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Apparent Patterns in Ambulance Response Time in Timişoara

Alexandru M. MORAR [1], Larisa EFLEIH-HASSAN [1], and Diana LUNGEANU [2,*]

[1] Department of Automation and Applied Informatics, University Politehnica Timişoara; Piaţa Victoriei No. 2, 300006 Timişoara, Romania.
[2] Department of Functional Sciences, "Victor Babeş" University of Medicine and Pharmacy, Timişoara; Piaţa E. Murgu No. 2, 300041 Timişoara, Romania.
E-mails: alex93morar@gmail.com; efleih.larisa@yahoo.com; dlungeanu@umft.ro

* Author to whom correspondence should be addressed; Tel.: +40-256-490288; Fax: +40-256-490288

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Abstract

Objective: The objective of our study was to explore the explanatory factors for ambulance response time. *Methods:* Four area quarters were delimited in the city geographical territory, based on natural barriers and large crossover roads. These zones were further considered for analysis of the call data over the year 2018, in a cross-sectional study. The data collected by the Ambulance Service of Timişoara on all solved cases comprised the city streets with: (a) the total number of calls and the four-level emergency number of requests for each; and (b) shortest, longest, and average response time. Additionally, for each street, the geographical coordinates (latitude and longitude) were approximated, and the distance to the corresponding dispatch center was calculated based on the equirectangular approximation. Descriptive statistics and a multi-variable General Linear Model (GLM) were applied for data analysis, with further Bonferroni adjustments for post-hoc comparisons. *Results:* Although the number of calls and the patterns of priority were indistinctive within the four zones, we found an apparent North-South pattern for the mean time to arrival. Adjacent areas would display differences of up to 2.82 minutes (169.3 seconds). GLM analysis indicated the mean time to arrival as significantly influenced by zone, medical emergency level, geographical distance, and interactions of the latter two factors with the former ($p<0.001$ for the model). On the other hand, the standardized R-squared=0.22 and partial Eta-squared values between 0.027 and 0.053 would require more explanatory factors for the variability in the time to arrival to be sought.

Keywords: Emergency Medical Services; Ambulance Dispatch Centers; Ambulance Time to Arrival; Pre-Hospital Delay

Introduction

Emergency medical service is activated at the community level when someone identifies a perceived emergency condition requiring urgent medical care and makes an emergency phone call. Such a call triggers a cascade of events resulting in a timely response and service directed to patient stabilization and/or safe transportation to the nearest appropriate care facility. Delivery of efficient emergency medical services is critical in reducing mortality and disability rates. The response time is defined as the interval from receiving the call by the dispatch center to the arrival of the ambulance at the emergency scene. This time elapse is the main indicator of the ambulance performance [1]. Prompt response in the ambulance services is an essential factor for favorable outcomes in time-critical situations [2-5]. Required ambulance response time varies within large limits from country to country, e.g. 8 minutes in the UK, and 27 minutes in Brazil. In most European countries, it is 15 minutes or less for high priority red codes [1]. The Romanian emergency services reported a 12-minute average response time in 2018, with no more details about distribution on emergency codes or across the geographical areas for this performance indicator [6].

Organization of the ambulance services is a key factor in assuring appropriate response times, with similar regulations and examples of best practices at the European level [7]. The outcomes of emergency care services are dependent on this performance [1, 8]. They are also related to the public health expenditures, life expectancy, and even to the Human Development Index (HDI, http://hdr.undp.org/en/content/human-development-index-hdi).

Efforts have been made to improve the policies of resources' allocation, all over the world from Brazil to Europe, with proposed solutions on a wide range: from many smaller dispatch centers evenly distributed on geographical areas, to fewer but larger centers with concentrated resources, and dynamic allocation [9-12].

Timiş County is one of the largest in the country (both in terms of geographical territory and population density) and used to operate two dispatch centers in Timişoara metropolitan area. The city undertakes over 60% of the total emergency services in the county. We conducted a retrospective investigation on the performance of the Ambulance Service of Timişoara in the prospect of reorganizing the ambulance fleet and a possible new dispatch center versus a dynamic deployment of resources.

Data and Methods

This cross-sectional study comprised the data collected by the Ambulance Service of Timişoara on all solved cases in 2018, streets with the total number of calls and the four-level emergency number of calls for each; and shortest, longest, and average response time for each street. The Ambulance Service Administration approved the research project and no further approval of the Ethics Committee or informed consents were necessary, as the data concerned the service workflow and were already summarized at the street level, with no health-related or personally identifiable information.

At the time of the analysis, Timişoara had two dispatch centers, shown on the map in Figure 1. A total number of 1067 streets were recorded in 2018. The data set had many spurious streets with few registered calls and we identified two sources of errors: (i) duplicated streets written with and without diacritical marks; (ii) non-identifiable streets, with misspelled registered names. No selection constriction was put on the time to arrival. Interested in the traffic patterns and response issues across the city, we considered the small streets with low population density as too fine-grained for the present analysis; therefore we selected the streets with at least 50 total calls over the four emergency codes in 2018.

After the data cleansing, a total of 234 streets were selected for the final analysis.

The transport and crew allocation policy would ground on the river geographical position across the city, from East to West: the central center takes all calls from the northern region and the other one takes those from the southern region. Based on the river as a natural barrier between North and South and the large crossover roads, four area quarters were delimited in the city geographical territory and used in our analysis (see Figure 1).

For each street, the geographical coordinates (latitude and longitude) were approximated, and the distance to the corresponding dispatch center was calculated based on the equirectangular approximation using the tool available at *www.movable-type.co.uk/scripts/latlong.html*.

A composite priority code was calculated as the emergency-code weighted value based on the recorded number of calls for each street, as shown in equation (1).

$$CompositePriorityCode = 4*Red + 3*Yellow + 2*Green + 1*Black \tag{1}$$

where *Red*, *Yellow*, *Green*, and *Black* are the numbers of calls for each emergency code, with *Red* and *Black* having the highest and lowest emergency levels, respectively

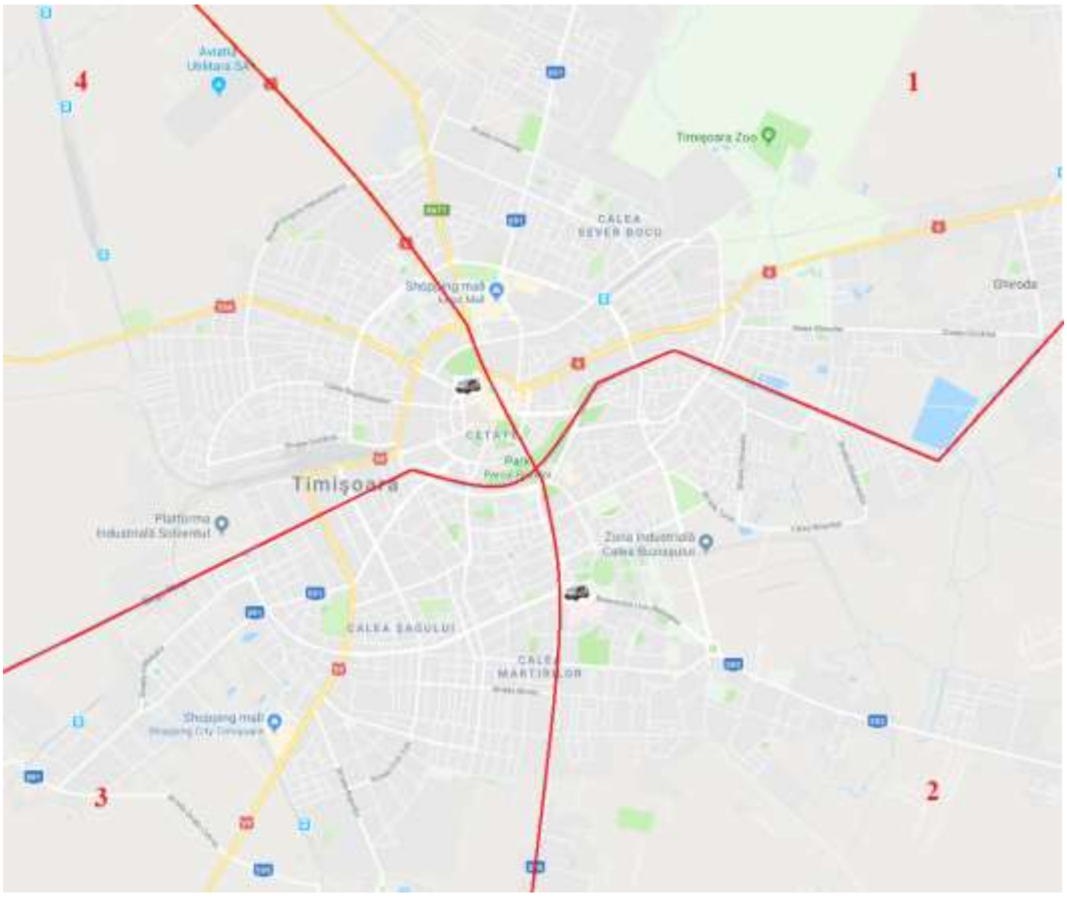

Figure 1. Map of Timişoara with the existing two ambulance dispatch centers in 2018 (marked with ambulance cars) and the four geographical zones considered for time response analysis

Descriptive statistics and multi-variable General Linear Model (GLM) were applied to summarize and analyze the input. Bonferroni adjustments for post-hoc comparisons were applied whenever necessary. All reported probability values were two-tailed, and a 0.05 level of significance was considered (with a corresponding 0.95 level of confidence for the estimates), while marking the highly significant values, as well. The analysis was conducted with the statistical software IBM SPSS trial version.

Results

The descriptive statistics for the time to arrival are shown in Table 1. The covered physical distance (in kilometers) for the four geographical zones, together with the composite priority code descriptive statistics are shown in Table 2. Figure 2 synthesizes the composite priority code and shows there is no apparent relationship between the priority code and the mean time to arrival. Nevertheless, Figure 3 would suggest a difference in this metric between the four zones.

Table 1. Descriptive statistics for the time to arrival. For each street in the zone, the shortest, longest, and average time (all in seconds) were retrieved from the database based on all solved cases in 2018. Based on street-level data, further zone-based statistics were calculated.

Time	Zone (no. of streets)	Min.	mean ± std. dev.	Max.
shortest [s]	**1** (n=56)	2	11.66 ± 33.175	209
	2 (n=49)	2	16.90 ± 35.992	194
	3 (n=81)	2	24.85 ± 48.67	252
	4 (n=48)	2	31.85 ± 60.1	272
longest [s]	**1** (n=56)	632	1489.05 ± 564.492	3754
	2 (n=49)	324	1399.67 ± 590.540	3693
	3 (n=81)	579	1744.69 ± 1384.128	9552
	4 (n=48)	651	3248.73 ± 12292.321	86586
average [s]	**1** (n=56)	268	488.29 ± 93.991	725
	2 (n=49)	139	398.67 ± 112.817	576
	3 (n=81)	183	427.02 ± 97.919	661
	4 (n=48)	279	519.27 ± 184.618	1577

Table 2. Descriptive statistics for the geographical distances (in kilometers) and the composite priority codes in each zone.

Zone	Distance [km] to the corresponding dispatch center			Composite priority code for a street		
	Q1	median	Q3	Q1	median	Q3
1	5.64	7.97	10.66	2.83	2.97	3.07
2	3.16	7.36	10.80	2.73	2.93	3.00
3	3.87	5.06	7.27	2.78	2.92	3.00
4	3.23	4.62	6.75	2.84	2.96	3.08

The Levene test for the equality of variances in time for the four zone was applied (p = 0.108), and subsequent GLM analysis was conducted. The results are presented in Table 3, with the estimates for the time to arrival in Table 4.

The results of the post-hoc comparisons with Bonferroni adjustments are presented in Table 5.

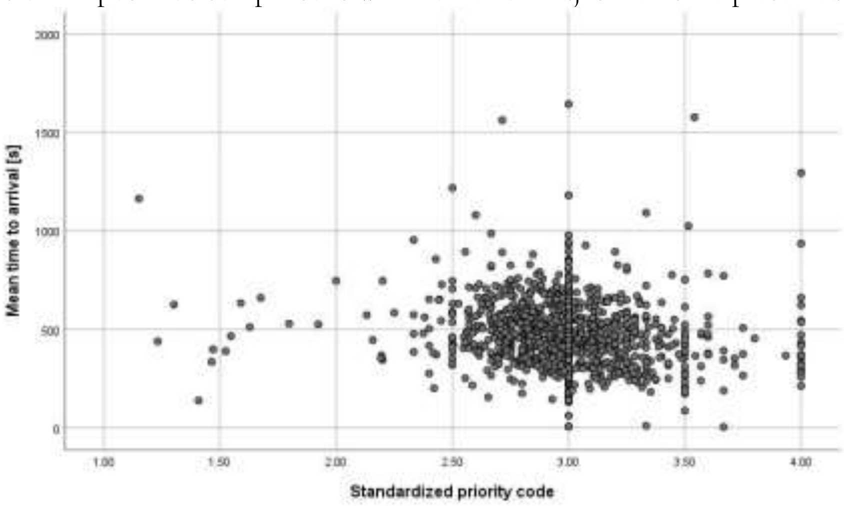

Figure 2. The mean time to arrival *vs.* the composite priority code: there is no apparent relationship between the two

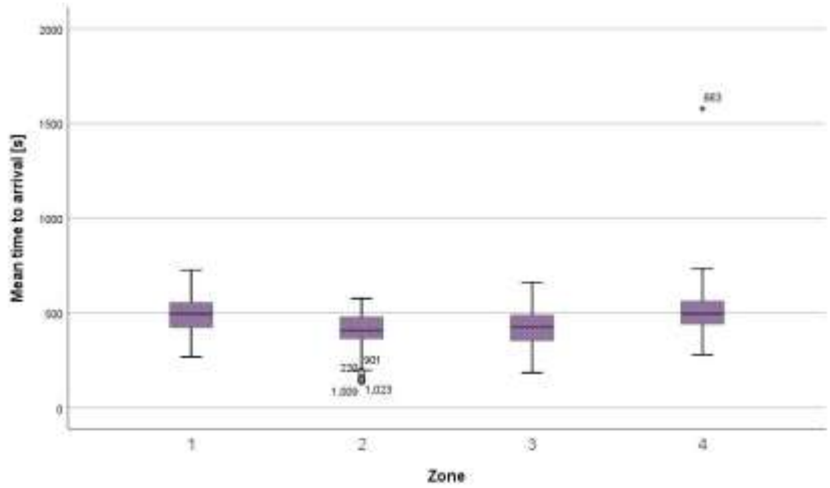

Figure 3. The mean time to arrival in the four zones. The bottom and top of each box indicate the 25th and 75th percentile, respectively, while the middle line is the median. The T-bars (*i.e.* "whiskers") extend 1.5 times the height of the box (*i.e.* the Inter-Quartile Range, IQR), thus approximately 95% of the values are expected to lie between these T-limits. The points below T-limit in Zone 2 are automatically assessed outliers. The star above the T-limit in Zone 4 would be an extreme outlier. The point- and star-labels indicate the record number in the data set.

Table 3. The results of the multi-variable GLM analysis

Source	Type III Sum of Squares	df	Mean Square	F	p-value	Partial Eta Squared
Corrected Model	1012740.205	11	92067.291	6.971	<0.001**	0.257
Intercept	869908.852	1	869908.852	65.862	<0.001**	0.229
Zone	114988.473	3	38329.491	2.902	0.036*	0.038
Priority code (PC)	114706.379	1	114706.379	8.685	0.004**	0.038
Distance [km] (D)	82680.164	1	82680.164	6.260	0.013*	0.027
Zone * PC	109788.608	3	36596.203	2.771	0.042*	0.036
Zone * D	162972.362	3	54324.121	4.113	0.007**	0.053
Error	2932203.457	222	13208.124			
Total	52318749.000	234				
Corrected Total	3944943.662	233				

R-squared = 0.257 (Adjusted R-squared = 0.22);
* statistical significance (p <0.05); ** highly statistical significance (p <0.01)

Table 4. Estimates for the mean time to arrival [s]. Covariates appearing in the model are evaluated at the following values: Priority code = 2.8688: Distance in km = 6.7953

Zone	Mean	Std. Error	95% Confidence Interval for Mean	
			Lower Bound	Upper Bound
1	495.540	18.224	459.625	531.455
2	391.982	16.675	359.121	424.842
3	423.866	12.857	398.529	449.203
4	513.129	20.563	472.606	553.652

Table 5. Pairwise comparisons for the mean time to arrival [s], based on Bonferroni adjustments

(I) Zone	(J) Zone	Mean Difference (I-J)	Std. Error	p-value	Bounds of 95% Confidence Interval for Difference	
					Lower	Upper
1	2	103.558*	24.702	<0.001**	37.800	169.316
	3	71.674*	22.303	0.009**	12.300	131.047
	4	-17.590	27.476	>0.999	-90.735	55.556
2	1	-103.558*	24.702	<0.001**	-169.316	-37.800
	3	-31.884	21.056	0.788	-87.937	24.168
	4	-121.148*	26.474	<0.001**	-191.624	-50.671
3	1	-71.674*	22.303	0.009**	-131.047	-12.300
	2	31.884	21.056	0.788	-24.168	87.937
	4	-89.263*	24.251	0.002**	-153.823	-24.704

* statistical significance (p <0.05); ** highly statistical significance (p <0.01)

Discussion

For the Ambulance Service of Timişoara, time to arrival showed an apparent North-South pattern, which proved to be significantly related to the river as a natural barrier for the ambulance vehicles. Adjacent geographical areas would have differences of up to 2.82 minutes (169.3 seconds), in the mean time to arrival, as shown in Table 5 for Zones 1 and 2, for a 95% level of confidence. The differences were even larger for opposite areas, up to 3.19 minutes (191.6 seconds), as for Zones 2 and 4.

In time-critical situations (such as major trauma, cardiac arrest, or acute ischemic cerebrovascular syndrome), three minutes is a significant difference for a performance metric in the ambulance response time. There is no clear evidence regarding the critical population catchment for the dispatch centers [9, 11] or the influence of distance and site of the incident [13, 14].

In our analysis, the medical emergency level for the calls seemed to be *Yellow* (i.e. medium high) with median values between 2.92 and 2.97 and narrow IQRs across all the four zones (Table 2), suggesting a homogeneous population in the city. Little less than half the calls originated in the northern area (104 out of the total 234). Taking all these into consideration, and based on discrepancy issues and their roots reported in other healthcare systems [15, 16], one would have expected less heterogeneity in the mean response time across Timisoara.

The approximated average distance to be travelled by an ambulance vehicle proved similar within each zone (results reported in Table 2), with median (IQR) within narrow ranges, although these are urban areas with speed limitation between 30 and 50 km/hour. Results in Table 2 show there is no "priviledged distance" for the South compared to the North of the city, as reported in other analyses [1, 15-18]. Therefore, the expected values for the mean time to arrival (reported in Table 4) with point-values of 7 minutes or less for South (392 seconds in Zone 2) and more than 8 minutes for North (513 seconds in Zone 4) would demand an explanation. In addition to these point estimates, the 95% confidence intervals for the mean time to arrival within North and South did not overlap, e.g. (6 to 7) minutes in Zone 2 and (7.88 to 9.22) minutes in Zone 4.

The GLM analysis (Table 3) indicated a highly significant influence of zone, medical emergency level, and distance from the dispatch center, on the mean time to arrival, thus proving a high level of confidence in generalizing the conclusions of the present analysis. Moreover, there was a statistically significant association of the latter two factors with the former (i.e. zone). On the other hand, the standardized R-squared of 0.22 means the model is able to explain only 22% of the variability in the mean time to arrival. Not surprisingly, the partial Eta-squared values are also rather small with the smallest contribution being the interaction between distance and zone (Table 3). Ranges in time to arrival of about 2 or 3 minutes have been considered of great importance [13, 14], thus such time discrepancies should not be underestimated and other explanatory factors for the variability in the mean time to arrival should be thoroughly sought.

Computer-based modeling and simulation have been harnessed for analyzing different scenarios or even trying to explain contributory factors to the outcomes in emergency healthcare [8, 9, 19-21]. Nonetheless, in addition to such powerful and promising instruments for conducting a research, all models need real and good quality data, both for training and validation. In the short time, we aim at developing strategies and protocols for collecting comprehensive and reliable data concerning the emergency healthcare in Timisoara, similar to other descriptive analysis [22].

The study we have reported had a few limitations. Firstly, we analyzed aggregated data and did not have any information concerning: (a) individual patients' health condition and co-morbidities; (b) availability of ambulance vehicles at the time of call; (c) time-related traffic patterns and conditions; (d) whether or not the emergency response was a standard arriving, i.e. complying with all the traffic signals, road signs, or speed limitations. Secondly, we focused on the coarse-grained data and discarded the streets with less than 50 calls in total for 2018.

In September 2019, the Ambulance Service of Timişoara opened a third dispatch center in the northern area of the city (Zone 1 in Figure 1), close to the highway exit and the nearby villages. Besides the financial effort to establish the new center (e.g. computer-aided dispatch systems, telecommunication hardware and software), no additional expenses were involved: both the car fleet and medical personnel were re-allocated from the other two existing facilities.

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgements

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