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Establishing Patterns of the Urban Transport Flows Functioning On Urban Network Parameters

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Abstract

The paper attempts to use the motorization levels for analyzing the increase in traffic volume across road links and network for roads of various hierarchies. Using a gravity model approach and traffic volume and flow survey along the nodes and links, it found that increase in per capita vehicle ownership leads to relatively higher increase in traffic load and the relationship can be used to predict the future traffic projections, based on motorization levels of the residents and the traffic zones. Further, predicting motorization level by using economic and income indicators can link, increase in traffic demand with economic and other welfare policies allowing planning of long term of infrastructural development.

Keywords: road traffic, transport network, motorization level, traffic characteristics

1. Introduction

The intensification of transport problems in large cities and cities of Ukraine in particular, is associated with an increase in private vehicle ownership (Gyulyev, et. al., 2018; Lobashov, et. al., 2018). The phenomenon takes place against the backdrop of development of transport networks lagging behind the needs of road traffic. The number of vehicles owned by private owners provides a comparison regarding motorization level. Therefore, an approach can be developed to determine this indicator and its impact on the parameters of traffic flows.

The analysis of modern transport problems has revealed shortcomings in the process of managing urban traffic flows. Analysis of the issue shows use of different approaches to evaluate the motorization level (Lobashov, Burko,

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2017). Yannis, et. al. (2018) proposed the use of data extrapolation methods, the results and the forecast (funnel approach), as well as models based on multifactorial correlation were proposed to calculate this index. The motorization level was proposed to be determined using the growth forecast of the gross regional product, and the possibilities of the urban transport infrastructure using the per capita income (Antoniou, et. al., 2016; Litman, 2017). The disadvantages in this regard the lack of valuation of higher levels of traffic accidents (Afanasieva, Galkin, 2018), and the lack of development of transport networks against the motorization level. The aim of this research is to understand the patterns of the urban transport flow functioning on these urban network parameters.

2. Methodology, Data Collection and Analysis

The functional interrelation of the motorization level, parameters of the urban transport network and traffic flow characteristics has been shown in Fig. 1. The first part of the figure presents methods for determining the prospective traffic intensity at sections of the transport network. To determine the intensity of movement, various methods can be used, that can be divided into different categories e.g. extrapolation methods, analogy methods and expert assessment methods etc. Extrapolation methods include: linear function (Patriksson, 2015; Polson & Sokolov, 2017), non-linear function (Zhao, 2017), prediction using the formula of compound interest (Qu, Zhang & Wang, 2017). Analogy methods include the Fratar method and the Detroit method (Patriksson, 2015) and, simple-factor growth and single growth factors method (Rao & Rao, 2012). The third typology is expert assessment methods (Sundaram, S. et al., 2010). In addition, it is possible to use the methods of limited capacity, specific mobility, the synthetic method, the method of shortening and distribution upon a larger number of routes (Wald, 2004; Fuentes, et. al., 2017). In this paper we have adopted use of a single growth rate method, taking into account the variation in motorization level, number of inhabitants, average price of a car and purchasing power of inhabitants (Galkin, et. al, 2018) (Fig. 1).

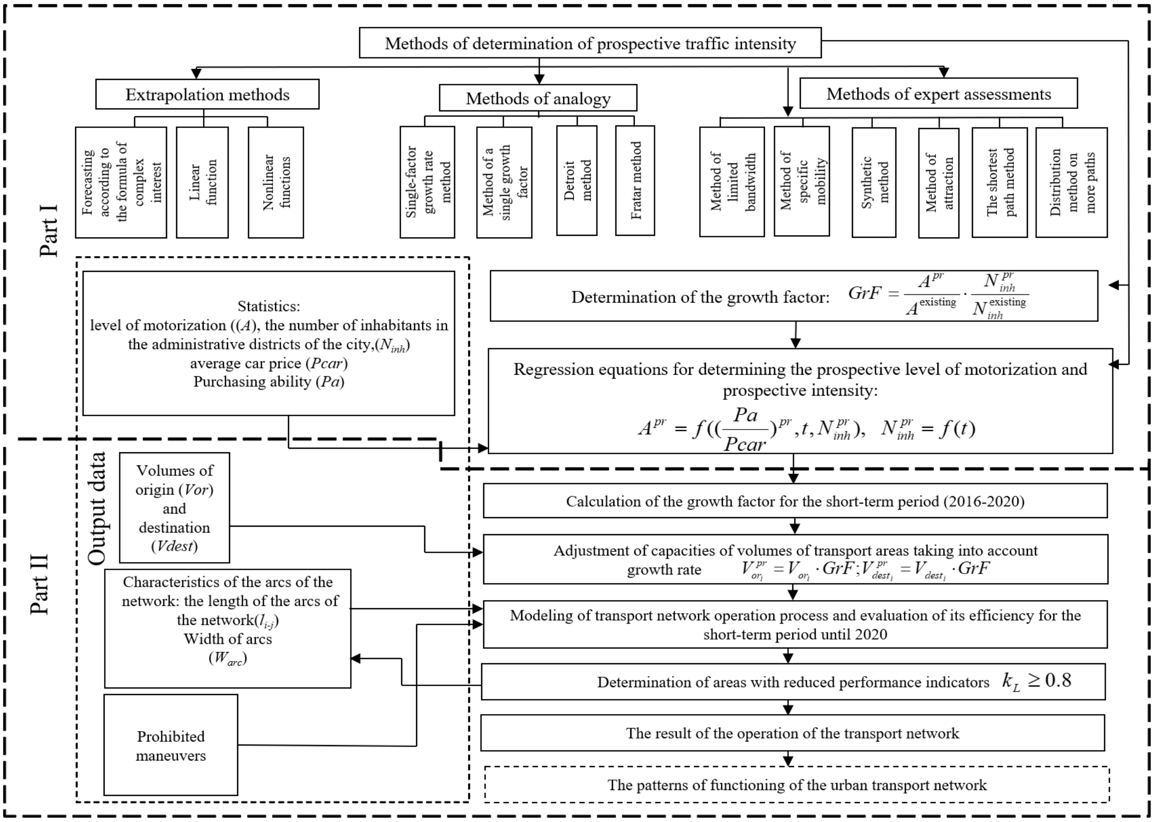

Fig. 1 – Structural scheme of research

Using growth factors, traffic volumes in the transport areas were adjusted. Similar approach for Annual Average Daily Traffic method was adopted by Gecchele, et., al., (2011). In the second part of Fig. 1, the topological network of Kharkiv (Ukraine) is developed, which has 842 nodes and 2362 arcs. Each connection was described mathematically using graph theory. For example, in one-way traffic, the oriented graph was used. To determine the characteristics of sections of the transport network and transport hubs, surveys were conducted on the network of city of Kharkov. In the course of the survey, basic data was collected related to intensity, speed of traffic flow and a number of other characteristics. The demand and supply (capacity) of traffic flow across the nodes, having information on transport movements were captured. On the transport network, arrival data collection survey was carried out at both within the network and at the fringes. At the fringes of the network, transport demand is equal to the intensity of incoming external transport. Within the transport network, the transport demand is determined on the basis of the conditional boundaries of the transport area and distribution of traffic flow.

To analyze the distribution of traffic flow on the urban transport network, gravity method was used for predicting movement within the transport network. The initial data for calculating the correspondence matrix was the origin-destination (O-D) demand of traffic flows within the network, the characteristics of the network, and (O-D) distance matrix.

Overall, movement from node i to node j is calculated by the formula:

$$H_{ij} = Vor_i \cdot \frac{Vdest_j \cdot D_{ij} \cdot K_j}{\sum_{t=1}^{n} Vdest_t \cdot D_{it} \cdot K_t}, \tag{1}$$

Where Vor_i - volume of origin from the i-th node, u / h; $Vdest_j$ - volume of destination in the j-th node, u / h; D_{ij} - the function of the i-th and j-th nodes; K_j - balancing factor; n - number of nodes in the transport network.

The function of the network between nodes, depending on the optimization criteria is determined by the formulas:

$$D_{ij} = L_{ij}^{-1}, \qquad D_{ij} = C_{ij}^{-1}, \qquad D_{ij} = T_{ij}^{-1} \tag{2}$$

Where L_{ij} – distance between nodes i and j; C_{ij} – transportation costs unit for vehicle travel between nodes i and j; T_{ij} – travel time between nodes i and j.

After distribution of all movements over the network, it is possible to determine the parameters of the transport network activity as a whole.

The efficiency of the transport network is determined taking into account the projected traffic intensity along the links of the network. The software presupposes the use of the following criteria of the transport network functioning effectiveness: total transport costs of all vehicles (C_{tr}); total network mileage (L_{tot}); total driving time (T_{tot}).

The efficiency criterion is calculated using one of the formulas:

$$C_{tr} = \sum_{i=1}^{k} N_i \cdot C_{tri}; \qquad L_{tot} = \sum_{i=1}^{k} N_i \cdot L_i; \qquad T_{tot} = \sum_{i=1}^{k} N_i \cdot T_i; \tag{3}$$

Where N_i - traffic flow on the i-th arc, units / h; k - number of arcs of the transport network.

The motorization level is associated with the characteristics of traffic flow (Schlosser, Schlosser, 2016; Saha, Sarkar & Pal, 2017). The traffic flow characteristics are interrelated with the parameters of the transport network and related functional indicators (Nuzzolo, Crisalli & Comi, 2015; Lobashov & Burko, 2017). The impact of the motorization level on transport demand is proposed to be estimated by the coefficient of growth of traffic volume in the urban zones i.e. weighted average traffic load factor ($k_L^{av.weighted}$):

$$k_L^{av.weighted} = \frac{\sum_{i=1}^{n} k_{L_i} \cdot N_i}{\sum_{i=1}^{n} N_i}, \tag{4}$$

Where, k_{L_i} – the load factor of the *i*-th arc of the transport network; N_i – intensity of movement on the *i*-th link; *n* – number of links within the network.

Reserve road capacity (*R*):

$$R = \frac{\sum_{i=1}^{n} P_i - N_i}{n}, \tag{5}$$

Where, P_i – road capacity in cars/hour.

Transport operation (*W*):

$$W = \sum_{i=1}^{n} N_i \cdot l_i, \tag{6}$$

Where, l_i – the length of the *i*-th link in kms.

3. Results

Calculated based on the equations (4) – (6) the indicators for different motorization levels values are shown in Fig. 2 and Table 1.

Sl. No.	Start of the Link	End of the Link	Link Length	Number of Lanes	Vehicular Intensity	Speed (kmph)	Load Factor	Load factor x Vehicular Intensity	R	W
1	213	180	11	2.0	2114	5.00	1.41	2979.33	-614.00	465.08
2	163	31	7	1.5	1467	5.00	1.32	1931.36	-352.71	205.38
3	502	824	26	1.3	1226	5.00	1.27	1558.75	-261.71	637.52
4	506	508	44	1.3	1185	5.00	1.23	1456.23	-220.71	1042.80
5	39	40	11	1.2	1082	5.00	1.20	1300.80	-182.00	238.04
6	504	506	15	1.0	892	5.00	1.19	1060.89	-142.00	267.60
…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…
227	346	337	30	1.7	1042	30.25	0.81	844.48	243.71	625.20
228	64	65	6	0.6	382	30.26	0.81	309.54	89.43	45.84
229	292	276	29	2.6	1562	30.29	0.81	1265.10	366.57	905.96
230	17	11	5	1.1	694	30.30	0.81	561.91	163.14	69.40
231	594	593	27	1.1	693	30.38	0.81	560.29	164.14	374.22
232	533	534	49	2.0	1211	30.45	0.81	977.68	289.00	1186.78
233	11	4	6	1.1	692	30.45	0.81	558.67	165.14	83.04
234	59	52	8	1.1	692	30.45	0.81	558.67	165.14	110.72
235	622	619	13	1.0	605	30.49	0.81	488.03	145.00	157.30
236	824	220	14	1.0	604	30.57	0.81	486.42	146.00	169.12
237	756	758	8	1.7	1034	30.64	0.80	831.57	251.71	165.44
238	268	261	15	2.0	1206	30.66	0.80	969.62	294.00	361.80
239	228	225	25	2.6	1546	30.81	0.80	1239.32	382.57	773.00
240	306	284	16	2.6	1545	30.84	0.80	1237.72	383.57	494.40
241	75	74	8	1.1	685	30.96	0.80	547.43	172.14	109.60

Sl. No.	Start of the Link	End of the Link	Link Length	Number of Lanes	Vehicular Intensity	Speed (kmph)	Load Factor	Load factor x Vehicular Intensity	R	W
242	151	148	13	1.7	1027	30.98	0.80	820.34	258.71	267.02
243	28	26	7	2.6	1539	31.03	0.80	1228.12	389.57	215.46
244	74	73	17	1.1	684	31.03	0.80	545.83	173.14	232.56
245	162	163	21	2.0	1196	31.07	0.80	953.61	304.00	502.32
246	465	464	24	2.0	1195	31.12	0.80	952.02	305.00	573.60
…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…
2357	742	743	25	1.1	0	50.00	0.00	0.00	857.14	0.00
2358	743	744	29	2.0	0	50.00	0.00	0.00	1500.00	0.00
2359	744	740	25	1.1	0	50.00	0.00	0.00	857.14	0.00
2360	747	745	15	1.0	0	35.00	0.00	0.00	750.00	0.00
2361	748	747	22	1.0	0	35.00	0.00	0.00	750.00	0.00
2362	754	753	25	1.0	0	30.00	0.00	0.00	750.00	0.00

Fig. 2 – Calculation results

According to Ukrainian transport policy, the following types of streets and roads were considered in the City of Kharkiv:

- Urban Roads - Main streets and roads of the city–wide value of regulated traffic (MSRUV);
- District Roads - Main streets and roads of district significance (MSRDS);
- Local Roads - Streets and roads of local importance (SRLI).

Table 1. Values of the indicators being studied for different types of streets and roads

Indicator	Indicator street type (Road)	Motorization level (*A*), car/1000 inh.				
		152	154	156	158	160
$k_L^{av.weighted}$	MSRUV	0,593	0,602	0,613	0,623	0,631
	MSRDS	0,653	0,658	0,666	0,673	0,682
	SRLI	0,400	0,415	0,431	0,444	0,458
R, car/h	MSRUV	733	720	703	689	676
	MSRDS	672	665	656	646	638
	SRLI	686	682	675	669	664
W, car · km	MSRUV	346.262	352.143	359.739	365.893	371.732
	MSRDS	164.335	168.539	173.603	178.831	183.331
	SRLI	26.534	26.871	28.051	28.998	30.083

Fig. 3 and 4 have been developed using results shown in Table 1.

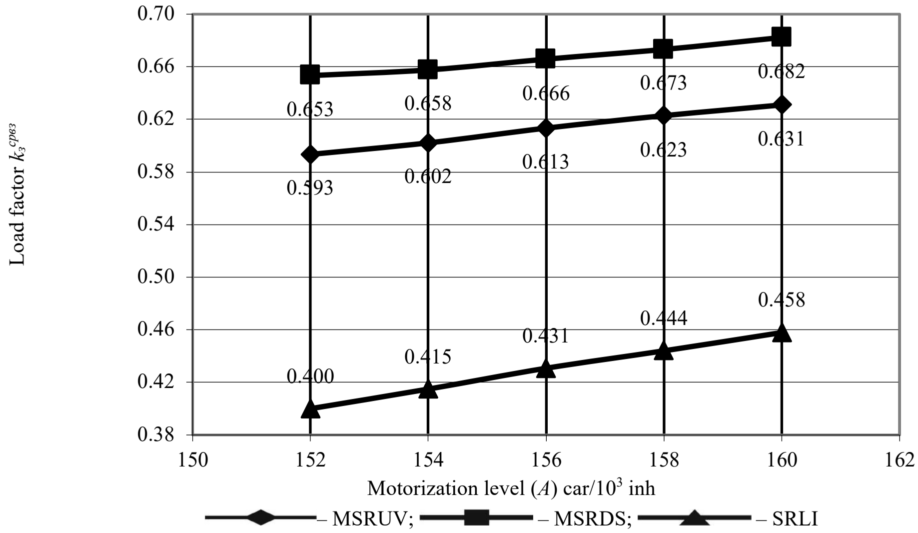

Fig. 3. Relationship between average weighted value of the load factor ($K_з^{срвз}$) and motorization level (*A*) for different roads types

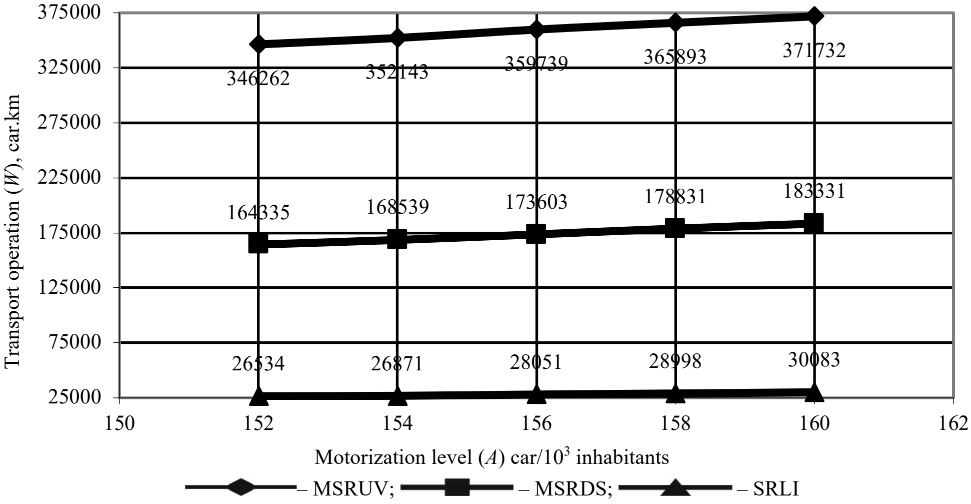

Fig. 4. Relationship between transport operation (W) and motorization level for different roads types

As shown in Fig. 3 it is evident that increase in motorization level leads to increase in traffic load factor. It should be noted that the value of this indicator for district roads is higher as against for urban roads. This is due to the concentration of large number of vehicles along the "approaches" of the urban highways and with complex access design for them. For highways of all-city significance with the increase of the motorization level from 152 cars/ 1,000 inhabitants up to 160 cars/1,000 inhabitants (5.2%), the load factor will increase from 0.593 to 0.631 or 6.4%; for highways of district significance – from 0.653 to 0.682 or by 4.4%; for roads of local importance – from 0.400 to 0.458 or by 14.5%.

As shown in Fig. 4, it should be noted that the increase in motorization level leads to increase in Transport activity. The highest importance of transport operations is for the urban highways, then on district, and then on local roads. With increase in motorization levels from 152 cars/ 1000 inhabitants up to 160 cars/ 1000 inhabitants (5.2%), transport activity will increase on urban streets from 346,262 cars km to 371,732 cars km, which is an increase of 7.4%; at the district level roads it increases from 164,335 cars. km to 183,331 car. km, which is 11.6% and for local roads it increases from 26,534 cars km to 30,083 cars km, which is an increase of 13.4%.

4. Discussion

Existing approaches to determine the motorization level require additional consideration of people's purchasing power indicators. The impact of the motorization level on urban transport demand was proposed to be estimated by the growth coefficient of traffic volumes in the urban areas. The analysis of the methods of studying the distribution of traffic flows indicates the necessity of applying the gravity method for calculating transport correspondence in the urban transport network. The study of the patterns of urban traffic flow formation was proposed to be carried out by using estimated indicators (load factor for traffic, traffic reserving capacity, transport operation), considering the impact on their motorization level.

This approach to determining the motorization level can be used to calculate the parameters of traffic flows in the transport networks of cities. The offered toolkit allows to estimate influence of motorization level on patterns of transportation flows formation and to plan actions for increase of efficiency of urban transport networks functioning.

5. Conclusions on the research and prospects, further development in this direction

We found that transport demand is a function of motorization level. Further, we found that growth in motorization levels leads in higher percentage growth in traffic and vehicular kilometers travelled and the relationship between them can be used to estimate future traffic growth, based on the network characteristics and road typology. Further, based on the relationship and data, traffic can be improved as functions to achieve a certain level of traffic management.

The developed models determine network characteristics based on motorization level. The motorization levels further, can be backwardly modeled based on combination of factors such as purchasing power of the population and the number of inhabitants, thereby, economic growth and development can be linked to forecasting vehicular growth and development can be planned accordingly in the long-term based on economic policies.

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