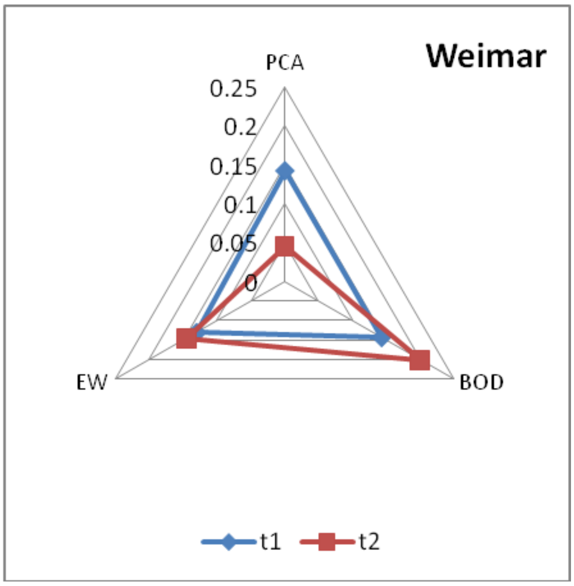

Figure 9 – CI scores for Weimar city for two moments of time

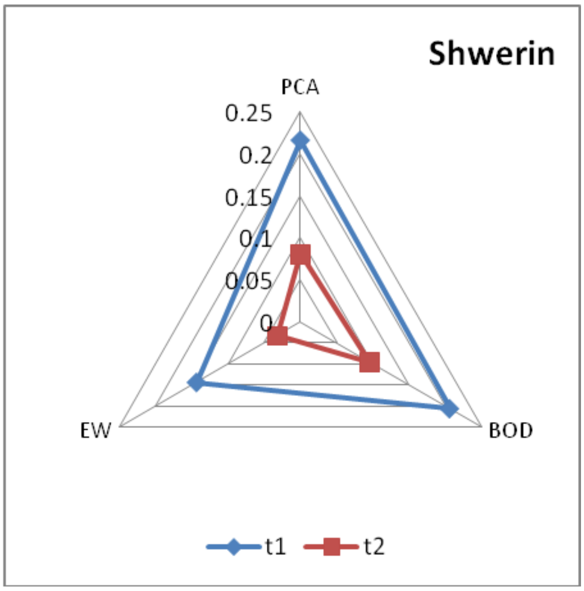

Figure 10 – CI scores for Shwerin city for two moments of time

CONCLUSION

As a result of research the variant of constructing the composite indicator UPTQI characterising the urban public transport system on the basis of which it is possible to compare the urban public transport system quality in various cities estimation is present.
Further authors assume to develop the given research in following directions:

- To consider other methods of the weights estimation, for example Unobserved components model (UCM) and methods based on experts opinion - Analytic hierarchy process (AHP),
- To analyse influence of methods of filling of missing data at not random missing, and at missing in the most difficultly "measured" data, for example, “Proportion of journeys to work by public transport (rail, metro, bus, and tram)” or in the most significant for distinction of objects
- To consider group of the European cities, for example, capitals.

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REFERENCES

Abreha, D. A. (2007). Analysing Public transport performance using efficiency measures and spatial analysis; the case of Addis Ababa, Ethiopia

Coelho Patricia, Ľos Peter, Spina Giuseppe Fabio, Karyda Markella. (2008). Assessment of the urban mobility system. University of the AEGEAN, Greece.

Gertsbakh, I., Yatskiv, I, Platonova, O. (2008). Constructing Social and Economic Indicators for EU Countries Using Dynamic Classification: Case Studies. Proceeding of International Conference "Data mining-2008", 26-28 May 2008, Cadiz, p.153-162

Gitelman, V. (2009). Designing a composite index for road safety. 4th Irtad Conference Road safety data: collection and analysis for target setting and monitoring performances and progress, Seoul

Jabkowski, P. (2005) Evaluation of public transport in the project of Poznan quality of life indicators

Murray, A. T. (2001), "Strategic analysis of public transport coverage", Socio-Economic Planning Sciences, 35,3:ppl 175-188

Logistics Performance Index. http://info.worldbank.org/etools/tradesurvey/Mode1a.asp.

Nardo, M. (2005) a.o. Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD Statistics Working Paper, 2005/3. 108 p.

Nicoletti, G., Scarpetta S. and Boylaud O. (2000) – Summary indicators of product market regulation with an extension to employment protection legislation, OECD Economics Department Working papers No. 226.

Seco, A. J. M. and Gonçalves, J. H. G. (2007). The quality of public transport: relative importance of different performance indicators and their potential to explain modal choice

Standard "Quality of service EN 13816" April 2002

Urban Audit http://www.urbanaudit.org

ANNEX - WEIGHTS ESTIMATED WITH THE BOD APROACH

Table 1 – Weights at 2003-2006

Cities	x1	x2	x3	x4	x5	x6	x7	x8
Düsseldorf	0.174	0.26	0.174	0.26	0.174	0.26	0.174	0.26
Halle an der Saale	0.274	0.183	0.183	0.274	0.274	0.183	0.274	0.183
Kiel	0.165	0.165	0.248	0.216	0.232	0.248	0.165	0.213
München	0.266	0.178	0.178	0.266	0.178	0.178	0.266	0.266
Berlin	0.249	0.176	0.249	0.166	0.176	0.243	0.166	0.233
Dresden	0.275	0.184	0.184	0.275	0.214	0.275	0.244	0.184
Leipzig	0.239	0.185	0.185	0.278	0.278	0.225	0.278	0.185
Nürnberg	0.266	0.178	0.178	0.266	0.178	0.178	0.266	0.266
Regensburg	0.182	0.199	0.182	0.274	0.182	0.257	0.274	0.274
Göttingen	0.185	0.241	0.185	0.278	0.278	0.222	0.278	0.185
Augsburg	0.275	0.183	0.183	0.183	0.275	0.275	0.275	0.183
Bonn	0.27	0.27	0.18	0.27	0.18	0.18	0.27	0.18
Dortmund	0.253	0.253	0.168	0.253	0.168	0.168	0.168	0.253
Frankfurt am Main	0.267	0.184	0.178	0.178	0.178	0.26	0.267	0.267
Magdeburg	0.279	0.186	0.186	0.279	0.186	0.279	0.279	0.186
Hannover	0.253	0.253	0.168	0.253	0.168	0.168	0.168	0.253
Potsdam	0.239	0.185	0.185	0.278	0.278	0.225	0.278	0.185
Mainz	0.177	0.213	0.177	0.177	0.265	0.265	0.228	0.265
Mülheim a.d.Ruhr	0.198	0.182	0.182	0.274	0.182	0.258	0.274	0.274
Frankfurt (Oder)	0.239	0.185	0.185	0.278	0.278	0.225	0.278	0.185
Bremen	0.279	0.186	0.186	0.279	0.186	0.279	0.279	0.186
Karlsruhe	0.198	0.182	0.182	0.274	0.182	0.258	0.274	0.274
Essen	0.253	0.253	0.168	0.253	0.168	0.168	0.168	0.253
Bochum	0.174	0.26	0.174	0.26	0.174	0.26	0.174	0.26
Mönchengladbach	0.171	0.256	0.171	0.256	0.256	0.171	0.171	0.256
Köln	0.266	0.178	0.178	0.266	0.178	0.178	0.266	0.266
Hamburg	0.279	0.186	0.186	0.279	0.186	0.279	0.279	0.186
Darmstadt	0.27	0.27	0.18	0.27	0.18	0.18	0.27	0.18
Saarbrucken	0.185	0.241	0.185	0.278	0.278	0.222	0.278	0.185
Erfurt	0.27	0.18	0.18	0.27	0.27	0.244	0.206	0.18
Schwerin	0.185	0.241	0.185	0.278	0.278	0.222	0.278	0.185
Koblenz	0.169	0.169	0.169	0.253	0.253	0.253	0.169	0.253
Weimar	0.275	0.183	0.183	0.183	0.275	0.275	0.275	0.183
Moers	0.198	0.182	0.182	0.274	0.182	0.258	0.274	0.274
Trier	0.184	0.267	0.184	0.193	0.276	0.276	0.276	0.184
Wiesbaden	0.26	0.174	0.174	0.26	0.174	0.26	0.174	0.26
Bielefeld	0.279	0.186	0.186	0.279	0.186	0.279	0.279	0.186

Table 2 – Weights at 1999-2002

Cities	x1	x2	x3	x4	x5	x6	x7	x8
Düsseldorf	0.151	0.216	0.151	0.173	0.226	0.215	0.151	0.223
Halle an der Saale	0.229	0.229	0.152	0.152	0.229	0.152	0.229	0.152
Kiel	0.15	0.15	0.225	0.15	0.225	0.225	0.15	0.225
München	0.226	0.226	0.151	0.151	0.151	0.151	0.226	0.226
Berlin	0.231	0.154	0.231	0.154	0.154	0.231	0.231	0.154
Dresden	0.236	0.157	0.157	0.157	0.236	0.236	0.236	0.157
Leipzig	0.229	0.153	0.153	0.229	0.153	0.229	0.229	0.153
Nürnberg	0.226	0.226	0.151	0.151	0.151	0.151	0.226	0.226
Regensburg	0.149	0.149	0.149	0.224	0.224	0.224	0.149	0.224
Göttingen	0.148	0.148	0.221	0.221	0.221	0.221	0.148	0.148
Augsburg	0.226	0.15	0.226	0.15	0.226	0.226	0.15	0.15
Bonn	0.226	0.226	0.151	0.151	0.151	0.151	0.226	0.226
Dortmund	0.226	0.226	0.151	0.151	0.151	0.226	0.151	0.226
Frankfurt am Main	0.233	0.155	0.155	0.155	0.155	0.233	0.233	0.233
Magdeburg	0.229	0.153	0.153	0.229	0.153	0.229	0.229	0.153
Hannover	0.226	0.226	0.151	0.151	0.151	0.226	0.151	0.226
Potsdam	0.154	0.154	0.154	0.231	0.231	0.231	0.231	0.154
Mainz	0.152	0.228	0.152	0.152	0.228	0.228	0.152	0.228
Mülheim a.d.Ruhr	0.152	0.152	0.152	0.229	0.152	0.229	0.229	0.229
Frankfurt (Oder)	0.154	0.154	0.154	0.231	0.231	0.231	0.231	0.154
Bremen	0.229	0.153	0.153	0.229	0.153	0.229	0.229	0.153
Karlsruhe	0.152	0.152	0.152	0.229	0.152	0.229	0.229	0.229
Essen	0.226	0.226	0.151	0.151	0.151	0.226	0.151	0.226
Bochum	0.226	0.226	0.151	0.151	0.151	0.226	0.151	0.226
Mönchengladbach	0.152	0.228	0.152	0.152	0.228	0.228	0.152	0.228
Köln	0.233	0.155	0.155	0.155	0.155	0.233	0.233	0.233
Hamburg	0.233	0.155	0.155	0.155	0.155	0.233	0.233	0.233
Darmstadt	0.222	0.222	0.148	0.222	0.148	0.148	0.222	0.148
Saarbrucken	0.15	0.224	0.15	0.224	0.224	0.224	0.15	0.15
Erfurt	0.224	0.149	0.149	0.224	0.224	0.224	0.149	0.149
Schwerin	0.154	0.154	0.154	0.231	0.231	0.231	0.231	0.154
Koblenz	0.149	0.149	0.149	0.224	0.224	0.224	0.149	0.224
Weimar	0.224	0.149	0.149	0.224	0.224	0.224	0.149	0.149
Moers	0.152	0.152	0.152	0.229	0.152	0.229	0.229	0.229
Trier	0.152	0.228	0.152	0.152	0.228	0.228	0.152	0.228
Wiesbaden	0.228	0.152	0.152	0.152	0.228	0.228	0.152	0.228
Bielefeld	0.224	0.149	0.149	0.224	0.224	0.224	0.149	0.149