

ANALYSIS OF SPATIOTEMPORAL DATA TO PREDICT TRAFFIC CONDITIONS AIMING AT A SMART NAVIGATION SYSTEM FOR SUSTAINABLE URBAN MOBILITY

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Abstract:

Urban traffic congestion created by unsustainable transport systems and considered as a crucial problem for the urbanised areas provoking air pollution, heavy economic losses due to the time and fuel wasted and social inequity. The mitigation of this problem can improve efficiency, connectivity, accessibility, safety and quality of life, which are crucial parameters of sustainable urban mobility. Encouraging sustainable urban mobility through smart solutions is essential to make the cities more liveable, sustainable and smarter. In this context, this research aims to use spatiotemporal data that taxi vehicles adequately provide, to develop an intelligent system able to predict traffic conditions and provide navigation based on these predictions. GPS (Global Positioning System) data from taxi are analysed for the case of Thessaloniki city. Through data mining and map-matching process, the most appropriate data are selected for travel time calculations and predictions. Several algorithms are investigated to find the optimum for traffic states prediction for the specific case study concluding that ANN (Artificial Neural Networks) outperforms. Then, a new road network map is created by producing spatiotemporal models for every road segment under investigation through a linear regression implementation. Moreover, the possibility to predict vehicle emissions from travel times is investigated. Finally, an application with a graphical user interface is developed, that navigates the users with the criteria of the shortest path in terms of trip length, travel time shortest path and “eco” path. The outcome of this research is an essential tool for drivers to avoid congestion spots saving time and fuel, for stakeholders to reveal the problematic of the road network that needs amendments and for emergency vehicles to arrive at the emergency spot faster. Besides that, according to an indicator-based qualitative assessment of the proposed navigation system, it is concluded that it contributes significantly to environmental protection and economy enhancing sustainable urban mobility.

Keywords: spatiotemporal data, travel time prediction, smart navigation, urban mobility

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1. Introduction

In the era of “Big Data”, spatiotemporal data dominate many domains such as climate science, social science, epidemiology, transportations, mobile health and Earth sciences (Atluri et al., 2017). As far as the domain of transportation is concerned, Intelligent Transportation Systems (ITSs) are increasingly turning to be essential (Cotton, 2013). ITS use sensor technology such as Global Positioning System (GPS) to gather spatiotemporal data (D’Andrea et al., 2016). GPS devices enable the continuous data logging of equipment location in addition to simultaneously recording timestamps (Pradhananga et al., 2013); thus, they provide precious spatiotemporal data that can contribute to various studies. More specifically, vehicles and mobile phones can benefit from GPS data. Amongst them, taxi-vehicles can give as well data with broader coverage of road network and high frequency (Zhang et al., 2017). Nowadays, many taxis have installed GPS receivers contributing to the production of massive trajectory data (Cai et al., 2017). Data collection from taxis’ GPS receivers is significantly much more comfortable in comparison with mobile phone data, floating car data and cargo transport vehicle. What is more, these data can provide accurate information concerning the travel route and travel time (Zhang et al., 2017). Taxis’ GPS data are valuable for the development of solutions that can mitigate the traffic congestion problem and ameliorate mobility in urban areas. Mobility is a crucial issue as it is constrained significantly in these areas (D’Orey et al., 2014). The majority of the population, as well as economic development, exist in urban areas, especially in European countries, thus intensifying the traffic congestions problems. As a result, the traditional transport system comprises a sizeable percentage of total carbon emissions, air pollution, degraded health, resource inefficiencies leading to oil price increase and traffic congestion (Lam et al., 2012). In the USA, traffic congestion is responsible for the waste of 1.9 billion gallons of fuel, of 4.8 billion hours of extra time and 101 billion dollars of delay and fuel cost while in European Union, congestions cost 1% of the total GDP annually (D’Orey et al., 2014). For all the above reasons, the transport sector is of prime importance to achieve sustainable development as it has been defined in the “Brundtland Commission” (United Nations, 1987). Transportation affects significantly all the pillars of sustainable development,

namely environment, economy and society (Sdoukopoulos et al., 2019). For this reason, green papers have been devoted to urban mobility, where environmental degradation is identified. According to the European Commission, there is the need to develop ecological transport systems, environmentally and human-friendly (Ambroziak et al., 2014).

Trying to mitigate the aforementioned problems, EU has set the concept of Sustainable Urban Mobility Plans (SUMP), which have as a goal to improve the accessibility of urban areas and to provide high-quality and sustainable mobility and transport, through and within the urban areas (European Commission, 2013). Also, the United Nations have defined a “Global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development” (United Nations, 2017).

In this paper, we, therefore, aim to use spatiotemporal data for the development of a system that can contribute significantly to Sustainable Development by enhancing Sustainable Urban Mobility through traffic congestion mitigation. The proposed system predicts travel time and further navigates the drivers based on traffic predictions by gathering spatiotemporal data from GPS receivers of taxi vehicles. The predictions of future conditions of roads segments contribute significantly to traffic congestion reduction (Lécué et al., 2013). Namely, the objectives of the proposed system are the followings: (1) Development of a generic methodology beneficial for every urban road network. (2) Development of an automated smart system that will be ameliorated by itself without requiring human intervention. (3) Development of a GIS-based system independent from every external GIS software. The integration of GPS data to GIS for systems’ development provides a wide variety of applications in the land transportation offering improved accuracy of spatial data, speed of data transmission and low cost (Mintsis et al., 2004). (4) Development of a system that can produce an autonomous road network map making the system independent of any external map. (5) Development of a tool that facilitates the navigation process, finding the optimum paths based on travel time predictions and fuel emissions.

In the following paragraphs, a literature review is presented (section 2) followed by a thorough presentation of the methodology (section 3). Section 4 portrays a comparative analysis amongst the proposed

system and other related systems. In section 5, the contribution to sustainable urban mobility of the proposed system is presented, which is followed by the conclusions (section 6).

2. Related work

2.1. Use of GPS data in transportation research

GPS data contain valuable information, and since 1970 many researchers have used in a great variety of studies such as driver's behaviour, demand pattern, traffic conditions and signal-timing estimation (Schäfer et al., 2002, Yang et al., 2014; Keler et al., 2016; Ferreira et al., 2013b; Sohr et al., 2016; Zhang et al., 2017).

More precisely, in 2002, Schafer et al. used taxi GPS data to analyse the travel time in Berlin (Schäfer et al., 2002). Kamran et al. used real-time GPS traces to detect incidents in Coventry based on vehicles velocity and anomalous road segments (Kamran et al., 2007). Li et al. used taxi GPS trajectories to study the passengers' behaviour to predict the spots with high demand for the taxi. Thus, they suggested the optimum positions for taxi drivers (Li et al., 2011). Yang et al., proposed their methodology to investigate the typical demand for transport in Boston, aiming at the optimum traffic management system (Yang et al., 2014). Yu et al. collected historic trajectory data from the taxi in Beijing to investigate the traffic and develop a system to navigate drivers (Cai et al., 2017; Zheng, 2015). Respectively, Ranjit et al. implemented the same study for Nepal (Ranjit et al., 2016). Many researchers proposed the use of taxi GPS traces for the visualisation of traffic congestion spots in various cities such as Shanghai and New York (Keler et al., 2016; Ferreira et al., 2013). In 2016, Sohr et al. used these data to develop an information system for the traffic condition in Vietnam (Sohr et al., 2016). Xiao et al. used taxi GPS traces in the city of Nanjing, China, to understand urban taxi mobility. They analysed the spatial distributions of the trips (distances and time) to explore the factors which influence the urban taxi carpooling (Xiao et al., 2018).

2.2. Map-matching

Vehicle position is a crucial task mainly in urban areas with narrow roads, tall buildings and other signal degrading environments (Lakakis et al., 2014a). Thus, wrongly positioning is likely to happen (Jiménez et al., 2016). The map-matching process assigns the location of the vehicle to a road segment

on a digital map. Several map-matching algorithms have been developed, which are categorised as follows:

- Geometric: these approaches use the geometry of the study area. The most common methodologies are point-to-point, point-to-curve and curve-to-curve.
 - Topological: they use the geometry of the area, the connectivity and the continuity.
 - Probabilistic: they use a confidence area which may be ellipsoid or rectangular.
 - Based on statistical models: these methods use statistical models such as Hidden Markov or linear regression
 - Advanced algorithms: Fuzzy logic, Kalman Filter, Neural Networks
- Their accuracies vary from 85% to 98.5% (Kyriakou, 2017).

2.3. Algorithms for traffic prediction

The literature review reveals a rich repertoire of algorithms which have been used for traffic predictions. The algorithms are categorised as following parametric (Exponential smoothing, ARMA, Kalman Filter, etc.) and non-parametric. The most commonly used algorithms are the following: Spectral analysis, autoregressive integrated moving average model (ARIMA), Historical Average, Kalman Filter, K-Nearest Neighbourhood (KNN), Artificial Neural Networks and Random Forest. The process for the selection of optimum algorithm is a crucial and complicated task as each algorithm has negatives and positives. The historical average cannot respond immediately to unexpected events, and this is likely to happen in a road network such as an accident. In the case of the Kalman filter, the accuracy significantly decreases when there are significant changes. For the ANN, the accuracy is heavily depended on the training and more precisely on the quality of the data, the number of hidden layers and the epochs. ARIMA is prone to missing values (Kyriakou, 2017).

The use of statistical indicators may suggest the most accurate algorithm for each case. However, it is required at least two different statistic indicators to select the most effective algorithm (Shin, 2017). The most common indicators for the selection of an algorithm are presenting below (Kyriakou 2017):

- Mean Square Error (MSE),
- Mean Absolute Error (MAE),

- Root Mean Square Error (RMSE),
- Mean Absolute Percentage Error (MAPE),
- Mean Bias Error (MBE),
- Normalized Mean Square Error (NMSE).

2.4. Eco-routing

Many studies have shown that selecting different travel paths between the same origin and destination can contribute significantly to diminish the amount of fuel consumed and the produced emissions (Boriboonsomsin et al., 2012). The results for the case study of Thessaloniki showed that if 50 drivers had opted the “eco-route” the produced emissions would be diminished by 10% (Lakakis et al., 2015). Also, according to Ericsson et al., the “eco-route” selection can contribute to 8.2% fuel saving (Ericsson et al., 2006). So finding the most environmentally friendly route is formulated as “eco-routing” problem and many methods have been proposed the last years (Ericsson et al., 2006; Barth et al., 2007; Boriboonsomsin et al., 2012; Nie et al., 2013).

The calculation of emissions is a process that requires many factors to be taken into consideration such as vehicle age, fuel type, vehicle type (EURO 4, 5 et-c.), environmental temperature, use of air-conditioning, etc. (Abo-Qudais et al., 2005). Nowadays, various software permits the emissions calculation with high accuracy such as COPERT.

3. Methodology

The proposed system is designed to predict travel times and navigate the drivers based on the shortest travel time instead of the shortest distance integrating a module for eco-navigation. As a first step, a data mining system is used to select the appropriate GPS data amongst the millions of provided data. Second, a map-matching process is implemented to assign with high accuracy the GPS points to the road segments. This process also leads to the production of a road network map. Then an investigation of the algorithms is carried out to find out the most accurate for the current study and further predict travel times. Calculated travel times from GPS data are used for both the investigation of algorithms and the prediction through the selected one. Furthermore, an eco-route approach is presented based on the calculated travel times. Part of the proposed methodology is used for the development of a GIS-based application that navigates the drivers based on shortest travel time or the “green” path.

3.1. Study area

The study area is the urban road network of the city centre in Thessaloniki, which is the second biggest city in Greece. This area consists a typical central business district as many land uses are concentrated such as residential areas, public services, health, shopping areas, industrial, commercial and service areas, education, tourism, churches etc. (GeoSpatial Enabling Technologies, 2016). The land uses affect the attracted direction, the traffic flow, the travel model and the public traffic demand (Zhang et al., 2017). Approximately 2.4 million daily travels take place in the city of Thessaloniki (Papaioannou, 2012). According to estimations, 94500 vehicles cross the main central arterials daily, and the average peak-hour velocity in the city centre is 6 km/h approximately. Private transportation has been increased in the last years, reaching a percentage of 70%, and the average ratio person per vehicle is only 1.1 (Klotildi, 2014).

For the implementation of the proposed methodology, the urban road network of Thessaloniki was divided into road segments. The criterion was the existence of a node with a traffic light. Figure 1 presents the 78 road segments, the 64 nodes and the hierarchy of roads.

Table 1 presents the roads under study with their characteristics. Most of the road segments have one direction and one to four lanes.

3.2. Spatiotemporal data

Taxi provided the required spatiotemporal data, which use GPS receivers for navigation in the city. While these taxis travel at the road network of Thessaloniki following the general traffic flow, they provide a large amount of GPS traces that include vehicles’ unique ID, coordinates, velocity, orientation, time and date. The laboratory of Geodesy and Geomatics of the Faculty of Civil Engineering of Aristotle University of Thessaloniki and Compucon Company collected the required data. The spatiotemporal data concerned September of 2007 (105000 points per day) and September of 2015 (1 million points per day). The drivers did not follow a predefined path; they travelled without any restrictions in the city. Figure 2 depicts the big data that allows creating the road network of Thessaloniki by just plotting the GPS points.

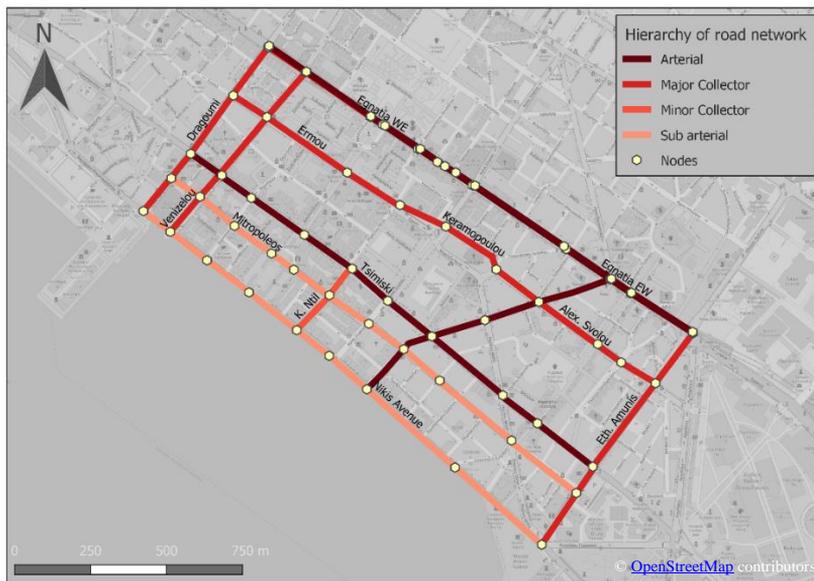


Fig. 1. Road network under-study in Thessaloniki city and its hierarchy

Table 1. Studying road segments of the road network in Thessaloniki city

Road	Hierarchy	Direction	Lanes per direction	Num. Of Road Segments
Tsimiski	Arterial	Single	4	9
Egnatia	Arterial	Double	3	LR* 11, RL** 10
Mitropoleos	Sub arterial	Single	1	10
Nikis Avenue	Sub arterial	Single	2	5
Ermou	Major Collector	Double	1	4
Svolou	Major Collector	Single	1	4
Dragoumi	Major Collector	Single	2	2
Benizelou	Major Collector	Single	2	2
Eth. Amunis	Major Collector	Single	3	4
Bogatsikou	Minor Collector	Single	1	1
Keramopoulou	Minor Collector	Single	1	1
Kouskoura	Minor Collector	Single	1	1
P.P. Germanou	Minor Collector	Single	1	2
K. Ntill	Minor Collector	Single	1	2

*Left to Right, **Right to Left

A data mining system has been developed with the use of the programming language MatLab and ArcGIS and Model Builder, which are provided by ESRI. The stages of the data mining system are briefly described below:

– **GPS Point classification:** the raw data (stored in CSV files) are clustered per day per year using a script which was developed in MatLab for the needs of the current study.

- **Conversion of GPS points to geospatial vector data:** the classified data are stored as Shapefiles (shp) which are compatible with various GIS software using a MatLab-based script.
- **Creation of a database management system:** the significant amount of data leads to a great number of shapefiles. Therefore, it is essential to structure them in a geodatabase which has a comprehensive information model for representing and managing the data. For this step, ArcGIS software was used.

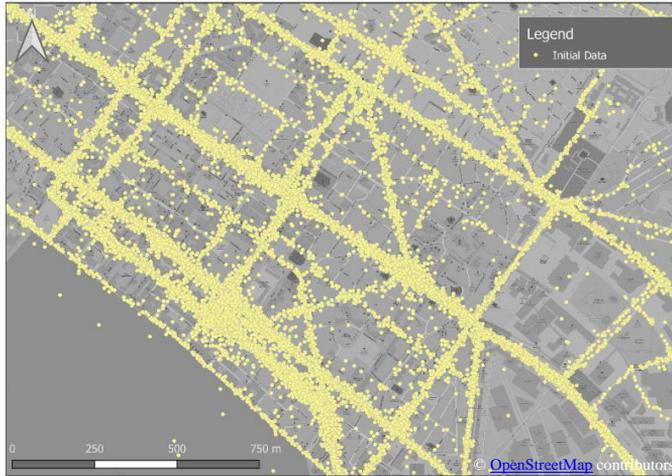


Fig. 2. Reconstructed structure of the road network in Thessaloniki from taxi traces

- **Selection of roads segments under study:** in this stage, the road network of the city in vector format is used, and then the study area is extracted through Model Builder. The outcome is a map of vectors presenting only the road segments under study.
- **Selection of GPS points for the study area:** the stored shapefiles contain GPS points for the whole city. Thus in this stage, the GPS points for the study area are selected using a buffer tool in model builder.
- **Evaluation of orientation rule fulfilment:** the selected GPS data from the previous step may include GPS for road segments that are not under study. Hence, the rule of orientation is used to exclude data that are not for the study area. This rule is based on the assumption that the GPS points must have orientation values in a specific range as all the vehicle travel to the same direction or the opposite (depending on the road segment on which they travel). GPS points with different values of orientation indicate vehicle which travels at other road segments that may be connected to the road segments under study. The outcome of this step (which is the outcome of the entire process) is a bunch of GPS points assigned to the road segments which are under study. The model builder tool is also used for this step.

Figure 3 portrays the stages with the associated outcomes of the entire process and the used tools (MatLab, ArcGIS and Model Builder).

A map-matching process follows on the assigned GPS points that are produced from the mining system. The map-matching was implemented through linear regression as the accuracy is about 2.5 m for a confidence level of 99.5% (Lakakis et al., 2004). The outcome of this process was GPS points assigned to the actual road segment on which they travel with higher accuracy. On the same time, this process ensured the use of the proper traces for the study area. Through equation (1) of linear regression, a spatial model was also produced for each road segment using coordinates.

$$\hat{y} = \hat{\alpha} + \hat{\beta} * x + \varepsilon \quad (1)$$

where: \hat{y} is the predicted value for a specific value of x .

Table 2 depicts a sample of the produced spatial models for the years 2007 and 2015 for all the road segments of Niki's Avenue. Additionally, a prediction zone has been calculated for each road segment for a 97.5% confidence level. The smaller prediction zones, the higher accuracies. The prediction zones of the spatial models of 2015 are smaller than 2017 and this is expected as there were more data for this year. Coefficient R^2 has also been calculated to evaluate the accuracy of the spatial models. The high values of R^2 indicate the high accuracy of the spatial models.

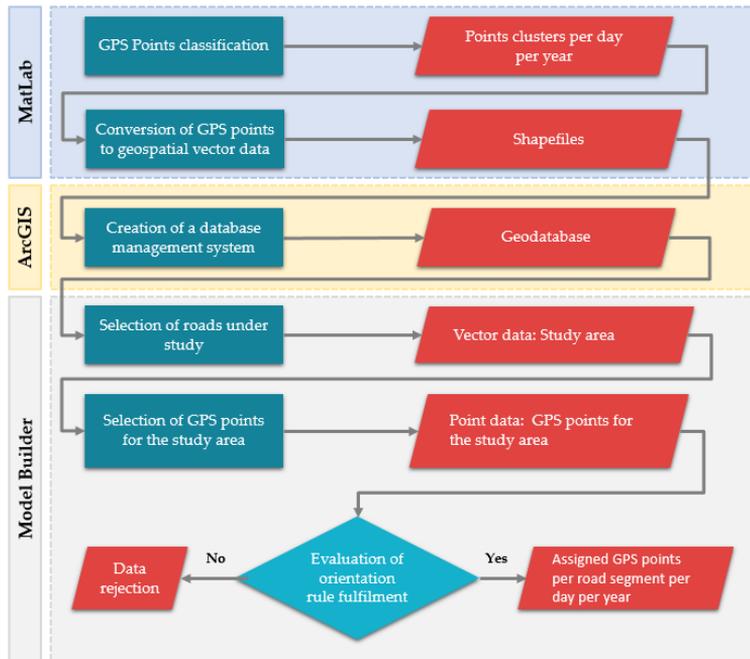


Figure 3. Flowchart of the data mining process

Table 2. Spatiotemporal models of road segments for 2007 and 2015

Code	Spatial Model 2007	Prediction Zone (m) 2007	R ²	Spatial Model 2015	Prediction Zone (m) 2015	R ²
NOT1	$Y = 4812692.653326 - 0.766698 * x$	6.0282	0.97	$Y = 4825478.705944 - 0.797876 * x$	5.8063	0.99
NOT2	$Y = 4814727.696726 - 0.771664 * x$	6.5251	0.95	$Y = 4818300.270773 - 0.780374 * x$	6.093	0.99
NOT3	$Y = 4825093.818733 - 0.796935 * x$	6.7506	0.97	$Y = 4832772.633873 - 0.815654 * x$	5.9964	0.99
NOT4	$Y = 4877631.531434 - 0.924939 * x$	6.8503	0.98	$Y = 4873755.452305 - 0.915506 * x$	5.3613	0.99
NOT5	$Y = 4851915.079020 - 0.862334 * x$	7.8382	0.95	$Y = 4872846.680328 - 0.913294 * x$	6.6986	0.99

3.3. Background map production of the road network and qualitative assessment

Implementing the map-matching process for every single road segment contributed to the creation of a road network map. Consequently, the proposed system itself can produce the required background map of the road network. This is very important, as it permits the system to be independent of a background map. Simultaneously, it works as a “closed system”,

which uses input data to produce a map for navigation purposes. Moreover, this is also vital, as the system can be flexible to every change of the road network; for instance, some constructions may lead to the closure of road segments. The proposed system can realise this change, so it will not navigate the driver through the closed road segment. Finally, yet importantly, the system can be ameliorated by itself without any human intervention. Every time that

new data are inserted at the system, the accuracy is improved due to big data, so it is a smart system. A high accuracy integrated system is also developed for the produced map quality assessment using the inertial system ELLIPSE N of the SBG Company. The GPS/INS system collects spatiotemporal data communicating with the following systems:

- Global Navigation Satellite System (GLONASS)
- Quasi-Zenith Satellite System (QZSS)
- BeiDou Navigation Satellite System,
- Satellite-based Augmentation Systems (SBAS)
- GALILEO.

Figure 4a presents the installation of the GPS/INS system on a private vehicle. The GPS was installed on the top of a private car, and the inertial system was installed inside the car exactly above the GPS. Both of them were fixed to avoid any movements that may contribute to noisy measurements. Figure 4b shows a sample of sensor data that were collected through a real-world field-study at the road network

in the urban environment of Thessaloniki. These data were used to calculate the confidence interval based on equations of linear regression that are given below (Lakakis et al., 2004):

$$\hat{\alpha} \pm s_{\alpha} * t_{\frac{\alpha}{2}} \tag{2}$$

$$\hat{\beta} \pm s_{\beta} * t_{\frac{\beta}{2}} \tag{3}$$

where: s is the estimator of variance and $t_{\frac{\alpha}{2}}$ is the value of distribution t for n-2 freedom degrees for significance level α . The smaller confidence intervals for the parameters α and β the more qualitative measurements. The confidence intervals were used for the qualitative assessment of the produced map. In Table 3 confidence intervals are presented for all the road segments of Venizelou Street that were produced based on the equations (2) and (3), and Table 4 shows the associated ranges of confidence intervals.



GPS Time (s)	Roll (°)	Pitch (°)	Yaw (°)	Latitude (°)	Longitude (°)	Altitude (m)
153196.000	0.893	0.246	304.288	40.636270772	22.043408712	23.752
153197.000	1.196	0.282	304.258	40.636307611	22.043397998	23.484
153198.000	1.226	0.386	304.156	40.636345380	22.043325840	23.224
153199.000	1.227	0.273	303.545	40.636381641	22.043252327	22.954
153200.000	1.078	0.421	303.209	40.636419637	22.043180378	22.718
153201.000	1.272	0.676	302.129	40.636456505	22.043106180	22.532
153202.000	0.762	0.568	300.732	40.636493068	22.043032414	22.308
153203.000	-0.755	-0.841	298.244	40.636534348	22.042933762	21.999
153204.000	-0.169	0.505	296.950	40.636572482	22.042863674	21.792
153205.000	-1.437	0.234	294.919	40.636608866	22.042737792	21.601
153206.000	-2.472	-0.220	294.975	40.636640325	22.042666843	21.392
153207.000	-2.991	-0.365	297.233	40.636670699	22.042595548	21.208
153208.000	-2.728	0.143	299.748	40.636699834	22.042526048	21.033
153209.000	-2.857	0.179	302.179	40.636725442	22.042454114	20.869
153210.000	-3.217	0.175	304.171	40.636745185	22.042382475	20.852
153211.000	-3.087	0.234	305.478	40.636762028	22.042317801	20.714
153212.000	-2.957	0.337	305.913	40.636765192	22.042266932	20.643
153213.000	-2.849	0.467	305.098	40.636766873	22.042216417	20.595
153214.000	-2.843	0.636	305.892	40.636766088	22.042164295	20.549
153215.000	-2.837	0.640	305.895	40.636767022	22.042164848	20.562
153216.000	-2.833	0.641	305.899	40.636767423	22.042164362	20.597
153217.000	-2.833	0.647	305.893	40.636767328	22.042164652	20.647
153218.000	-2.828	0.655	305.884	40.636767345	22.042164649	20.723
153219.000	-2.830	0.634	305.880	40.636767955	22.042164386	20.786
153220.000	-2.837	0.632	305.892	40.636767655	22.042163831	20.881
153221.000	-2.833	0.619	305.872	40.636767813	22.042163380	20.978
153222.000	-2.750	0.833	305.831	40.636769805	22.042159649	21.068
153223.000	-2.630	1.093	305.714	40.636778931	22.042143186	21.189

a)

b)

Fig. 4. GPS/ INS system: (a) installation of GPS/INS system, (b) a sample of sensor data collecting through a real-world field-study at the road network in the urban environment of Thessaloniki

Table 3. Confidence Intervals for parameters α and β for the road segments of Venizelou Street

Road Segment	Confidence Intervals							
	GPS				GPS/INS			
	β		α		β		α	
	Lower limit	Upper limit	Lower limit	Upper limit	Lower limit	Upper limit	Lower limit	Upper limit
1	0.942185294	1.066042612	4061199.287	4111993.692	1.238077241	1.241602434	3989192.646	3990638.334
2	0.903888979	0.97394134	4098978.581	4127710.113	1.166247797	1.169303386	4018842.686	4020095.891
3	1.146647652	1.177229792	4015595.994	4028142.023	1.20272244	1.204398601	4004447.762	4005135.336
4	1.222758596	1.257759191	3982555.971	3996917.685	1.214155162	1.215173753	4000027.218	4000445.176

Table 4. Range of confidence intervals for the qualitative assessment of produced road network map for Venizelou Street

Range of confidence intervals			
GPS		GPS/INS	
β	α	β	α
0.123857319	50794.40496	0.0035252	1445.6873743
0.070052362	28731.53227	0.0030556	1253.2049708
0.03058214	12546.02919	0.0016762	687.5732302
0.035000595	14361.71442	0.0010186	417.9580612

A plot was created for every single road segment to investigate if the produced road network map is between the calculated upper and lower limits. Figure 5 presents the qualitative assessment for all the road segments of Niki’s Avenue. For every single road segment, the evaluation was positive. In some cases, the limits were extremely narrow, and this augmented the accuracy of results.

3.4. Travel time calculation and prediction

The method for the travel time calculation has been presented in detail by some of the co-authors at previous publications (Lakakis et al., 2014b), (Lakakis et al., 2014a). However, it is worth mentioning that time periods and homogenous time zones were defined based on the hours, and the land uses that pre-

dominate. These travel times were used in the following algorithms to predict travel times: Kalman Filter, Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Networks (ANN), k-nearest neighbour. The parameters for the predictions were the day, the hour and the homogenous time zone, time periods and velocity of vehicles which varied from 10km/h to 80 km/h despite the limits (50km/h). The use of the velocity as a parameter for the algorithms increased the accuracy of the predictions significantly. The following statistical indicators were calculated for each algorithm to select the most accurate for the current study:

- Mean Square Error (MSE)
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

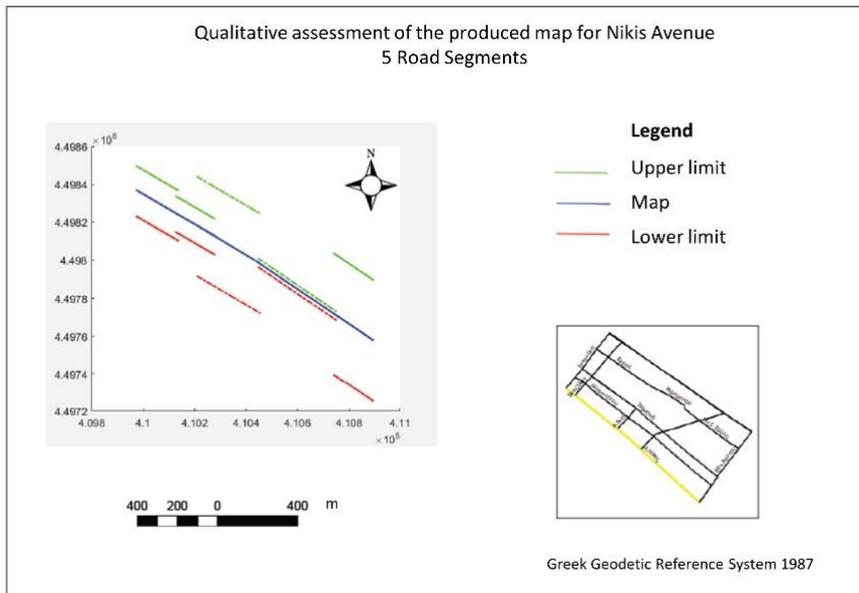


Fig. 5. Qualitative assessment of the produced map for Nikis Avenue

Table 5 shows the calculated statistical indicators for every algorithm. ANN was selected as the optimum since ANN had the minimum values at three different indicators as Table 5 presents. The architecture of the selected ANN models was one hidden layer and 17 neurons.

3.5. Eco-routing

In the current research, the potential of integrating an eco-routing module at the proposed smart navigation system is investigated. The aim is not to calculate the emission with the highest possible accuracy. Instead, the possibility of integrating the module of green navigation at the proposed system is examined. The equations presented hereinafter were used to calculate the amount of CO, NO and NO₂ emissions. These are the most important emissions (Elefteriadou, 2013). The equations are the following (Al-Khateeb, 1993):

$$CO(ppm) = 0.004331 * (vph)^{0.993} \quad (4)$$

$$NO(ppm) = 0.000147 * (vph)^{0.949} \quad (5)$$

$$NO_2(ppm) = 0.000038 * (vph)^{1.008} \quad (6)$$

Where vph is the traffic volume of vehicles per hour.

The formulation for the calculation of traffic volume is given below (Frantzeskakis et al., 1986):

$$Q = 122 * \bar{V} - 1.65 * \bar{V}^2 \quad (7)$$

where \bar{V} is the average vehicle's velocity based on the following equation:

$$\bar{V} = V_f - \frac{V_f}{K_j} \quad (8)$$

where \bar{V} is the average vehicle's velocity, V_f the free flow velocity and K_j the traffic density in case of traffic congestion. However, there are some constraints for the use of the above equations. The researcher should define thresholds values concerning the free flow velocity and traffic density velocity (Wilson, 2011).

3.6. Software development

Part of the proposed methodology was used for the development of an application that navigates the drivers based on shortest travel time or the "green" path. The proposed method and the custom code attempted to integrate the following disciplines: geoinformatics, spatiotemporal data analysis and optimum prediction algorithm. This integration constitutes an effective process to predict travel time for every urban area. The GIS-based application is user-friendly, open-source and is characterised by open architecture. Every user who needs to make a decision can use this application without being a specialist. The results can be exported to files, which are compatible with GIS software.

The software named SmARt - Ur -Navigation (SmARt Urban Navigation) and it is a GIS-based software. It runs on desktops and laptops, and it does not require the installation of any external software. Figure 6 depicts the architecture of the developed software and Figure 7 presents the relational databases that software uses.

Table 5. Statistical indicators for the implemented algorithms

Algorithms	Model	Mean Square Error (MSE)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	Mean Absolute Percentage Error (MAPE)
KNN	K = 100	1.335*10 ⁻⁸	1.70539*10⁻⁶	1.155659*10 ⁻⁴	25.9106
Kalman filter		2.555*10 ⁻⁸	1.42694*10 ⁻⁵	1.598533*10 ⁻⁴	36.1709
ARIMA	(0,0,3) (0,1,3)	4.319*10 ⁻⁸	1.79206*10 ⁻⁶	2.078455*10 ⁻⁴	31.5872
ANN	17 Neurons	6.894*10⁻⁹	1.80238*10 ⁻⁵	8.303113*10⁻⁵	15.5584

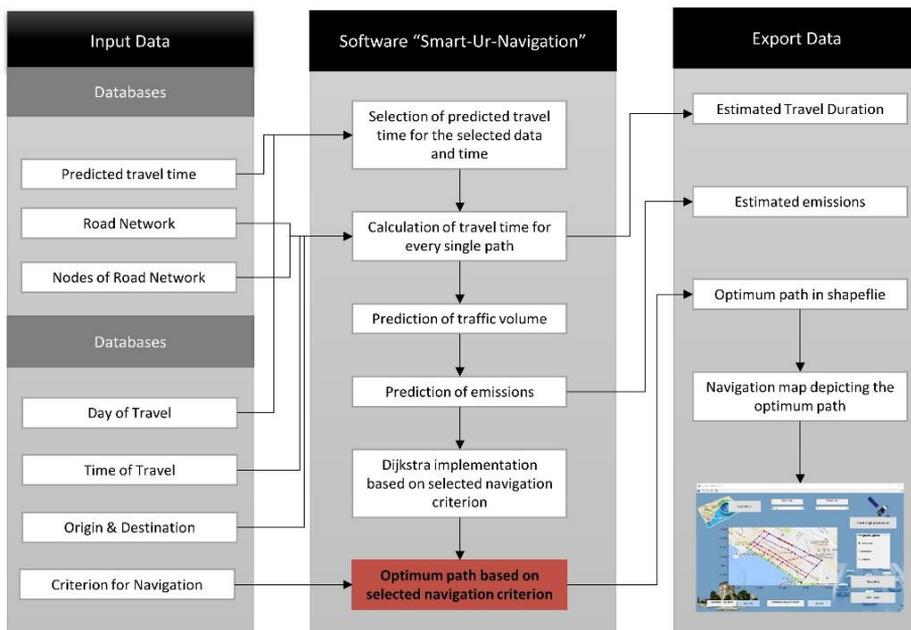


Figure 6. Software's architecture – from input data (left) to navigation map (right)

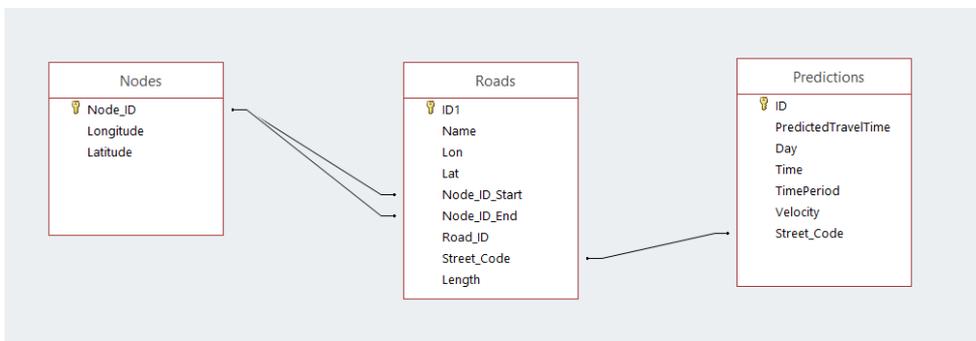


Figure 7. Relational databases of software

3.7. Case-study

A driver wishes to travel from node A to node B on Friday night at 21.00. According to our proposed system, if the driver opts the travel time as navigation criterion, the driver will travel 1.74 km and will need 4 minutes and 49 seconds while the produced emissions will be 35.72 ppm as it is presented in Figure 8. If the driver opts the “eco-route”, the system proposes the path that it is depicted in Figure 9. The total distance will be 1.68 km, the entire duration 5

minutes and 31 second and the produced emissions will be 35.64 ppm. Therefore, in this case, the shortest path is the same as the eco-path but not the same as the shortest travel time path. Boriboonsomsin et al. noticed the same for the case-study of Los Angeles. According to their study, the shortest route was the same as the eco-path but not the same as the shortest travel time path (Boriboonsomsin et al., 2012).



Figure 8 and 9. The outcome of the software based on user's selection

In this scenario, the influence of traffic congestion on travel time. A driver needs to drive from node A to node B that has a distance of 1.38 km on Tuesday morning at 11.00 and the same day at 21.00 at night is investigated. For the morning path, the optimum path based on shortest travel time criterion has duration 5 minutes and 54 seconds and 29.6 ppm produced emissions. On the contrary, if the driver follows the same path at night will need only 2 minutes and 47 seconds. This is expected, as the city centre of Thessaloniki is a Central Business Center and concentrates many land-uses, attracting too many transportations and provoking traffic congestion. The peaking patterns of traffic congestion in the morning and afternoon hours is the same as the pattern of every big urban centre (National Association of City Transportation Officials, 2012).

4. Comparative analysis of related and proposed system

The most recent navigation system for the city of Thessaloniki is Google maps from Google. This system provides the possibility to navigate based on travel times in real-time. Besides, it predicts travel times. However, travel time predictions are not accurate for short distances. The system was tested for travel time predictions for an accidentally Monday at 18.00. It was asked to predict the travel time for short routes such as 30m, 100m, 150m and 290m. The prediction was the same for each case, 1 minute. Consequently, the system cannot predict with high accuracy for the case study of Thessaloniki city. Finally, yet importantly, the system does not provide the possibility of eco navigation.

The next system that was studied is the "WISERIDE" that was developed by the company Emisia in 2014 incorporation with the Faculty of Civil En-

gineering of the Aristotle University of Thessaloniki. This system provides information about the current traffic conditions, the traffic volume and the associated emissions. The users can use the system both on a computer and on smartphone and can choose to be navigated based on travel time, shortest path and economic path. There is not an option for eco navigation. Besides, the users cannot select the day but only the hour of the travel. This system predicts travel time based on the relation between velocity and flow. Also, it predicts the emissions implementing the COPERT 4 methodology (Gavanas et al., 2014).

The last system was Thessaloniki's Intelligent Urban Mobility Management System (mobithess) which was developed by the Hellenic Institute of Transport – Centre for Research and Technology Hellas incorporation with Municipality of Thessaloniki, Thessaloniki's Integrated Transport Authority, Region of Central Macedonia and Norwegian Centre for Transport Research. It is a web-based platform with a friendly graphical user interface. This platform provides with various criteria for navigation, environmentally friendly, economic, shortest path and travel time. However, only time can be defined so the user can use it the same day of the travel. The emissions are calculated using real-time sensors while for the traffic prediction, dynamic and static models are used (Mitsakis et al., 2013).

From the comparative analysis, it is concluded that all the relative systems can work in real-time except from the proposed system in the framework of the current research that can work in almost real-time if it is connected to a real-time data provider. Smart-Ur-Navigation, WISERIDE and Mobithess use taxi GPS data while Google Maps used the GPS positions of the users who use a smartphone with the homonym application. Smart-Ur-Navigation and

Mobithess give the possibility to opt the “eco” path while the last one and WISERIDE provide the economic path option. Concerning the limitations, for the proposed system, it is required a considerable amount of data to work. Google Maps has not such a high accuracy for short distances. All the other systems depend on external road network maps while Smart-Ur-Navigation systems produce itself the required maps permitting to be independent of any external map. Lastly, WISERIDE and Mobithess can make predictions only for the current day. Table 6 summarises the comparative analysis of the studied navigation systems.

5. Contribution of the proposed system to sustainable urban mobility

At the current study, some indicators were selected to assess the contribution of the smart navigation system to sustainable urban mobility. Sdoukopoulos

et al. presented a methodological approach to finding out the most representative indicators related to every single pillar of sustainable development, Economy (EC), Environment (EN), Society (SC). Despite these pillars, indicators for safety were also considered as it is a crucial domain for urban mobility.

They carried out a descriptive statistical analysis of various sustainable transport indicators and then they carried out a comprehensive analysis (Sdoukopoulos et al., 2019). Therefore, their outcome was selected as it is quite recent and covers a great variety of themes. Some indicators may have an impact on more than one pillar, for example, traffic congestions increase the air pollution (EN), cause waste of time for the passengers (SC) and have associated costs (EV) (WBCSD, 2015). In Table 7, the indicators are depicted and the assessment.

Table 6. Comparative analysis of related navigation and prediction systems for the case study of Thessaloniki

	Smart-Ur-Navigation	Google Maps	WISERIDE	Mobithess
Institution	Laboratory of Geodesy & Geomatics, Department of Civil Engineering, Aristotle University of Thessaloniki	Google	– Transport and Project Management, Department of Civil Engineering, Aristotle University of Thessaloniki – EMISIA S.A.	– Hellenic Institute of Transport – Center for Research and Technology Hellas – Municipality of Thessaloniki – Thessaloniki’s Integrated Transport Authority – Region of Central Macedonia – Norwegian Centre for Transport Research.
Real-time predictions	Feasible if it is connected with a real-time data provider	YES	YES	YES
Data provider	Taxi – Vehicles	A smartphone which has the application Google Maps	Taxi – Vehicles	Taxi – Vehicles
«Green» Navigation	YES	NO	NO	YES
Economic Navigation	NO	NO	YES	YES
Limitations	It is needed a great amount of data	Reduced accuracy for short distances It is depended from the external background map.	Time of route can be selected but only for the current day It is depended from the external background map.	Time of route can be selected but only for the current day It is depended from the external background map.

Table 7. Indicators for assessing the contribution of the proposed smart navigation system to sustainable urban mobility

Dimensions	Indicators	Contribution of the proposed system	Type of contribution	Qualitative scale of contribution
Environment (EN)	Air pollutant emissions per capita	YES	Direct	High
	Air quality: Concentrations ($\mu\text{g}/\text{m}^3$) of air pollutant emissions	YES	Direct	High
	Energy efficiency: Ratio of passenger-km travelled to the respective energy consumption	YES	Direct	High
	Per capita fossil fuel energy consumption by transport sector	YES	Direct	High
	Greenhouse gas emissions per capita	YES	Direct	High
	Number of tonne-km referring to transport of hazardous materials by mode	NO	-	-
	Annual number of collisions with wildlife	NO	-	-
	Deterioration of historical buildings and other cultural assets due to acidification	YES	Indirect	High
	Area taken by transport infrastructure	YES	Indirect	Medium
	Recycling rate for end-of-life vehicles	NO	-	-
	Share of renewable energy in total energy consumption by transport sector	NO	-	-
	Total volume of raw materials used in vehicle manufacturing	NO	-	-
	Traffic noise levels/Share of population exposed to noise levels above the statutory threshold	YES	Direct	High
	Transport solid waste per capita	NO	-	-
Transport infrastructure impervious area per capita	NO	-	-	
Environment (EN) & Economy (EC)	Share of employees participating in teleworking programmes/Share of vehicle fleet powered by alternative propulsion technologies (electric, hybrid and fuel cell vehicles)	NO	-	-
	Number of cars per 1,000 inh	NO	-	-
Economy (EC)	Share of GDP contributed by transport sector/Share of GVA generated by transport sector	NO	-	-
	Ratio of public transport revenues to the respective maintenance and operation cost	NO	-	-
	Modal split of freight transport/Average freight transport speed and reliability	YES	Indirect	Low
	Existence or not of transport and environment observatories	NO	-	-
	Public subsidies to transport system	NO	-	-
	Fuel prices and taxes	YES	Indirect	Low
	Occupancy rate of passenger vehicles	YES	Indirect	Low
Economy (EC) & Social (SC)	Share of household income devoted to transport	NO	-	-
	Average commuting travel time	YES	Direct	High
	GDP per capita	NO	-	-
	Average time spent travelling under congested conditions per year per capita	YES	Direct	High

Social (SC) Safety	Share of population living within 300 –500 m from public transport stations/ stops	NO	-	-
	Degree to which public is involved in transport planning process	NO	-	-
	Degree to which cultural aspects are considered in transport planning process	NO	-	-
	Number of chronic respiratory illnesses, asthma attacks, respiratory restricted activity days and premature deaths due to air pollution	YES	Indirect	Medium
	Number of road fatalities per 100,000 inh.	YES	Direct	High
	Share of population feeling safe from violations and other relevant incidents during travelling	NO	-	-
	Equity/ justice of exposure to air pollution emissions	YES	Direct	Medium
	Modal split of trips to school/Share of children driven to school by car	NO	-	-
Social (SC) & Environment (EN)	Fragmentation of urban space	YES	Indirect	Low
	Total area of green spaces and parks per capita/Green areas as a share of the total urban area	NO	-	-
Economy (EC), Social (SC) & Environment (EN)	Road network length per 1.000 inh	NO	-	-
	Degree to which transport planning is comprehensive by considering all significant impacts and using the best evaluation practices	YES	Indirect	Low
	Modal split	NO	-	-
	Number of available transport modes	NO	-	-
	Share of trips by non-motorised modes	NO	-	-
	Share of free parking spaces	NO	-	-
	Share of trips by public transport	NO	-	-
	Total cost due to transport externalities	YES	Indirect	Low
	Population density	NO	-	-

Figure 10 shows the overall contribution of the proposed system to sustainable urban mobility based on the selected indicators. The proposed system contributes significantly to sustainable urban mobility. More precisely, the proposed navigation system contributes mainly to the indicators of environment, economy, environment and social, and economy and social with a percentage of more than 50%. The contribution to social indicators is 38%, and the percentage of contribution to the indicators that combine all the pillars, environment, economy and social, is 24%.

In Figure 11, the type of contribution, direct or indirect, is presented. It is evident that the proposed system contributes directly to the indicators of environment, economy and social, and social and safety. On the contrary, it contributes indirectly to the other sectors while it has no contribution to the sector of environment and economy.

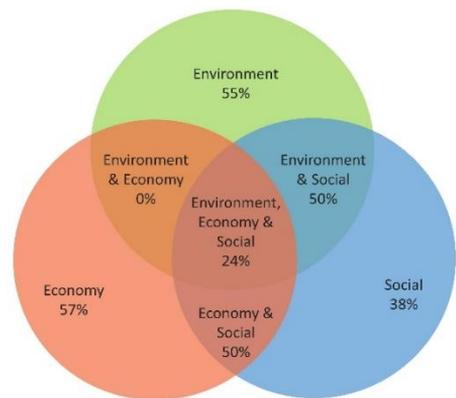


Fig. 10. The overall contribution of the proposed navigation system to the indicators of sustainable urban mobility

Last, Figure 12 presents the degree of contribution to each sector based on a qualitative scale, high, medium and low. The indicators of the aforementioned sectors that are affected directly by the proposed system have a contribution degree from medium to high. The indicators of the other sectors are affected to a low degree except from the sector of environment and economy that is not influenced at all.

6. Conclusions

Sustainable urban mobility is a crucial issue that should comprise a vision for every urban area. Urban traffic congestion cause large-scale impacts including air pollution, increased commute times and

health issues intensifying the unsustainable mobility since human and ecological values are at high risk. In the framework of sustainable urban mobility, the current paper endeavours to contribute to the above-mentioned considerations by proposing a solution to reduce urban traffic congestion. The main objectives were (1) to develop a generic methodology beneficial for every urban road network, (2) to develop a smart GIS-based system independent from external GIS software (3) to establish a system that produces an autonomous road network map (4) to develop a decision support tool for urban navigation based on predicted travel time and fuel emissions.

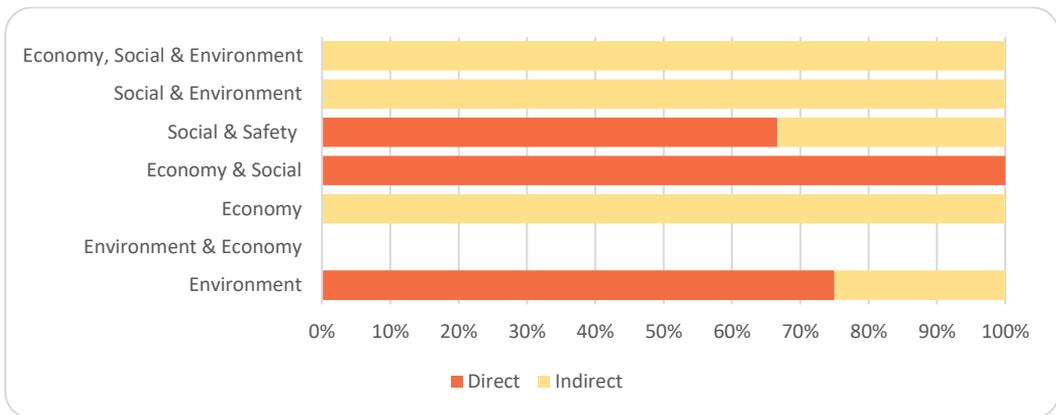


Fig. 11. Direct and indirect contribution of the proposed navigation system to the indicators of sustainable urban mobility

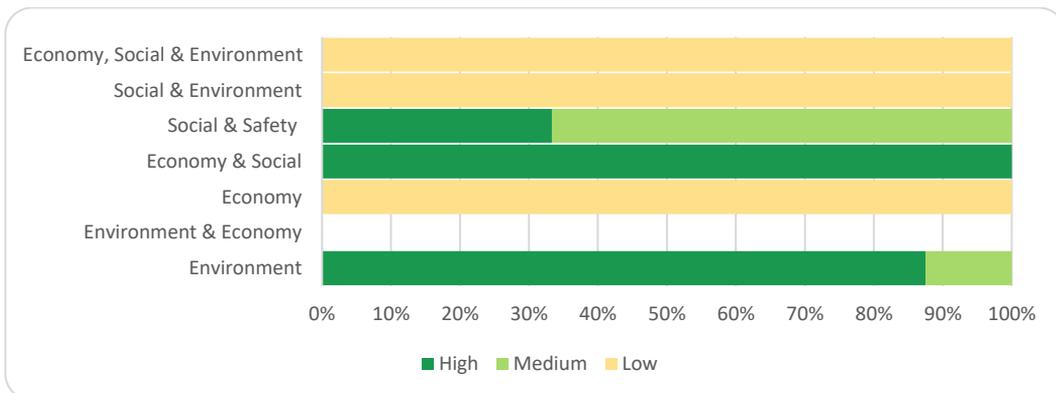


Fig. 12. Qualitative assessment of the degree of contribution of the proposed navigation system to sustainable urban mobility

Spatiotemporal data from GPS receivers of taxis were collected and analysed to develop a navigation system based on travel time. The GPS taxi data contained vital information for the development of our system. The significant amount of data required the development of a data mining system. Thus, it was feasible for the proposed system to predict travel times and navigate the drivers based on the shortest travel time. This contributes remarkably to decrease traffic congestion, and travel time as it helps drivers not to waste their time in idling vehicles. The implementation of a map-matching process contributed to a more accurate data selection. Also, this process made the proposed system outperform as it generates an autonomous road network map by itself. Hence, the system produces an updated road network map identifying any changes at the road network, giving the possibility to detect an incident or some constructions that may have led to close road segments. Consequently, the system contributes to the drivers' safety, helping them to avoid incidents. The optimum algorithm for the travel times prediction was ANN for the current case study, taking into consideration the day, the time, the time period, the homogenous time zone and the velocity. The GIS-based software that was developed is user-friendly and does not require external GIS software; instead, it provides data for GIS software in a compatible format. Finally, yet importantly, in case of connecting a real-time data provider with the proposed system, it can lead to an almost real-time system.

The amount of data per road segment is a significant limitation of the proposed methodology. It was not feasible to calculate several travel times and then to predict for road segments with inadequate data. Furthermore, the implemented method for emissions predictions was not optimum, leading to inaccurate predictions. However, this was not the aim of this paper. Instead, the possibility to predict emissions based on travel times was investigated. For forecasts with higher accuracy, a more advanced method is required, and this constitutes another limitation for this research.

The innovative points of the current research could be summarised as follows: (1) it is the only system amongst the studied system that implements a map-matching process for more accurate data selection. (2) The system uses machine learning through the ANN and can be ameliorated continuously. (3) The system produces the necessary road network map

using the GPS taxi data permitting thus an immediate map update. (4) The software is open-source, freely distributed and has open architecture allowing changes and amendments by anyone. The studied systems were open-source but not freely distributed. To conclude, the proposed system is a valuable support decision tool mainly for emergency vehicles such as ambulances and fire vehicles. Additionally, it is a vital tool to identify traffic congestion spots detecting simultaneously possible points for car accidents. Thus, stakeholders can use this tool to ameliorate traffic signs and enhance road security.

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References

- [1] ABO-QUADAIS, S., QDAIS, H. A. 2005. Performance evaluation of vehicles emissions prediction models. *Clean Technologies and Environmental Policy*, 7(4), pp. 279–284. doi: 10.1007/s10098-005-0279-x.
- [2] AL-KHATEEB, G. 1993. *Effect of traffic movement and volume on air pollution in irbid city*. Jordan University of Science and Technology.
- [3] ALTURI, G., KARPATNE, A., KUMAR, V. 2017. Spatio-Temporal Data Mining: A Survey of Problems and Methods, *ACM Computing Surveys*, 1(1), pp. 1–37. doi: 10.1145/nnnnnnn.nnnnnnn.
- [4] AMBROZIAK, T., JACHIMOWSKI, R., PYZA, D., SZCZEPANSKI, E. 2014. Analysis of the traffic stream distribution in terms of identification of areas with the highest exhaust pollution. *The Archives of Transport*, 32(4), 7-16
- [5] BORIBOONSOMSIN, BARTH, M. 2012. Eco-routing navigation system based on multisource historical and real-time traffic information, *IEEE Transactions on Intelligent Transportation Systems*, 13(4), pp. 1694–1704. doi: 10.1109/TITS.2012.2204051.
- [6] CAI, L., ZHOU, Y., LIANG, Y., HE, J. 2017. Research and Application of GPS Trajectory Data Visualization', *Annals of Data Science*. Springer Berlin Heidelberg, (November). doi:

- 10.1007/s40745-017-0132-1.
- [7] COTTON, B. 2013. Intelligent Urban Transportation Predicting, Managing, and Integrating Traffic Operations in Smarter Cities, *A Frost & Sullivan White Paper*.
- [8] D'ANDREA, E., MARCELLONI, F. 2016. Incident Detection by Spatiotemporal Analysis of GPS Data, *2016 IEEE International Conference on Smart Computing, SMARTCOMP 2016*. IEEE, pp. 1–5. doi: 10.1109/SMARTCOMP.2016.7501698.
- [9] D'OREY, P. M., FERREIRA, M. 2014. ITS for sustainable mobility: A survey on applications and impact assessment tools, *IEEE Transactions on Intelligent Transportation Systems*. IEEE, 15(2), pp. 477–493. doi: 10.1109/TITS.2013.2287257.
- [10] ELEFTERIADOU, L. 2013. *An Introduction to Traffic Flow Theory*. Gainesville: Springer Science & Business Media.
- [11] ERICSSON, E., LARSSON, H., BRUNDELL-FREIJ, K. 2006. Optimizing route choice for lowest fuel consumption - Potential effects of a new driver support tool, *Transportation Research Part C: Emerging Technologies*, 14(6), pp. 369–383. doi: 10.1016/j.trc.2006.10.001.
- [12] FERREIRA, N., POCO, J., VO, H., FREIRE, J., SILVA, C. 2013. Visual Exploration of Big Spatio-Temporal Urban Data : A Study of New York City Cab Trips, *IEEE Transactions on Visualization and Computer Graphics*, 19(12), pp. 2149–2158. doi: 10.1109/TVCG.2013.226.
- [13] FRANTZESKAKIS, I., GIANNOPOULOS, G. 1986. *Transport designing and techniques*. Thessaloniki: Epikentro.
- [14] GAVANAS, N., TSAKALIDIS, A., VERANI, E., SDOUKOPOULOS, A., PITSIAVALATINOPOULOU, M. 2014. Real-Time Information and Guidance based on Road Traffic and Environmental Criteria, in *Real-time information and guidance based on road traffic and environmental criteria*. Patras, Greece, pp. 1–9.
- [15] GEOSPATIAL ENABLING TECHNOLOGIES. 2016. *Geospatial Information Infrastructure of Municipality of Thessaloniki*. Available at: <http://gis.thessaloniki.gr/sdi/> (Accessed: 15 September 2018).
- [16] JIMENEZ, F., MONZON, S., NARANJO, J. E. (2016) 'Definition of an enhanced map-matching algorithm for urban environments with poor GNSS signal quality', *Sensors (Switzerland)*, 16(2), pp. 1–14. doi: 10.3390/s16020193.
- [17] KAMRAN, S., HAAS, O. 2007. A Multilevel Traffic Incidents Detection Approach: Identifying Traffic Patterns and Vehicle Behaviours using real-time GPS data, pp. 912–917. doi: 10.1109/ivs.2007.4290233.
- [18] KELER, A., KRISP, J. M., Ding, L. 2016. Visualization of traffic congestion based on Floating Taxi Data, *Kartographische Nachrichten*, 66(1), pp. 7–13. Available at: https://www.researchgate.net/publication/296705533_Visualization_of_traffic_congestion_based_on_Floating_Taxi_Data.
- [19] KLOTILDI, S. 2014. Public Transport Integration: the case study of Thessaloniki, Greece, *mobil.TUM 2014 International Scientific Conference on Mobility and Transport Sustainable Mobility in Metropolitan Regions*. Available at: http://www.mobil-tum.vt.bgu.tum.de/fileadmin/w00bqi/www/downloads/mobil_TUM_2014_Call_for_Papers.pdf.
- [20] KYRIAKOU, K. 2017. Geoinformatics and spatio-temporal data analysis for the development of a smart vehicle navigation system at the urban street network. Doctoral Dissertation. Civil Engineering. AUTH.
- [21] LAKAKIS, K., KYRIAKOU, K. 2015. Environmental impact analysis of an advanced navigation system for urban areas using GIS, in *CEMEPE*.
- [22] LAKAKIS, K., KYRIAKOU, K., SAVVAIDIS, P. 2014a. Investigation and Prediction of Traffic Travel Time for the Road Network of, *Fresenius Environmental Bulletin (Feb)*, 23(11), pp. 2832–2839.
- [23] LAKAKIS, K., KYRIAKOU, K., SAVVAIDIS, P. 2014b. Investigation and prediction of traffic travel time for the road network of Thessaloniki through spatial temporal model, *FRESENIUS ENVIRONMENTAL BULLETIN (FEB)*, 23(11), pp. 2832–2839.
- [24] LAKAKIS, K., SAVVAIDIS, P., IFADIS, I. M. 2004. Quality of Map-Matching Procedures

- Based on DGPS and Stand-Alone GPS Positioning in an Urban Area Quality of Map-Matching Procedures Based on DGPS and Stand-Alone GPS Positioning in an Urban Area, *FIG Working Week 2004*.
- [25] LAM, D., HEAD, P. 2012. Sustainable Urban Mobility, in Inderwildi, O. and King, D. (eds) *Energy, Transport, & the Environment*. Springer, London.
- [26] LÉCUE, F., TUCKER, R., BICER, V., TOMMASI, P., TALLEVI-DIOTALLEVI, S., SBODIO, M. 2013. Predicting Severity of Road Traffic Congestion using Semantic Web Technologies, *The Semantic Web: Trends and Challenges*. Springer International Publishing, 8465, pp. 611–627. doi: 10.1007/978-3-319-07443-6_41.
- [27] LI, B., ZHANG, D., SUN, L., CHEN, C., LI, S., QI, G., YANG, Q. 2011. Hunting or waiting? Discovering passenger-finding strategies from a large-scale real-world taxi dataset, *2011 IEEE International Conference on Pervasive Computing and Communications Workshops, PERCOM Workshops 2011*. IEEE, pp. 63–68. doi: 10.1109/PERCOMW.2011.5766967.
- [28] MINTSIS, G., BASBAS, S. PAPAIOANNOU, P., TAXILTARIS, C., TZIAVOS, I.N. 2004. Applications of GPS technology in the land transportation system., *European Journal of Operational Research* 152, pp. 399-409
- [29] MITSAKIS, E.; SALONOVA GRAU, J.M.; AIFADOPOULOU, G.; TZENOS, P. 2013. Real-time traffic estimation and forecast for advanced traveler information services in Thessaloniki.
- [30] National Association of City Transportation Officials (2012) *Urban Street Design Guide*. New York: Island Press.
- [31] NIE, Y., LI, Q. 2013. An eco-routing model considering microscopic vehicle operating conditions, *Transportation Research Part B: Methodological*. Elsevier Ltd, 55, pp. 154–170. doi: 10.1016/j.trb.2013.06.004.
- [32] PAPAIOANNOU, P. (2012) Sustainable mobility in Thessaloniki: *The today and future role of S.A.S.TH*.
- [33] PRADHANANGA, N., TEIZER, J. 2013. Automatic spatio-temporal analysis of construction site equipment operations using GPS data, *Automation in Construction*. Elsevier B.V., 29, pp. 107–122. doi: 10.1016/j.autcon.2012.09.004.
- [34] RANJIT, S., SHIBASAKI, R., NAGAI, M., WITAYANGKURN, A., MANANDHAR, D. 2016. Utilization of GPS/GNSS Big Data from Probe Vehicle for Traffic Management in the context of Nepal, in *Workshop on the Applications of Global Navigation Satellite Systems*. Kathmandu, Nepal. Available at: <http://www.unoosa.org/pdf/icg/2016/nepal-workshop/2-06.pdf>.
- [35] SCHÄFER, R.-P., THIESSENHUSE, K.-U., BROCKFELD, E., WAGNER, P. 2002. Analysis of Travel Times and Routes on Urban Roads by Means of Floating Car Data, *Association for European Transport*. Available at: <http://abstracts.aetransport.org/paper/index/id/1399/confid/8>.
- [36] SDOUKOPOULOS, A., PITSIAVA-LATINOPOULOU, M., BASBAS, S., PAPAIOANNOU, P. 2019. Measuring progress towards transport sustainability through indicators: Analysis and metrics of the main indicator initiatives, *Transportation Research Part D: Transport and Environment*. Elsevier, 67, pp. 316–333. doi: 10.1016/j.trd.2018.11.020.
- [37] SHIN, Y. 2017. *Time Series Analysis in the Social Sciences: The Fundamentals*. Oakland: University of California Press.
- [38] SOHR, A., BROCKFELDA, E., SAUERLÄNDERA, A., MELDE, E. (2016) ‘Traffic information system for Hanoi’, *Procedia Engineering*. Elsevier B.V., 142, pp. 221–228. doi: 10.1016/j.proeng.2016.02.035.
- [39] UNITED NATIONS (1987) *Report of the World Commission on Environment and Development: Our Common Future*. doi: 10.1016/0022-2364(91)90424-R.
- [40] UNITED NATIONS (2017) *Resolution adopted by the General Assembly on Work of the Statistical Commission pertaining to the 2030 Agenda for Sustainable Development (A/RES/71/313), Annex*. Available at: https://unstats.un.org/sdgs/indicators/GlobalIndicatorFrameworkafterrefinement_Eng.pdf.
- [41] WILSON, E. 2011. From Inductance Loops to Vehicle Trajectories, in *75 Years of the Fundamental Diagram for Traffic Flow Theory*, p. 134. Available at:

- <http://onlinepubs.trb.org/onlinepubs/circulars/c149.pdf#page=53>.
- [42] WORLD BUSINESS COUNCIL FOR SUSTAINABLE DEVELOPMENT. 2015. *Sustainable Urban Mobility*.
- [43] XIAO, Q., HE, R., MA, C. 2018. The analysis of urban taxi carpooling impact from taxi GPS data, *Archive of Transport*, 47(3), pp.109-120. DOI: 10.5604/01.3001.0012.6514
- [44] YANG, Y., COLAK, S., TOOLE, J., DESU, S., ALEXANDER, L. 2014. *Finding patterns in taxi demand. MIT Big Data Challenge: Transportation in the City of Boston (Competition)*. Boston.
- [45] ZHANG, K., SUN, D., SHEN, S., ZHU, Y. 2017. Analyzing spatiotemporal congestion pattern on urban roads based on taxi GPS data, *Journal of Transport and Land Use*, 10(1), pp. 675–694. doi: 10.5198/jtlu.2017.954.
- [46] ZHANG, T., SUN, L., YAO, L., RONG, J. 2017. Impact Analysis of Land Use on Traffic Congestion Using Real-Time Traffic and POI, *Journal of Advanced Transportation*, 2017(1985). doi: 10.1155/2017/7164790.
- [47] ZHENG, Y. 2015. Trajectory Data Mining: An overview. *ACM Transactions on Intelligent Systems and Technology*, 6(3), pp. 29–41. doi: 10.1145/2743025.