DOI: 10.46541/978-86-7233-406-7_244

27th International Scientific Conference
Strategic Management
and Decision Support Systems
in Strategic Management
SM2022

Subotica (Serbia), 20th May, 2022

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PUBLIC TRANSPORT MANAGEMENT IN SMART ENVIRONMENTAL PROTECTION – CASE STUDY OF SUBOTICA, SERBIA

Abstract: Energy consumption of transport sector in Serbia is estimated at 32% of final national energy consumption. The road transport consumes approximately three quarters. This consumption produced a poor quality of life, which means that it caused a real deterioration of public health through increase of respiratory diseases and the worsening of cancer risks, etc. Moreover, according to the National Agency of Environmental Protection, the traffic of Serbian public transport would be responsible for at least 42% of the emissions of CO, NOX and PM.
In this paper authors expand previous research by introducing private and special vehicles and measure their impact on the city health apart from the impact of public transport. Reducing the number of vehicles in the transport chain, reducing the number of traffic accidents and improving living conditions in the city are just few tasks to be executed in sustainable way. Challenges like reduction of pollutants, noise reduction and decreasing the degree of vulnerability of habitat are addressed simultaneously solving the multiple criteria programming problem. The coefficients of the observed constraints are modeled using fuzzy values, i.e. linguistic expressions due to short periods of observation and non-normal distributions. We measure the age, number and fuel consumption and estimate the average millage for private, public and ambulance transport within the Subotica city limits and estimate the impact on environment measured by indicators available for the city, namely air and water pollution and number of lung diseases. These issues are a part of more profound problem of urban transformation which relates to a multitude of urban sustainability issues, ranging from segregation and growing social tensions to local traffic problems, solid waste generation and the large consumption of energy and material in developed countries.
Keywords: smart city, environment, city transport, smart technologies, optimization techniques

1. INTRODUCTION

The aim of this paper is to address the problems of environmental sustainability in the smart city from the viewpoint of both technological and social aspects of smartness. The paper studies the environmental sustainability development opportunities through the prism of three types of transport in the mid-sized city of Subotica, Serbia: public passenger, private and special transport. This consumption produced a poor quality of life, which means that it caused a real deterioration of public health through increase of respiratory diseases and the worsening of cancer risks, etc. Moreover, according to the National Agency of Environmental Protection, the traffic of Serbian public transport would be responsible for at least 42% of the emissions of CO and NOX. Hence, it is of utmost importance to estimate the impact of decreasing the emission of pollutants on lung diseases.
Shekarrizfard et al. (2016) developed the three-phase model for measuring the individual's exposure to air pollution in the city of Montreal, while Su et al. (2015)estimate portions of population potentially exposed to traffic-related air

pollution(TRAP) across seven global cities of various urban forms. Based on a most likely scenario with impacts from highways up to 300 meters, the authors identified that 'the portions of population potentially exposed for the seven cities ranged from 23 to 96%.'
The exposure to pollution was observed though the prism of spatial associations between socioeconomic groups in Pinault et al. (2016). The authors brought to light the problem of environmental justice for linking lower socioeconomic status to greater air pollution. NO2 was used as a marker for traffic-related pollution. Lindén et al. (2012) further introduce different climate areas as a factor that affects the air pollution Morelli et al. (2016) measured the levels of health risks and exposure to noise and air pollution and concluded that higher risk levels are associated with the 'neighborhoods with intermediate to higher social deprivation', while Tenailleau et al. (2015) showed that various definitions of 'neighborhoods' impact exposure assessment. Power (2012) concluded that 'Low income households in poorer neighborhoods have far lower levels of car ownership than average and yet suffer higher levels of traffic and environmental damage. Several authors addressed the issue of traffic induced air pollution and noise and their connection with various illnesses: Sørensen et al. (2015) learnt that air pollution may be associated with slightly higher levels of cholesterol while Allen et al. (2009) and Halonen et al. (2016) found support of the spatial relationship between pollution and noise on one hand and cardiovascular morbidity on other. Cardiac, vascular and respiratory diseases were investigated by Carugno et al. (2016), while pollution measured by levels of sulphur and nickel in particulate matter (PM 10) could be associated with lung cancer (Raaschou-Nielsen et al., 2016)
The vulnerability of eco and man-made systems are not easy to be measured (Abhas et al., 2013), therefore it is of utmost importance to find simplified proxies and to employ relevant factors. The indicator-based approach is considered most suitable for the assessment of exposure.
Exposures to natural and human induced hazards that can affect urban and peri-urban areas are better assessed by a number of simple indicators that are able to show if not a comprehensive at least a reiterative and improvable image of primary vulnerability.

2. METHODOLOGICAL FRAMEWORK

All of the studies mentioned in the introduction used some form of land use regression analysis (LUR). The LUR is a well established methodology aiming specifically at problems of monitoring and estimating effects of air pollution by using data collected through geographic information system (GIS).
The study area in our research focuses on the downtown Subotica, city in northern Serbia with the population of just over 100.000. The city core is not completely car free, and the transversal road splitting the city center into two halves is especially busy and open to all types of vehicles. The two major crossroads are located on the eastern and western edges of the city center, as denoted in Figure 1 and Figure 2 with stars.

Figure 1: Map of downtown Subotica

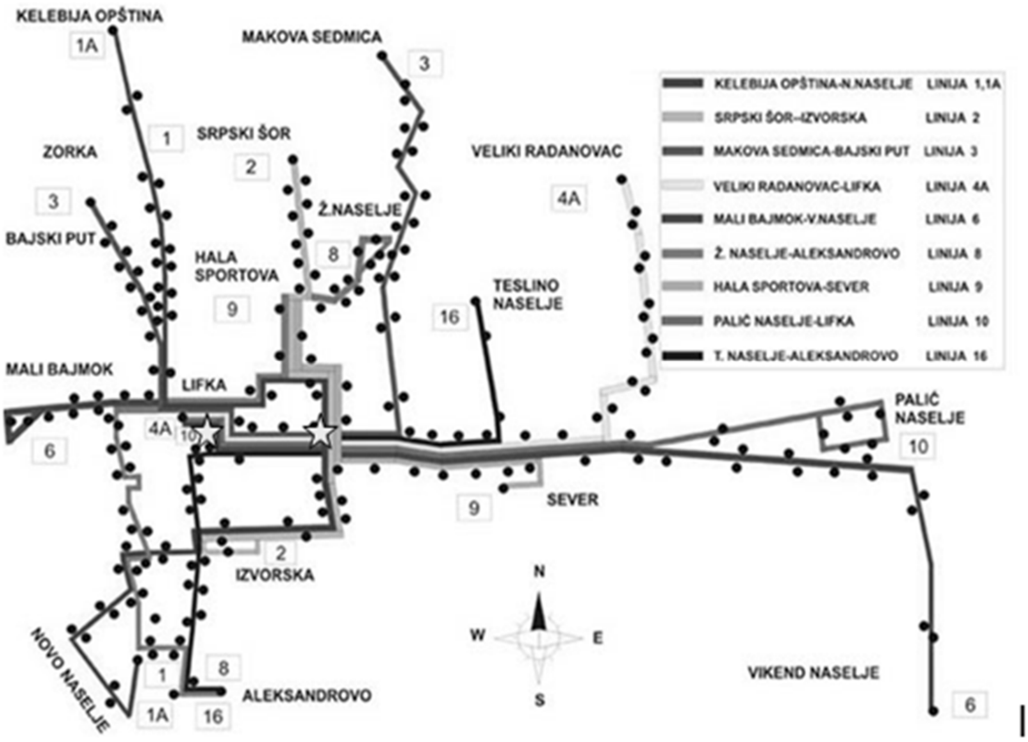

Figure 2: Public transport network

During two consecutive days, on September 26th and September 27th, the direct traffic count took place on both locations from 8 AM until 5 PM. The vehicles counted were divided into 5 groups: motorcycles (M), private cars (P), public busses (A), light trucks (up to 3,5t) (L) and heavy trucks and trucks with trailers (over 3,5t) (T). The distance between the two crossroads is 900meters, and the fixed passive sampler is placed at the right crossroad. The sampler continuously collects data on concentration of carbon oxide (CO), nitrogen oxide (NO2) and fine particulate matter ($PM_{2.5}$). The hourly averages were used as dependent variables. The number of vehicles passing through the crossroad on hour basis is given in the Table 1:

Table 1: Data from traffic counting

	8h	9h	10h	11h	12h
motorcycle	64	70	54	76	80
private car	2344	2583	2537	2461	2553
bus	82	42	47	39	49
light truck	143	133	181	174	170
heavy truck	58	59	54	67	68
	13h	**14h**	**15h**	**16h**	**17h**
motorcycle	60	37	51	43	17
private car	2437	2344	2467	2334	2008
bus	63	64	61	51	40
light truck	237	230	196	191	115
heavy truck	77	67	68	53	40

Source: author's calculations

The data on emissions from individual types of vehicles were taken from the study of Papic et al. (2010). The study explored the COPERT IV, a software tool for estimating the emission of major air pollutants emanating from the road traffic, based on particular vehicle activity. Since the data on average speed for each vehicle, as well as data on vehicle technologies were unavailable, we used Tier 1 method which utilizes fuel as an indicator of road traffic activity, together with the specific fuel emission factors.

The minimal and maximal emission levels of carbon oxide, nitrogen oxide and particulate matter (in grams per 1kg of fuel consumed), as well as average fuel consumption per each type of vehicle observed is given in Table 2. Comparatively little exploration has been done on spatial components, hence for example the wind speed has not been added in the examination.

Table 2: Average consumption and emission statistics for five types of vehicles

Type of vehicle	Type of fuel	Fuel consum. g/km	Emission levels (g/kg of fuel)					
			CO min	CO max	NOx min	NOx max	PM min	PM max
Private car	Petrol	70	50	350	6	35	0,03	0,045
	Diesel	60	2	11	9	14	0,7	4
	LPG*	57,5	40	115	6	40	0	0
Light truck	Petrol	100	80	300	14	40	0,02	0,045
	Diesel	80	8	15	13	18	2	4
Heavy truck	Diesel	240	6,5	10	30	45	0,7	2
	CNG**	500	2,2	15	5,5	30	0,01	0,036
Motorcycle	Petrol	35	340	700	11	8	1,5	5
Public bus	CNG	500	2,2	15	,5,5	30	0,01	0,036

Adapted from Papic et al. (2010), p. 20.
*liquefied petroleum gas
** compressed natural gas

3. RESULTS AND DISCUSSION

The area around the crossroads and the sampler is industry free so we assume that most of the measurements recorded by the sampler is mostly due to the traffic. We estimate the per type impact on total air pollution measured by concentration of CO, NOx and $PM_{2.5}$ through series of regressions of the type:

$$P_t = C + \alpha_1 P_{At} + \alpha_2 P_{Lt} + \alpha_3 P_{Mt} + \alpha_4 P_{Pt} + \alpha_5 P_{Tt} + u_t,$$

Where P stands for the pollutant CO, NOx and PM obtained from the sampler (in $\mu g/m^3$), while P_A, P_L, P_M, P_P and P_T are explanatory variables representing emission levels (in g/km) for each type of vehicle; u_t is the error term and t is the time index.
All series were tested for the unit root and the hypotheses of the existence of the unit root in levels were rejected.
The estimation coefficients are presented for each pollutant individually in Table 3a, 3b and 3c below:

Table 3a: Estimation outputs for Carbon oxide

Dependent Variable: CO				
Variable	Coeff	Std. Error	t-Statistic	Prob.
CO_A	0,39	0,014	2,715	0,021
CO_L	2,39	0,406	5,893	0,002
CO_M	1,600	0,191	8,363	0,000
CO_P	0,56	0,019	2,947	0,032
CO_T	0,024	0,005	4,773	0,005
R-squared	0,956	Mean dependent var		66,128

Source: author's calculations

Table 3b: Estimation outputs for Nitrogen oxide

Dependent Variable: NOX				
Variable	Coeff	Std. Error	t-Statistic	Prob.
NOx_A	0,125	0,036	3,516	0,017
NOx_L	0,568	0,124	4,570	0,006
NOx_M	0,047	0,015	3,095	0,027
NOx_P	0,812	0,151	5,376	0,003
NOX_T	0,245	0,047	5,224	0,003
R-squared	0,949	Mean dependent var		76,320

Source: author's calculations

Table 3c: Estimation outputs for PM

Dependent Variable: PM				
Variable	Coeff	Std. Error	t-Statistic	Prob.
PM_A	0,117	0,027	4,403	0,007
PM_L	1,158	0,199	5,829	0,002
PM_M	2,812	1,004	2,800	0,038
PM_P	0,838	0,359	2,332	0,067
PM_T	1,075	0,235	4,570	0.006
R-squared	0,907	Mean dependent var		41,940

Source: author's calculations

We observe from all three tables high explanatory power of the model, and the 'correct' signs of all coefficients. When it comes to carbon oxide emission, the biggest pollutants are light trucks running on petrol, and the decrease in emission by 1g/km could decrease the CO levels by 2,4μg/m^3. Also motorcycles could decrease the CO levels in air by 1,6 μg/m^3. The diesel trucks have a significantly smaller CO emission. The motorcycle engine construction is the biggest issue, enabling the high levels of gas emission.
The Nitrogen oxide emission is dominated by private cars since the coefficient NOx_P is the highest. The private cars running on petroleum gas produce highest levels of NO. Due to the current price of gas it is unlikely to see the decrease in NO emissions.
Finally, when it comes to particulate matter, the biggest emission comes from motorcycles, and the decrease in emission by 1g/km could decrease the levels of $PM_{2.5}$ by 2,8 μg/m^3. This study only covered motorcycles running on gas, while for other types of vehicles the range of consumptions and types of fuels were used in order to obtain weighted consumption.

4. CONCLUSIONS

Land-use regression combines monitoring of air pollution and development of stochastic models using predictor variables obtained through geographic information systems. Monitoring is temporally limited: one to four surveys of typically one or two weeks duration. Significant predictor variables include various traffic representations, population density, land use, physical geography (e.g. altitude) and climate.'
Using a quantitative approach could help decision makers to set targets for their actions and to monitor the results over time.
This compact study aimed at showing the impact of five types of vehicles on emission of polluters in down town area of the city of Subotica, Serbia. The results show that almost all of the air pollutants in the city center can be explained by the traffic emission. Hence, technological modernization and renewable energy access as well as investments in environmentally friendly projects should gain momentum in the years to come in order to decrease the emission of potentially harming substances.

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