Advances in Intelligent Traffic and Transportation Systems
M. Shafik (Ed.)

doi:10.3233/ATDE230005

A Review and Analysis of Traffic Data Sources

Elia BALUGANI[1], Samuele MARINELLO, Rita GAMBERINI and Maria Angela BUTTURI
Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Amendola 2, Padiglione Morselli, 42122 Reggio Emilia, Italy

Abstract. Transportation is essential for economic and social development, and vehicle flow data can be used for safety monitoring, pollution analysis, and traffic flow management. Unfortunately, traffic management and control centres do not always comply with codified standards, making it difficult to obtain up-to-date data. This paper analyses open traffic datasets and Italian public traffic data sources available online, providing a knowledge base for transportation managers and researchers. Open traffic datasets are dimensionality-reduced and clustered. An event with 209,135 visitors is used to benchmark the public data sources, the time series of traffic flows are decomposed and a regression tree is used to identify different periods. The results suggest that the available Italian sensor grid is not fine enough to identify all incoming and outgoing traffic, more infrastructure investments are required or the available measurements should be coupled with other evaluation approaches capable of extending the punctual data through mathematical means.

Keywords. Traffic data, traffic flow, mobility, mobility data, dimensionality reduction, Isomap, K-means, time series decomposition, regression tree

1. Introduction

Faced with the extreme variety and complexity of traffic phenomena on road networks, alongside a growing demand from users, the need for monitoring and controlling the flow of traffic is growing. Transport is crucial for the economic and social development of every nation, and it is difficult to imagine strong economic growth occurring in the absence of an efficient transport system [1, 2]. These circumstances pose a major challenge for traffic management and control centres, as traffic flow data do not always comply with codified standards. The use of open data is promoted by administrations around the world to tackle this problem, but data availability and access are not widespread [3]. As a result, the purchase of databases or the organization of dedicated monitoring campaigns is often necessary, making these activities expensive, redundant, and inefficient. Direct road traffic monitoring systems require the installation of traffic detection tools on roads managed (and financed) by local administrations or by agents with road concessions [4]. The complexity of the system can be described in terms of the territorial and spatial scope of investigations and the types of road infrastructure to be

[1] Corresponding Author, Elia BALUGANI, Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Amendola 2, Padiglione Morselli, 42122 Reggio Emilia, Italy; E-mail: elia.balugani@unimore.it.

monitored. Monitoring systems can be divided into manual detection techniques (which require the continuous presence of operators) and automatic techniques [5]. Manual systems are preferable for counting vehicles over short periods of time, and human operators can not only detect vehicles and recognize their type but also evaluate their manoeuvres and the drivers' behaviours. However, human observers' limitations can compromise data quality, especially for long-term campaigns. Automatic detection tools can instead operate continuously over long-term campaigns, but they are much more expensive. Automatic systems encompass different technologies used either in an intrusive (e.g., inductive loops and magneto-dynamic sensors) or in a nonintrusive way (e.g., infrared sensors, video images and satellite technologies). The use of unmanned aerial vehicles (UAVs) has also become widespread [6-8]. These elements make up an intelligent transportation system (ITS), an integrated system that implements existing or emerging computer, communication, information, and vehicle-sensing technologies [9] to coordinate transportation systems, monitor traffic conditions, control the traffic flow, and provide information about traffic conditions to the public [1, 10]. The implementation of road traffic monitoring systems appears appropriate for increasing traffic safety levels, for responding to multiple needs in territory management and for developing appropriate local policies and strategies. Some applications are listed below, representing only a few articles in a very large literature. The first operational application of road traffic monitoring is the analysis of the behaviour and regulation of traffic congestion, particularly in urban areas, at traffic light intersections or on high-flow road infrastructures [11-14]. Directly linked to this application is the opportunity to estimate and predict traffic flows [15-17]. A further application is represented by the control of parking and the management of tolls through monitoring parking lots and stall occupancy and facilitating access by users through an information system, as well as the management of parking fees [18-21]. Knowledge of road traffic behaviours provides driving assistance, increasing driving safety and improving driving effectiveness (e.g., by providing general information on traffic conditions) [22-25]. Monitoring tolls supports the battle against infringements and makes it possible to improve safety and dissuade illegal behaviour [26-28]. The data collected can be useful for technical and scientific research, supporting, for example, analyses of the impact of traffic on air quality and noise by studying the effect of tourist flows on the environment and on residents [29-32]. Furthermore, such data can support the development of policies and strategies for the regulation of vehicular traffic and the reduction of its environmental impacts [33-36], as well as the formulation of emergency and intervention plans, supporting the planning and management of emergency vehicle flows during emergency situations [37-40]. The objective of this paper is to provide information on open-data traffic monitoring sources, particularly for Italian roads. These data are also clustered and analysed through a practical application as in [41]: the evaluation of the effect induced by an international event in a northern Italian city. In the authors' opinion public events are ideal to test for the effectiveness of traffic monitoring systems, as the incoming and outgoing flows can be differentiated from the systems' baseline before and after the events. The paper is structured as follows: Section 2 provides a literature review on vehicular traffic in the context of tourism, the benchmark case of the case study, Section 3 analyses the open datasets available on Kaggle [42], Section 4 analyses Italian public data sources, Section 5 proposes a case study to measure the effectiveness of those data sources, and Section 6 contains conclusions and outlines further research efforts.

2. Vehicular Traffic in the Context of Tourism

Tourist destinations are often very crowded and, for this reason, they can be used to outline traffic congestion problems and test traffic monitoring systems. Congested beaches, endless queues to access tourist attractions, perpetually congested traffic and blocked historic centres are some of the effects that visitors and residents of tourist resorts suffer from all over the world. Today, more than ever, the evolution of tourism is affected by the influence of global events and trends. These include the evolution of mobility, demographic changes, and digitization, as well as increasing urbanization, which pushes an increasing number of people into urban areas. The control of vehicle flows makes it possible to support better management of tourist destinations, improving their quality, competitiveness, and attractiveness, with a view towards sustainability. Contextualized to mountain environments and natural areas, [43] applied spatial data to analyse the effect of vehicle quotas meant to limit their negative impacts in natural tourist destinations through the combination of agent-based modelling and standards of quality. [44] analyse the effect of the expansion of road networks and increases in traffic and their effect on protected areas and biodiversity, while [45] analyse the tourism experience in alpine areas, studying the application of the mobility as a service (MaaS) model in terms of its contribution to the definition of sustainable transport services. In a study by [46], the flow of the non-resident population at a destination is used to understand the effect of the non-resident population on traffic congestion. Regression analyses based on traffic flow, speed data and congestion were applied. [47] study the sustainability of tourism development models through an analysis of the effect of private vehicles for tourist or residential purposes, demonstrating how private vehicle use is more intensive in residential destinations than in vacation destinations. In the research conducted by [2], various macroscopic models are combined to detect congested situations. [48] apply the ecological footprint approach to assess the use of road transport on the island of Lanzarote and to assess its implications for the development of sustainable tourism. [49], analysing the road network of the islands considered, identify alternative routes to diffuse tourist flows. [50] address the problem represented by transport infrastructures, highlighting shortcomings in the current system with respect to the detected flows. [51] specifically study rural tourism, with the Austrian situation being dominated by car transport. By applying mobility data to the assessment of air pollution induced by tourist flows, [52] evaluate the opportunity to improve fuel efficiency and reduce CO_2 emissions for a fleet of vehicles in the largest ski resort in Ontario (Canada). [53] empirically investigate the spatial and direct spill-over effects of tourism development on air pollution in China. Finally, in the context of events, [36] investigate the traffic management plans used for sporting events with objective and quantitative data over a five-year period, while [54] analyses the need to manage vehicular traffic during sporting events and, applying simulation approaches, evaluates various alternative solutions. In the context of theme parks, [55], apply a multiple regression model to forecast tourism traffic volume.

3. Open Datasets

Kaggle [42] is a data science community whose users provide open datasets for analysis and machine learning, a subset of which contain traffic data. The datasets of interest were identified by searching on Kaggle with the keyword “traffic” and by manually removing the off-topic datasets (e.g., related to data traffic). The remaining datasets were analysed and categorized according to the following features: Time step, the target time step between data points on the same road; Time frame, the time difference between the most recent and the oldest data points; Location, the location of the dataset roads; Starting year, the year of the oldest data point; Size, the dataset size not considering accessory text and PDF files; Road identifiers, a flag indicating if the road is identifiable by its name or unique identifier; GPS coordinates, a flag indicating if the road is identifiable through GPS coordinates; Data type, the type of data available. Those with only a few data points for each road, no road identifiers, no time references, a focus on public transportation (e.g., busses), or a focus on alternative means of transportation (e.g., bicycles) were removed and only those listed in Table 1 remain. A categorization of the selected datasets is proposed in Table 2, most of which refer to roads in the United States. The datasets' quantitative features, time steps, time frames, starting year, and size were then standardized. Isomap [56] with a neighborhood of size 3 was used to depict the standardized data in a dimensionality-reduced space, presented in Figure 1. Readers interested in replicating these results can refer to [57] for the specific MATLAB toolbox used. The same developer provides a comparative review of dimensionality reduction methods in [58] and is also one of the authors of the popular t-SNE method [59]. Data visualization was leveraged in selecting three clusters for the following K-means algorithm [60,61]. The clusters are also depicted in Figure 1 with a different marker for each cluster. These three groups separate one sizeable dataset with historical data and fine-grained time steps, two datasets with historical data and course-grained time steps, and nine datasets with more recent data and fine-grained time steps.

Table 1. Kaggle datasets

Dataset	Link (available in November 2020)
US Traffic, 2015	https://www.kaggle.com/jboysen/us-traffic-2015
UK Traffic Counts	https://www.kaggle.com/sohier/uk-traffic-counts
Radar Traffic Data	https://www.kaggle.com/vinayshanbhag/radar-traffic-data
2016 NYC Real Time Traffic Speed Data Feed	https://www.kaggle.com/crailtap/nyc-real-time-traffic-speed-data-feed
2011 - 2013 NYC Traffic Volume Counts	https://www.kaggle.com/hanriver0618/2011-2013-nyc-traffic-volume-counts
Motorway traffic in Luxembourg	https://www.kaggle.com/fabmob/motorway-traffic-in-luxembourg
NY Traffic Volume Counts (2012-2013)	https://www.kaggle.com/new-york-city/ny-traffic-volume-counts-2012-2013
Chicago Traffic	https://www.kaggle.com/nhoues1997/chicago-traffic
NYC DOT Traffic Data	https://www.kaggle.com/caseyworks/dot-file
Highway Traffic M03A Taiwan	https://www.kaggle.com/phlinhng/highway-traffic-m03a-taiwan
NYS Annual Average Daily Traffic (AADT)	https://www.kaggle.com/new-york-state/nys-annual-average-daily-traffic-aadt
NY_traffic_data	https://www.kaggle.com/dawaasuren/ny-traffic-data

Table 2. Kaggle dataset categorization

Dataset	Time step	Time frame	Location	Starting year	Size	Road identifier	GPS coordinates	Data type
US Traffic, 2015	1 hour	8759 hours	United States	2015	2.183.839.608 byte	yes	yes	number of vehicles
UK Traffic Counts	1 year	16 years	United Kingdom	2000	1.028.520.087 byte	yes	yes	number of vehicles
Radar Traffic Data	15 minutes	1270980 minutes	City of Austin	2017	404.097.819 byte	yes	yes	number of vehicles
2016 NYC Real Time Traffic Speed Data Feed	5 minutes	527073 minutes	New York City	2016	721.872.569 byte	yes	yes	speed travel time
2011 - 2013 NYC Traffic Volume Counts	1 hour	10991 hours	New York City	2012	1.436.453 byte	yes	no	number of vehicles

Motorway traffic in Luxembourg	5 minutes	53395 minutes	Luxembourg	2019	382.188.337 byte	yes	yes	speed number of vehicles
NY Traffic Volume Counts (2012-2013)	1 hour	4655 hours	New York City	2012	1.555.550 byte	yes	no	number of vehicles
Chicago Traffic	10 minutes	1117001 minutes	City of Chicago	2018	664.722.821 byte	yes	yes	speed number of vehicles
NYC DOT Traffic Data	5 minutes	46410318 minutes	New York City	1930	6.625.968.064 byte	yes	yes	speed travel time
Highway Traffic M03A Taiwan	5 minutes	382485 minutes	Taiwan	2017	3.638.203.664 byte	yes	no	number of vehicles
NYS Annual Average Daily Traffic (AADT)	1 year	38 years	State of New York	1977	23.570.265 byte	yes	no	number of vehicles
NY_traffic_data	1 minute	262079 minutes	New York City	2016	191.352.763 byte	yes	yes	travel time between locations

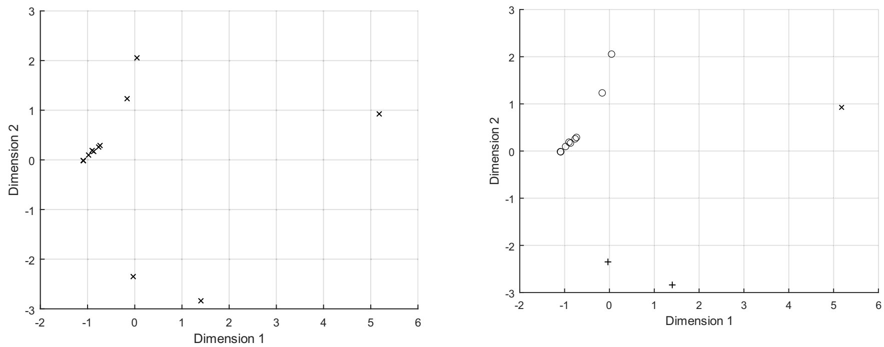

Figure 1. Kaggle dimensionality-reduced and clustered datasets.

4. Public Data Sources

Italian regional data sources were identified by searching Google [62] with the following keywords for each region: “dati traffico *region name*”, “dati viabilità *region name*”, “dati mobilità *region name*”, “open data *region name*”, and by searching through the mobility datasets in the Italian public administration datasets repository [63] and in the Italian territorial datasets repository [64]. Table 3 lists the sources identified, while Figure 2 depicts the regions with available data in black and those not providing traffic data in white. A categorization similar to the one proposed in Table 2 is provided in Table 4. Some of the sources provide both historical and live data.

Table 3. Regional data sources

Region	Link
Emilia-Romagna	https://servizissiir.regione.emilia-romagna.it/FlussiMTS/
Lazio	https://ceremsslazio.astralspa.it/ceremss/DatiStatistiche/FCD
Piemonte	http://www.dati.piemonte.it/catalogodati/datielenco.html?parextra=tag***%22Reti%20di%20trasporto%22
Toscana Dataset 1	https://www.regione.toscana.it/-/dati-di-traffico-sulle-strade-regionali
Toscana Dataset 2	http://dati.toscana.it/dataset?groups=infrastrutture-e-trasporti

Figure 2. Regional data sources.

Table 4. Regional data source categorization

Dataset	Time step	Time frame	Starting year	Road identifier	GPS coordinates	Data type
Emilia-Romagna	1 day	4292 days	2008	yes	no	number of vehicles
Lazio	1 month	28512 hours	2017	yes	no	number of vehicles
Piemonte	1 year	5 years	2014	no	no	number of vehicles
Toscana Dataset 1	1 month	31392 hours	2009	yes	no	number of vehicles
Toscana Dataset 2	1 day	43800 hours	2015	yes	yes	number of vehicles

Italian provincial and municipal data sources were also identified by searching Google with the following keywords for each province and municipality: "dati traffico *province/municipality name*", "dati viabilità *province/municipality name*", "dati mobilità *province/municipality name*", and "open data *province/municipality name*", and by searching through the mobility datasets listed above. Tables 5 and 7 list these data sources; of the municipalities, only those at the provincial level were considered. Tables 6 and 8 provide categorizations identical to those proposed in Table 4.

Table 5. Provincial data sources

Province	Link
Alessandria	http://www.provincia.alessandria.gov.it/index.php?ctl=news&fl=singola&id=4429&idbl=55
Asti	https://www.provincia.asti.it/it/page/rilevamento-del-traffico-veicolare
Belluno	http://www.provincia.belluno.it/nqcontent.cfm?a_id=4344
Bolzano	http://www.provincia.bz.it/it/servizi-a-z.asp?bnsv_svid=1003861
Macerata	https://istituzionale.provincia.mc.it/dati-traffico/
Torino	http://www.provincia.torino.gov.it/territorio/strat_strumenti/distr_dati/dbtrf.html
Trento	https://dati.trentino.it/dataset?tags=traffico
Treviso	https://www.provincia.treviso.it/index.php/conosci-la-sede-della-provincia/sede/edificio-8?id=10198:programmazione-e-autorizzazioni-stradali
Varese	http://www.provincia.va.it/code/11373/Flussi-di-Traffico
Vicenza	http://www.provincia.vicenza.it/ente/la-struttura-della-provincia/servizi/statistica/dati-statistici/viabilita_trasporti/traffico

Table 6. Provincial data source categorization

Dataset	Time step	Time frame	Starting year	Road identifier	GPS coordinates	Data type
Alessandria	1 month	25536 hours	2016	yes	no	number of vehicles
Asti	1 month	68664 hours	2012	yes	no	number of vehicles
Belluno	1 year	8 years	2000	yes	no	speed number of vehicles
Bolzano	1 hour	35040 hours	2016	yes	no	number of vehicles
Macerata	1 month	8016 hours	2005	yes	no	number of vehicles
Torino	1 hour	37608 hours	1999	yes	no	number of vehicles
Trento	1 day	13148 days	1980	yes	no	number of vehicles
Treviso	1 year	8 years	2010	yes	no	number of vehicles
Varese	1 year	10 years	2007	yes	no	number of vehicles
Vicenza	1 year	8 years	2000	yes	no	number of vehicles

Table 7. Municipal data sources

Municipality	Link
Cesena	http://dati.unionevallesavio.it/opendata/12284
Cremona	https://www.dati.lombardia.it/Statistica/Comune-di-Cremona-Rilievi-traffico/92py-znjr
Firenze	https://opendata.comune.fi.it/?q=metarepo/datasetinfo&id=rilevazione-sperimentale-continua-dati-traffico-veicolare-serie
Milano Dataset 1	https://www.cittametropolitana.mi.it/vecchio_viabilita/Traffico/index.html
Milano Dataset 2	https://www.dati.lombardia.it/browse?tags=traffico

Table 8. Municipal data source categorization

Dataset	Time step	Time frame	Starting year	Road identifier	GPS coordinates	Data type
Cesena	1 day	1460 days	2012	yes	no	number of vehicles
Cremona	1 year	9 years	2009	yes	no	number of vehicles
Firenze	1 year	2 years	2015	yes	no	number of vehicles
Milano Dataset 1	1 day	544 days	2015	yes	no	number of vehicles
Milano Dataset 2	1 day	544 days	2015	yes	no	number of vehicles

5. Case Study

The Emilia-Romagna data source listed in Table 4 was used to extract traffic flows for a 2018 [65] event in Rimini. Figure 3 depicts the selected measurement stations close to the city and along major roads, providing daily data on light vehicles coming through Station 182, Station 188, Station 350, and Station 354. Data were collected from the 10th of January 2018 to the 17th of April 2018, inclusive, while the event took place from the 20th of January 2018 to the 23rd of January 2018, inclusive. Such a data series was selected to identify long-term patterns and compare them with patterns during the event days; the event itself registered 209,135 visitors.

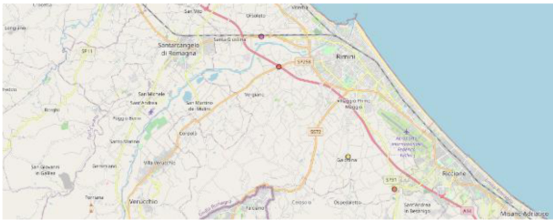

Figure 3. Traffic measurement stations.

The data were decomposed [66] with moving average and seasonality both equal to 7. The overall incoming and outgoing flow is depicted in Figure 4.

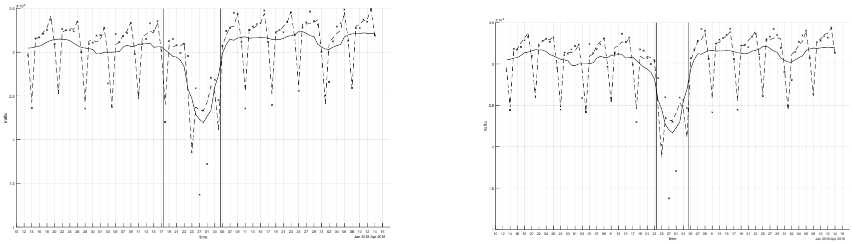

Figure 4. Incoming and outgoing flow.

There is no significant traffic increase during the event days, which might be due to use of public transportation (e.g., train), or use of major roads not equipped with sensors (e.g., highways). On the other hand, a significant flow reduction is measured in the subsequent month. This unexpected flow reduction, most likely due to a heavy snowfall, is uncovered by splitting the errors through a regression tree [67] in MATLAB, with minimum parent size before a split and maximum number of splits both equal to 2. The regression tree input is, in this case, the period, and its output the decomposed error. It should be noted that the regression tree in not directly used for prediction purposes, its leaves are instead used to identify periods characterized by different traffic behaviours. Figures 4 outlines with vertical lines the regression trees splits, those same splits can be found in Figures 5 where the regression trees are depicted.

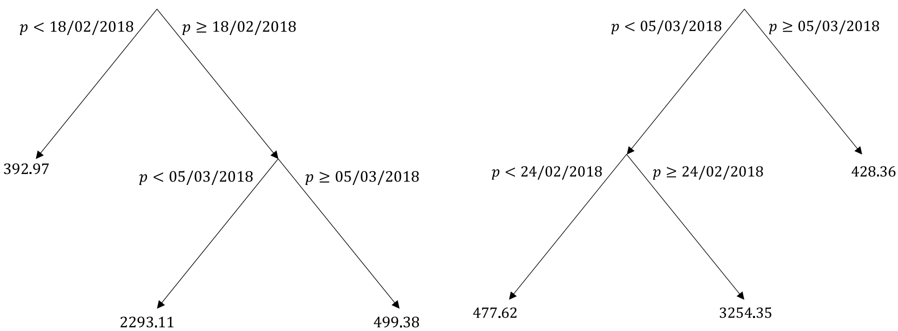

Figure 5. Incoming and outgoing flow regression trees.

Figure 6 shows the snow cover (purple) in the regional territory during the period characterized by the sharp decline in vehicular traffic. The data were provided by the Hydro-Meteo-Climate Service [68].

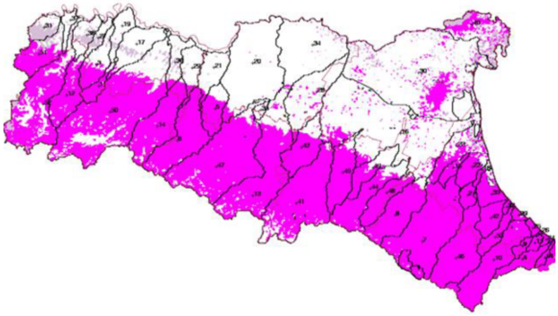

Figure 6. Snow cover (purple) during the last days of February 2018.

6. Conclusion

Traffic data are important for mobility planning, and the availability of open data sources allows public agents and mobility managers to act on them without incurring recurring expenses. This paper analysed and categorized some open datasets, finding that their quality varies considerably, and they mostly refer to roads in the United States. Italian public data sources were also analysed, and it was found that only a few regions provide traffic data and that the quality of the few provincial and municipal datasets is subpar. In a case study, an event with 209,135 visitors was analysed from a traffic flow standpoint using regional data to test the data's effectiveness. Such an experiment highlights the need for a finer grid of stations, in particular pinning down the major highways, and for interoperability with public transportation data. Further research efforts will be devoted to identifying which cities are already equipped with an array of sensors fine enough to identify major incoming and outgoing traffic flows and which, in our opinion, require further infrastructural investments. Alternatively, the information provided by the monitoring networks can be extended to portions of the road network not covered by sensors through modelling approaches. Obviously, the uncertainty associated with the estimated data is strongly influenced by the quality of the inputs and the extent of the investigated area.

Acknowledgement

This research is carried out within the framework of the POR-FESR 2014-2020 Project: Policy Support System for Smart City Data Governance - POLIS-EYE. PG/2018/631990. CUP E21F18000200007.

References

[1] J. Guerrero-Ibáñez, S. Zeadally, and J. Contreras-Castillo, Sensor Technologies for Intelligent Transportation Systems, *Sensors*. **18** (2018). doi:10.3390/s18041212.

[2] A. Zeroual, F. Harrou, Y. Sun, and N. Messai, Monitoring road traffic congestion using a macroscopic traffic model and a statistical monitoring scheme, *Sustainable Cities and Society*. **35** (2017). doi:10.1016/j.scs.2017.08.018.

[3] Y. Wen, S. Zhang, J. Zhang, S. Bao, X. Wu, D. Yang, and Y. Wu, Mapping dynamic road emissions for a megacity by using open-access traffic congestion index data, *Applied Energy*. **260** (2020). doi:10.1016/j.apenergy.2019.114357.
[4] M. Rodriguez-Vega, C. Canudas-de-Wit, and H. Fourati, Location of turning ratio and flow sensors for flow reconstruction in large traffic networks, *Transportation Research Part B: Methodological*. **121** (2019). doi:10.1016/j.trb.2018.12.005.
[5] G. Leduc, Road Traffic Data: Collection Methods and Applications, 2008.
[6] A. Alioua, H. Djeghri, M.E.T. Cherif, S.-M. Senouci, and H. Sedjelmaci, UAVs for traffic monitoring: A sequential game-based computation offloading/sharing approach, *Computer Networks*. **177** (2020). doi:10.1016/j.comnet.2020.107273.
[7] N.A. Khan, N.Z. Jhanjhi, S.N. Brohi, R.S.A. Usmani, and A. Nayyar, Smart traffic monitoring system using Unmanned Aerial Vehicles (UAVs), *Computer Communications*. **157** (2020). doi:10.1016/j.comcom.2020.04.049.
[8] J. Liu, J. Wu, and M. Liu, UAV monitoring and forecasting model in intelligent traffic oriented applications, *Computer Communications*. **153** (2020). doi:10.1016/j.comcom.2020.02.009.
[9] C. Ravi, A. Tigga, G.T. Reddy, S. Hakak, and M. Alazab, Driver Identification Using Optimized Deep Learning Model in Smart Transportation, *ACM Transactions on Internet Technology*. (2022). doi:10.1145/3412353.
[10] I. Gulati, and R. Srinivasan, Image Processing in Intelligent Traffic Management, *International Journal of Recent Technology and Engineering*. **8** (2019). doi:10.35940/ijrte.B1040.0782S419.
[11] D. Impedovo, F. Balducci, V. Dentamaro, and G. Pirlo, Vehicular Traffic Congestion Classification by Visual Features and Deep Learning Approaches: A Comparison, *Sensors*. **19** (2019). doi:10.3390/s19235213.
[12] A. Kanungo, A. Sharma, and C. Singla, Smart traffic lights switching and traffic density calculation using video processing, in: 2014 Recent Advances in Engineering and Computational Sciences (RAECS), IEEE, Chandigarh, India, 2014. doi:10.1109/RAECS.2014.6799542.
[13] K. Małecki, and P. Pietruszka, Comparative Analysis of Chosen Adaptive Traffic Control Algorithms, in: Lecture Notes in Networks and Systems, Springer, 2018. doi:10.1007/978-3-319-64084-6_18.
[14] B. Pratama, J. Christanto, M.T. Hadyantama, and A. Muis, Adaptive Traffic Lights through Traffic Density Calculation on Road Pattern, in: 2018 International Conference on Applied Science and Technology (ICAST), IEEE, Manado, Indonesia, 2018. doi:10.1109/iCAST1.2018.8751540.
[15] D. Impedovo, V. Dentamaro, G. Pirlo, and L. Sarcinella, TrafficWave: Generative Deep Learning Architecture for Vehicular Traffic Flow Prediction, *Applied Sciences*. **9** (2019). doi:10.3390/app9245504.
[16] A. Ramazani, and H. Vahdat-Nejad, A new context-aware approach to traffic congestion estimation, in: 2014 4th International Conference on Computer and Knowledge Engineering (ICCKE), IEEE, Mashhad, Iran, 2014. doi:10.1109/ICCKE.2014.6993372.
[17] S. Ryu, D. Kim, and J. Kim, Weather-Aware Long-Range Traffic Forecast Using Multi-Module Deep Neural Network, *Applied Sciences*. **10** (2020). doi:10.3390/app10061938.
[18] S.M. Dave, G.J. Joshi, K. Ravinder, and N. Gore, Data monitoring for the assessment of on-street parking demand in CBD areas of developing countries, *Transportation Research Part A: Policy and Practice*. **126** (2019). doi:10.1016/j.tra.2019.05.009.
[19] J. Hanzl, Parking Information Guidance Systems and Smart Technologies Application Used in Urban Areas and Multi-storey Car Parks, *Transportation Research Procedia*. **44** (2020). doi:10.1016/j.trpro.2020.02.030.
[20] C.K.B. Krishnamurthy, and N.S. Ngo, The effects of smart-parking on transit and traffic: Evidence from SFpark, *Journal of Environmental Economics and Management*. **99** (2020). doi:10.1016/j.jeem.2019.102273.
[21] M.G. Diaz Ogás, R. Fabregat, and S. Aciar, Survey of Smart Parking Systems, *Applied Sciences*. **10** (2020). doi:10.3390/app10113872.
[22] K. Chebanyuk, O. Prasolenko, D. Burko, A. Galkin, O. Lobashov, A. Shevchenko, D.S. Usami, and L. Persia, Pedestrians influence on the traffic flow parameters and road safety indicators at the pedestrian crossing, *Transportation Research Procedia*. **45** (2020). doi:10.1016/j.trpro.2020.02.083.
[23] P. Kumar, V. Singh, and D. Reddy, Advanced Traveler Information System for Hyderabad City, *IEEE Transactions on Intelligent Transportation Systems*. **6** (2005). doi:10.1109/TITS.2004.838179.
[24] F.O. Okorodudu, P.O. Okorodudu, and L.O. Atumah, A Novel Approach to Road Traffic Monitoring and Control System, *International Journal of Multidisciplinary Sciences and Engineering*. **9** (2018).
[25] J. Teixeira, E. Macedo, P. Fernandes, J.M. Bandeira, N. Rouphail, and M.C. Coelho, Assessing traffic-related environmental impacts based on different traffic monitoring applications, *Transportation Research Procedia*. **37** (2019). doi:10.1016/j.trpro.2018.12.172.
[26] S. Battiato, G.M. Farinella, G. Gallo, and O. Giudice, On-board monitoring system for road traffic safety analysis, *Computers in Industry*. **98** (2018). doi:10.1016/j.compind.2018.02.014.

[27] I. Malygin, V. Komashinskiy, and O. Korolev, Cognitive technologies for providing road traffic safety in intelligent transport systems, *Transportation Research Procedia*. **36** (2018). doi:10.1016/j.trpro.2018.12.134.

[28] H. McDonald, J. Berecki-Gisolf, K. Stephan, and S. Newstead, Preventing road crashes: Do infringements for traffic offences have a deterrent effect amongst drivers aged 40+? An examination of administrative data from Victoria, Australia, *Transportation Research Part F: Traffic Psychology and Behaviour*. **69** (2020). doi:10.1016/j.trf.2020.01.004.

[29] K. Brzozowski, A. Maczyński, and A. Ryguła, Monitoring road traffic participants' exposure to PM10 using a low-cost system, *Science of The Total Environment*. **728** (2020). doi:10.1016/j.scitotenv.2020.138718.

[30] S. Marinello, F. Lolli, and R. Gamberini, Roadway tunnels: A critical review of air pollutant concentrations and vehicular emissions, *Transportation Research Part D: Transport and Environment*. **86** (2020). doi:10.1016/j.trd.2020.102478.

[31] S.S. Marouf, M.C. Bell, P.S. Goodman, J. Neasham, J. Neasham, and A.K. Namdeo, Comprehensive study of the response of inexpensive low energy wireless sensors for traffic noise monitoring, *Applied Acoustics*. **169** (2020). doi:10.1016/j.apacoust.2020.107451.

[32] W. Yang, J. He, C. He, and M. Cai, Evaluation of urban traffic noise pollution based on noise maps, *Transportation Research Part D: Transport and Environment*. **87** (2020) 102516-undefined. doi:10.1016/j.trd.2020.102516.

[33] M. Farda, and C. Balijepalli, Exploring the effectiveness of demand management policy in reducing traffic congestion and environmental pollution: Car-free day and odd-even plate measures for Bandung city in Indonesia, *Case Studies on Transport Policy*. **6** (2018). doi:10.1016/j.cstp.2018.07.008.

[34] M. Kantor, R. State, T. Engel, and G. Ormazabal, A policy-based per-flow mobility management system design, in: Proceedings of the Principles, Systems and Applications on IP Telecommunications (IPTComm 2015), ACM Press, Chicago, Illinois, USA, 2015. doi:10.1145/2843491.2843835.

[35] J. Tang, A. McNabola, and B. Misstear, The potential impacts of different traffic management strategies on air pollution and public health for a more sustainable city: A modelling case study from Dublin, Ireland, *Sustainable Cities and Society*. **60** (2020). doi:10.1016/j.scs.2020.102229.

[36] C. Villiers, L.D. Nguyen, and J. Zalewski, Evaluation of traffic management strategies for special events using probe data, *Transportation Research Interdisciplinary Perspectives*. **2** (2019). doi:10.1016/j.trip.2019.100052.

[37] P.S. Chakraborty, A. Tiwari, and P.R. Sinha, Adaptive and Optimized Emergency Vehicle Dispatching Algorithm for Intelligent Traffic Management System, *Procedia Computer Science*. **57** (2015). doi:10.1016/j.procs.2015.07.454.

[38] S. Ghosal, and T. Chatterjee, Controlling Emergency Vehicles During Road Congestion—A Survey and Solution, in: 3rd International Conference on Computational Intelligence in Pattern Recognition (CIPR), Kolkata, 2020: pp. 529–538. doi:10.1007/978-981-15-2449-3_45.

[39] E.S. Podolskaia, K.A. Kovganko, D. v. Ershov, P.P. Shulyak, and A.I. Suchkov, Using of transport network model to estimate travelling time and distance for ground access a forest fire, *Forest Science Issues*. **2** (2019) 1–24. doi:10.31509/2658-607x-2019-2-2-1-22.

[40] A. Rego, L. Garcia, S. Sendra, and J. Lloret, Software Defined Network-based control system for an efficient traffic management for emergency situations in smart cities, *Future Generation Computer Systems*. **88** (2018). doi:10.1016/j.future.2018.05.054.

[41] S. Marinello, F. Lolli, and R. Gamberini, The Impact of the COVID-19 Emergency on Local Vehicular Traffic and Its Consequences for the Environment: The Case of the City of Reggio Emilia (Italy), *Sustainability*. **13** (2020). doi:10.3390/su13010118.

[42] Kaggle, (n.d.). https://www.kaggle.com/.

[43] F. Orsi, A. Scuttari, and A. Marcher, How much traffic is too much? Finding the right vehicle quota for a scenic mountain road in the Italian Alps, *Case Studies on Transport Policy*. (2020). doi:10.1016/j.cstp.2020.08.007.

[44] J.A. Donázar, O. Ceballos, and A. Cortés-Avizanda, Tourism in protected areas: Disentangling road and traffic effects on intra-guild scavenging processes, *Science of The Total Environment*. **630** (2018). doi:10.1016/j.scitotenv.2018.02.186.

[45] P. Signorile, V. Larosa, and A. Spiru, Mobility as a service: a new model for sustainable mobility in tourism, *Worldwide Hospitality and Tourism Themes*. **10** (2018). doi:10.1108/WHATT-12-2017-0083.

[46] O. Saenz-de-Miera, and J. Rosselló, The responsibility of tourism in traffic congestion and hyper-congestion: A case study from Mallorca, Spain, *Tourism Management*. **33** (2012). doi:10.1016/j.tourman.2011.06.015.

[47] J.F. Perles-Ribes, A.B. Ramón-Rodríguez, J. Ivars-Baidal, and M.J. Such-Devesa, The use of private vehicles in residential and holiday tourism destinations: the case of Spain, *Current Issues in Tourism*. **23** (2020). doi:10.1080/13683500.2018.1508427.

[48] R. Rendeiro Martín-Cejas, and P. Pablo Ramírez Sánchez, Ecological footprint analysis of road transport related to tourism activity: The case for Lanzarote Island, *Tourism Management*. **31** (2010). doi:10.1016/j.tourman.2009.01.007.
[49] D. Jeong, Y.E. Choi, L. Jin, and J. Chon, Impact of Spatial Change on Tourism by Bridge Connections between Islands: A Case Study of Ganghwa County in South Korea, *Sustainability*. **11** (2019). doi:10.3390/su11226516.
[50] V. Garaca, G. Jovanić, N. Ćurčić, and S. Vukosav, Spatial Planning for Transit Tourism on The Highway: A Case Study of Highway E-75 Through Vojvodina (Horgoš – Belgrade Section), *Transylvanian Review of Administrative Sciences*. **44** (2015) 126–143.
[51] M. Juschten, and R. Hössinger, Out of the city – but how and where? A mode-destination choice model for urban–rural tourism trips in Austria, *Current Issues in Tourism*. (2020). doi:10.1080/13683500.2020.1783645.
[52] M. Rutty, L. Matthews, D. Scott, and T. del Matto, Using vehicle monitoring technology and eco-driver training to reduce fuel use and emissions in tourism: a ski resort case study, *Journal of Sustainable Tourism*. **22** (2014). doi:10.1080/09669582.2013.855221.
[53] J. Zeng, Y. Wen, C. Bi, and R. Feiock, Effect of tourism development on urban air pollution in China: The moderating role of tourism infrastructure, *Journal of Cleaner Production*. **280** (2021). doi:10.1016/j.jclepro.2020.124397.
[54] R. Zagidullin, Model of Road Traffic Management in the City during Major Sporting Events, *Transportation Research Procedia*. **20** (2017). doi:10.1016/j.trpro.2017.01.115.
[55] Z. Mei, H. Qiu, C. Feng, and Y. Cheng, Research on a forecasting model of tourism traffic volume in theme parks in China, *Transportation Safety and Environment*. **1** (2019). doi:10.1093/tse/tdz011.
[56] J.B. Tenenbaum, V. de Silva, and J.C. Langford, A Global Geometric Framework for Nonlinear Dimensionality Reduction, *Science (1979)*. **290** (2000) 2319–2323. doi:10.1126/science.290.5500.2319.
[57] Matlab Toolbox for Dimensionality Reduction, (n.d.). https://lvdmaaten.github.io/drtoolbox/.
[58] L. van der Maaten, E. Postma, and J. van den Herik, Dimensionality Reduction: A Comparative Review, 2009.
[59] L. van der Maaten, and G. Hinton, Visualizing data using t-SNE, *Journal of Machine* Learning *Research*. **9** (2008) 2579–2625.
[60] J. MacQueen, Some methods for classification and analysis of multivariate observations, *Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability*. **1** (1967) 281–297.
[61] C.M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006.
[62] Google, (n.d.). https://www.google.com/.
[63] dati.gov.it, (n.d.). https://www.dati.gov.it/.
[64] geodati.gov.it, (n.d.). https://geodati.gov.it/geoportale/.
[65] Salone Internazionale Gelateria, Pasticceria, Panificazione Artigianali e Caffè, (n.d.). https://www.sigep.it/ (accessed November 6, 2020).
[66] S.G. Makridakis, S.C. Wheelwright, and R.J. Hyndman, Forecasting: Methods and Applications, 3rd ed., John Wiley & Sons Inc, 1997.
[67] L. Breiman, J. Friedman, C.J. Stone, and R.A. Olshen, Classification and Regression Trees, Chapman and Hall, 1984.
[68] Agenzia regionale per la prevenzione, l'ambiente e l'energia dell'Emilia-Romagna, (n.d.). https://www.arpae.it/ (accessed November 12, 2020).