

Juan M. Corchado
Saber Trabelsi *Editors*

Sustainable Smart Cities and Territories

Lecture Notes in Networks and Systems

Volume 253

Series Editor

Janusz Kacprzyk, Systems Research Institute, Polish Academy of Sciences,
Warsaw, Poland

Advisory Editors

Fernando Gomide, Department of Computer Engineering and Automation—DCA,
School of Electrical and Computer Engineering—FEEC, University of Campinas—
UNICAMP, São Paulo, Brazil

Okyay Kaynak, Department of Electrical and Electronic Engineering,
Bogazici University, Istanbul, Turkey

Derong Liu, Department of Electrical and Computer Engineering, University
of Illinois at Chicago, Chicago, USA, Institute of Automation, Chinese Academy
of Sciences, Beijing, China

Witold Pedrycz, Department of Electrical and Computer Engineering,
University of Alberta, Alberta, Canada, Systems Research Institute,
Polish Academy of Sciences, Warsaw, Poland

Marios M. Polycarpou, Department of Electrical and Computer Engineering,
KIOS Research Center for Intelligent Systems and Networks, University of Cyprus,
Nicosia, Cyprus

Imre J. Rudas, Óbuda University, Budapest, Hungary

Jun Wang, Department of Computer Science, City University of Hong Kong,
Kowloon, Hong Kong

The series “Lecture Notes in Networks and Systems” publishes the latest developments in Networks and Systems—quickly, informally and with high quality. Original research reported in proceedings and post-proceedings represents the core of LNNS.

Volumes published in LNNS embrace all aspects and subfields of, as well as new challenges in, Networks and Systems.

The series contains proceedings and edited volumes in systems and networks, spanning the areas of Cyber-Physical Systems, Autonomous Systems, Sensor Networks, Control Systems, Energy Systems, Automotive Systems, Biological Systems, Vehicular Networking and Connected Vehicles, Aerospace Systems, Automation, Manufacturing, Smart Grids, Nonlinear Systems, Power Systems, Robotics, Social Systems, Economic Systems and other. Of particular value to both the contributors and the readership are the short publication timeframe and the world-wide distribution and exposure which enable both a wide and rapid dissemination of research output.

The series covers the theory, applications, and perspectives on the state of the art and future developments relevant to systems and networks, decision making, control, complex processes and related areas, as embedded in the fields of interdisciplinary and applied sciences, engineering, computer science, physics, economics, social, and life sciences, as well as the paradigms and methodologies behind them.

Indexed by SCOPUS, INSPEC, WTI Frankfurt eG, zbMATH, SCImago.

All books published in the series are submitted for consideration in Web of Science.

More information about this series at <http://www.springer.com/series/15179>

Juan M. Corchado · Saber Trabelsi
Editors

Sustainable Smart Cities and Territories

 Springer

Editors

Juan M. Corchado
Department of Computing Science
Universidad Salamanca
Salamanca, Spain

Saber Trabelsi
Texas A&M University at Qatar
Doha, Qatar

ISSN 2367-3370 ISSN 2367-3389 (electronic)
Lecture Notes in Networks and Systems
ISBN 978-3-030-78900-8 ISBN 978-3-030-78901-5 (eBook)
<https://doi.org/10.1007/978-3-030-78901-5>

© The Editor(s) (if applicable) and The Author(s), under exclusive license
to Springer Nature Switzerland AG 2022

This work is subject to copyright. All rights are solely and exclusively licensed by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Reducing Emissions Prioritising Transport Utility 300
Holger Billhardt, Alberto Fernández, Sandra Gómez-Gálvez,
Pasqual Martí, Javier Prieto Tejedor, and Sascha Ossowski

Doctoral Consortium

**Gamification Proposal of an Improved Energy Saving System
for Smart Homes** 315
David García-Retuerta and Juan M. Corchado

A Decision Support System for Transit-Oriented Development 318
Aya Hasan AlKhereibi

**Smart-Heritage: An Intelligent Platform for the Monitoring
of Cultural Heritage in Smart Cities** 324
Marta Plaza-Hernández and Juan Manuel Corchado Rodríguez

Author Index. 329



Reducing Emissions Prioritising Transport Utility

Holger Billhardt¹, Alberto Fernández¹ (✉), Sandra Gómez-Gálvez¹, Pasqual Martí²,
Javier Prieto Tejedor³, and Sascha Ossowski¹

¹ CETINIA, Universidad Rey Juan Carlos, Madrid, Spain
{holger.billhardt, alberto.fernandez, sandra.gomez.galvez,
sascha.ossowski}@urjc.es

² Valencian Research Institute for Artificial Intelligence (VRAIN),
Universitat Politècnica de València, Valencia, Spain
pasmargi@vrain.upv.es

³ BISITE Research Group, University of Salamanca, Edificio Multiusos I+D+i,
37007 Salamanca, Spain
javierp@usal.es

Abstract. The regulation of mobility and traffic for the transportation of goods and the movement of people is one of the key issues local authorities are faced with, especially in large urban areas. The aim is to provide efficient mobility services that allow people the freedom to move within their cities as well as to facilitate the distribution of goods. However, the provisioning of transportation services should go in line with other general objectives, like reducing emissions and having more healthy living environments. In this context, we argue that one way to achieve objectives is to limit the use of transportation infrastructure elements and to assign the corresponding resources dynamically and in a prioritised manner to the traffic activities that have a higher utility from the point of view of the society, that is, activities that i) produce less pollution and ii) provide more value to society. Different mechanisms that restrict and control the access to an urban area based on pollution levels in that area are already in use in cities such as Madrid or London, but their level of dynamism and adaptiveness is limited. In this paper we go beyond these approaches, and propose a prioritised access control approach that is highly dynamic, specific to individual vehicles, and that considers social utility or transportation efficiency. We provide a general model for our approach and instantiate it on a use case for last-mile delivery. We accomplish several experiments using the SUMO traffic simulation tool, to evaluate our proposal.

Keywords: Traffic management · Last-mile delivery · Prioritized resource allocation · Agreement technologies

1 Introduction

The organization of urban mobility and transportation is a field that has received tremendous changes, as well as a remarkable interest in the last years. Not only the desire of

people to move freely within the cities, but also the transformation of customer habits towards a more and more online acquisition of goods and the subsequent logistic requirements, tend to increase the traffic in big cities. At the same time the consciousness and sensibility has grown regarding environmental pollution and its effects on public health and the quality of life of citizens. In this context, authorities of big cities all over the world are faced with the problem of providing efficient transportation solutions reducing at the same time traffic-related problems like traffic jams or environmental pollution. In parallel to this trend, both, research and industry, have proposed and provided new innovative solutions for more environmental-friendly means of transportations, like new types of vehicles (e.g., electric cars, scooters, bikes and so on) or new transportation services that are based on the concept of “collaborative economy” or “collaborative consumption” [1] and aim at a more efficient usage of available resources, e.g., the sharing of transportation means for several transportation tasks.

We argue that in this new context also the management of the usage of transportation infrastructures can help to control environmental pollution while facilitating at a same time the transportation of goods and people in big cities. Here we understand as infrastructures all those facilitating elements or resources of a transport system that are used in a shared manner by different users and at different times, such as traffic lights, roads, tracks and lanes, parking spaces, etc. The availability of such resources is usually limited, and we believe that new usage schemas should be set up that prioritize vehicles or transportation services that are more environmental-friendly and have a higher transportation efficiency or are more important from a social point of view. A simple, already existing example of this idea is the ability of ambulances to cross any crossroad when they carry patients in life-threatening situations.

In this paper, we present a novel approach towards smart infrastructures that adaptively limits the access of vehicles to certain parts of a city based on the measured pollution. The idea is to specify regulation devices at all entry points of a specific sensible area of a city that tracks the current pollution and dynamically grants or restricts the access of vehicles based on admissible pollution values. In this process, the devices prioritize the access of vehicles that have a higher importance from a social point of view.

Section 2 presents some related work and Sect. 3 gives a general formalisation for our prioritized access model. In Sect. 4 we instantiate the model with a use case of a parcel delivery service. Here, the importance of a delivery task is measured in terms of the number of parcels a vehicle is transporting. We present different experiments using the traffic simulation tool SUMO [10]. Finally, Sect. 5 concludes the paper.

2 Related Work

A lot of works can be found in the Intelligent Transportation Systems literature that aim at smart solutions to traffic control in big cities. The expansion of smart road infrastructures, supported by vehicle-to-vehicle and vehicle-to-infrastructure communications, opened a field for experimenting with a variety of methods and approaches to address different challenges.

The prioritised use of road traffic infrastructures has been commonly regulated by means of traffic lights or smart intersections [2]. While traffic light actions (phases) make

no distinction of the vehicles demanding access, intersection management can deal with individual agents. This is the case of the reservation-based control system proposed by [3], which allows autonomous vehicles to negotiate with intersection managers time and space slots to cross the intersection. That system has been extended by different authors, for example by market-based mechanisms to prioritise the access to networks of intersections [4].

Traffic control systems are mostly focused on regulating traffic flow to avoid congestion, thus indirectly reducing pollution. Recently, approaches that specifically account for pollution emissions are gaining interest. [5] analysed two control actions to reduce air pollution in urban areas caused by traffic, namely reducing speed and environmental restricted zone. The latter consists in restricting access to the most contaminant vehicles, which was based on their classification according to the European Emission Standards. The implementation was static, i.e. vehicles were classified in four categories and the two less polluting categories were permitted access. [6] evaluated different intersection control algorithms, showing that platoon-based algorithms obtain less pollutant emissions (higher throughput) but lower fairness than FIFO. [7] studied the effectiveness of traffic signal control and variable message signs for reducing traffic congestion and pollutant emissions. [8] proposed a Pareto-optimal Max Flow algorithm, which obtains multiple distinct possible paths with maximum flow between a pair of points. Thus, these solutions can be used to distribute traffic and pollution more evenly through a city. These works focus on simulating and assessing the performance of specific static actions. A dynamic traffic light control system based on traffic and air pollution was presented in [9].

Our objective is proposing a prioritised access control approach that is highly dynamic, specific to individual vehicles and that considers social utility or transportation efficiency.

3 Prioritised Access to Transport Infrastructures

In this section we propose a general model for a prioritized allocation of transport infrastructure resources. As pointed out earlier, we understand by transport infrastructure all elements that are provided to the general public facilitating mobility. Such elements may be static, like for instance, streets, lanes of a street, crossroads, parking spaces, etc. Other elements may be mobile, like vehicles of sharing systems or more classical public transportation facilities, like buses, trains or subways, and so on. Infrastructure elements may be used by any person, and their usage is usually regulated through specific norms or conventions. For example, the usage of a lane of a particular street is regulated through the corresponding traffic norms. Also, many elements may be used without charge (usually this holds for most static elements) and others may have some cost (e.g., public transportation).

Transportation infrastructure elements are intrinsically limited and typical traffic problems like traffic jams or excessive delays in movements arise when the usage demand of certain elements exceeds the available resources or capacities. Such mismatches between demands and available resources usually arise in big cities where the population density is very high. In addition, in many big cities, there might also be an

interest in putting additional limitations on the use of certain infrastructure elements. For instance, in many European cities, traffic is restricted in some ways in the centre with the aim of having more human-friendly environments or reducing the pollution.

Typically, the aforementioned situations lead to a problem of assigning limited resources to an excessive demand and the decision who should be allowed to access a given resource. In the traffic domain, such decisions are typically not taken in a goal-directed manner. Rather the rule of “who comes earlier wins” applies. In contrast, we believe that from the point of view of improving social welfare, limited infrastructure capacity should be preferably assigned to users or tasks that are more “important” or less harmful with respect to some global, social parameters. That is, the access to or use of limited transport infrastructures should be prioritized.

Our model is based on the notion of a *trip*. A trip refers to a movement activity carried out by an individual vehicle for accomplishing a certain transportation task (e.g., transporting one or more persons, parcels, etc.). Trips are accomplished by *vehicles*. Vehicles have different characteristics, like size, type, emissions, etc. During a trip, a vehicle will use elements of the transport infrastructure.

The accomplishment of a trip has a certain utility for the issuer of the trip (the user) that refers to the preferences of fulfilling the underlying task in an optimal manner. In general, the aim of a mobility infrastructure is to provide a set of services that contributes to the welfare of society as a whole. From this perspective, each trip can be conceived as providing some level of global utility to society.

Given a trip t , we define its utility as a function of two factors i) the global transportation utility of t ($UT(t)$), and ii) the cost of the trip $C(t)$:

$$U(t) = g(C(t), UT(t))$$

$UT(t)$ can be considered as the importance of the trip (e.g., of transporting the associated elements to a destination place) from the point of view of the society. For example, an ambulance movement will be more important than a simple movement of a person in her private car. Thus, the transportation utility will be higher. Regarding $C(t)$, we assume that any mobility activity, and the subsequent use of the transportation infrastructure, has an associated cost. This cost depends on the vehicle that carries out the trip and will include direct costs (e.g. due to the usage of infrastructure elements) as well as externalities as, for instance, the emissions produced. Usually, the global utility of a trip is correlated with $UT(t)$ and is inversely correlated with $C(t)$.

It should be noted that the global utility may be aligned with the individual utility of a user, but this must not be the case in all situations. For example, in the case of a patient who must be transported urgently to a hospital, the global utility will be very high (as for the patient herself, of course). In contrast, if a person moves in order to go shopping, the importance for the society will be usually much higher from that person’s perspective than from the point of view of the society.

A trip requires the use of elements in the transport infrastructure. If such elements are scarce, e.g., the demand exceeds the available resources, then the use or assignment of infrastructure elements should be prioritized in order to optimize global utility. This could be done in the following way. Let I be an infrastructure element with capacity $cap(I)$ during some time interval $\Delta time$. Furthermore, let $T = \{t_1, t_2, \dots, t_m\}$ be the

trips that claim some of I 's capacity during $\Delta time$, where $capR(I, t_i)$ denotes the portion of I that is requested by the trip t_i . The resources or capacities of I during the interval $\Delta time$ should be assigned by some *control strategy*. Here we define the objective of the control strategy to assign all available resources of I to the set of trips with highest utility. That is to a set $T' \subseteq T$, with:

$$\sum_{t_i \in T'} capR(I, t_i) = cap(I)$$

$$\forall t_i \in T', t_j \notin T' : U(t_i) \geq U(t_j)$$

We implicitly assume that a vehicle requests the use of element I in order to fulfil the underlying transportation task in the best possible manner. Thus, if the requested capacity is denied, the vehicle needs to find an alternative solution which may lead to a worse task completion.

In general, we consider that different elements of the transportation infrastructure should be regulated with different control strategies. The general objective here is to increase the global utility of the whole transportation system in a city in terms of the aggregation of the utilities of all transport trips and this can be obtained by prioritizing the trips with higher utility. In addition, giving privileges to more efficient trips (trips with less cost and higher importance) will promote such trips and may encourage users to invest in vehicles with less social costs or to optimize the loads of their trips.

The different parameters of the general model described in this section may be difficult to calculate. Usually, parameters like utilities and costs have to be estimated and will depend on the concrete application case. In the next section, we instantiate the described model for a use case of last-mile delivery and the regulation of the access to a certain area in a city in order to limit the pollution in that area.

4 Use Case. Last-Mile Delivery

4.1 Scenario

We consider a Last-Mile Delivery scenario where different vehicles deliver parcels in a city. In addition, there is an area in the city centre (the *control zone*) with dynamic access restrictions in order to keep the environmental pollution in this area below some threshold. In this context and with respect to the general model described in Sect. 3, the infrastructure element whose use is regulated through a control strategy is the access to the control area. Here, the proposed control system does not only have to assign limited resources to trips (e.g., permitting or denying the access to the control zone). It also controls dynamically the capacity of the control zone, that is, which vehicles are allowed to enter the control zone and which vehicles are rejected and need to take a detour. In particular, our aim is to dynamically increase or decrease the area access restrictions depending on the pollution in a given moment.

In the sequel we instantiate the model proposed in Sect. 3 to the use case under consideration. In this article, our aim is to analyse the general validity of our proposal. In order to keep the clarity of our description we apply a set of simplifying assumptions.

We assume that each trip includes one or more parcels, and we consider that all parcels in a vehicle trip have the same origin and destination. With this, we define the transportation utility of a trip by:

$$UT(t) = \frac{n(t)}{d(t) + 1}$$

where $n(t)$ is the number of parcels included in the trip t and $d(t)$ denotes the delay of the arrival time of the trip if it cannot access the control zone.

With respect to the cost of a trip t , our objective is to reduce the emissions in the control area and thus, we define:

$$C(t) = e(t)$$

where $e(t)$ is a measure representing the average emission the vehicle carrying out the trip t would emit in the control zone. We consider that vehicles belong to different emission types, which are known a priori and which are used to estimate $e(t)$.

4.2 Control Strategies

We analyse different control strategies. Each strategy determines the access restrictions to be applied at each moment and decides which vehicles can enter the control area.

We consider that the system implementing a control strategy works as follows. A vehicle that wants to enter the restricted area requests access at an entry point, and the control strategy either grants or denies this access.

The idea of the strategy is to restrict access to the control zone in such a way that the measured pollution in the area p_t is kept below a certain maximum at any time t .

For this we apply the following idea. We calculate an *access permission level* k_t to the control zone as follows:

$$k_t = \begin{cases} 1 & \text{if } p_t \leq \theta_L \text{ (no restrictions)} \\ 0 & \text{if } p_t \geq \theta_H \text{ (no vehicles allowed)} \\ \frac{(\theta_H - p_t)}{(\theta_H - \theta_L)} & \text{otherwise} \end{cases}$$

where θ_L and θ_H are two threshold values. θ_H represents the maximum allowed pollution, a value that should not be exceeded. θ_L is a lower bound on p_t that is used as a control point from which access restrictions are applied.

Given the access level k_t , we define the following different control strategies:

Baseline (B).

At each moment t , the value of k_t determines the ratio of trips that are allowed to enter the control zone. This strategy does not prioritize the access for different trips. That means, implicitly it employs a definition of $U(t_i)=c$, where c is a constant.

The strategy is implemented by randomly granting access with probability k to each trip that request access to the restricted area. The strategy is used as a baseline and represents the ad hoc idea of reducing the emissions by a proportional reduction of vehicles in the control zone.

Vehicle Emission (VE).

As in the baseline strategy, at each moment t , the value of k_t determines the ratio of trips that are allowed to enter the area. However, this strategy prioritizes trips having lower emissions. That is, the strategy employs a utility function:

$$U(t_i) = \frac{1}{C(t_i)} = \frac{1}{(1 + e(t_i))}$$

That is, access is allowed for the $(k_t \cdot 100)\%$ of vehicles with lowest emissions.

Vehicle Emission per Package (VEP).

Like the previous two strategies, at each moment t , the value of k_t determines the ratio of trips that are allowed to enter the area. The access is prioritized with respect to the emissions of a trip and the importance of a trip (number of parcels carried), using the following definition of global utility:

$$U(t_i) = \frac{UT(t_i)}{C(t_i)} = \frac{n}{(d(t_i) + 1) * (1 + e(t_i))} = \frac{n}{(1 + e(t_i))}$$

Note that $d(t_i) = 0$, if the trip is granted access to the control zone. The strategy allows the access for the $(k_t \cdot 100)\%$ of vehicles with the lowest emissions per package.

Ratio Reduction Emission (RRE).

In this case, the access value k_t is not applied to the ratio of cars that can enter the restricted area. Instead, k_t represents the ratio of emissions that are allowed to be generated with respect to the normally generated emissions in the same moment or time frame. Given k_t , we calculate the ratio k_t' of vehicles with lowest emissions (with respect to the normal demand) that together produce the $(k_t * 100)\%$ of the emissions normally generated in the same moment or time frame. It holds that $k_t' \geq k_t$. Afterwards, the strategy applies the same prioritization schema as VE.

Ratio Reduction Emission per Package (RREP).

As the RRE strategy, here k_t is translated to a ratio of vehicles k_t' . Then, the same prioritization schema as in VEP is employed with the new ratio.

In the strategies VE and VEP we use historical data to estimate the threshold value for emissions (emissions per package) to determine whether a vehicle belongs to the k_t vehicles with lowest emissions and access is granted to all these vehicles. In a similar way, in the strategies RRE and RREP, we use historical data to estimate the ratio k_t' and to decide whether or not a vehicle can access the area.

4.3 Experiments

We carried out experiments using SUMO [10], a popular open-source microscopic traffic simulator. SUMO includes several emission models. We used HBFA3, which is based on the database HBEFA¹ version 3.1. The model simulates several vehicle emission pollutants, and we chose NO_x as the reference in our experiments.

¹ <http://www.hbefa.net/>.

SUMO implements several vehicle emission classes including heavy duty, passenger and light delivery emission classes, combined with different EU emission standards (levels 0–6). In the experiments, we chose 7 different types of vehicles with different emission classes: eVehicle (“Zero/default”), gasolineEuroSix (“HBEFA3/LDV_G_EU6”), dieselEuroSix (“HBEFA3/LDV_D_EU6”), hovDieselEuroSix (“HBEFA3/PC_D_EU6”), normalVehicle (“HBEFA3/PC_G_EU4”), highEmissions (“HBEFA3/PC_G_EU3”), and truck (“HBEFA3/HDV_D_EU4”).

While SUMO is able to provide information about pollutants emitted by vehicles, it does not include a model of how those pollutants evolve in the air. These values depend on many different factors, not only different pollutant emission sources but also on weather conditions (wind, rain, temperature changes, etc.).

Typical access policies to city centres are taken based on pollution data measured by atmospheric stations, and not on the direct emissions of vehicles. This is the approach followed by the strategies proposed in Sect. 4.2, which are based on the pollutants in the air at a certain point in time t (denoted by p_t).

In our experiments, we have simulated air quality data through a simple model as follows. The basic idea is that pollution at time t is the sum of the previous pollution plus the amount emitted by vehicles during the last time period minus a quantity that is removed by atmospheric effects: $p_t = p_{t-1} + e_t - \lambda_t \cdot 45000$, where p_t is the pollution in the air at time t , e_t is the pollution emitted by vehicles between the time interval from $t-1$ to t , $\lambda_t \in [0.8, + 1.2]$ is a uniformly randomly generated factor that represents a ratio of pollutants removed from the air in time t (we set the constant 45000 empirically). While we recognise that this is a simplification of the real world, this measure allows us to analyse and compare the different control strategies.

For the experiments we designed a virtual city as shown in Fig. 1. It includes a 5×5 km square control zone with eight access points. The network is made up of road segments connected by intersections. All segments are bidirectional. The strategies control the access to the *control zone* (marked in red).

There is a set of vehicles carrying packages from an origin to a destination location. Each vehicle is characterised by origin, destination, number of packages and average pollutant emissions (mg/s). All trips start and end at one of the external points and, in principle, would pass through the control zone if access was granted. Upon reaching the border of the control zone, vehicles ask for permission to enter. If access is granted, they cross the control zone. If not, they have to find a route that bypasses the city centre, which will usually take longer.

We are only interested in trips whose planned routes cross the control zone. The rest does not provide any value for our evaluation. For this reason, trips were generated randomly connecting North-South and East-West, in both directions.

We run a simulation of 2.5 h. During the first hour, trips are generated at a rate of about 1000 per hour; during the next 30 min, at a rate of 2000; and during the last hour, with a rate of 1000. Origin and destination, number of packages (between 1 and 20), and vehicle type are chosen randomly. All vehicle types have the same probability, except *truck* and *highEmissions*, which have half the rate of the others.

We carried out simulations without control zone restrictions to set some initial parameters. Namely we set $p_o = 10^6$, $\theta_L = 0.8 \cdot 10^6$ and $\theta_H = 10^6$. The time interval to update k is set to 60 s.

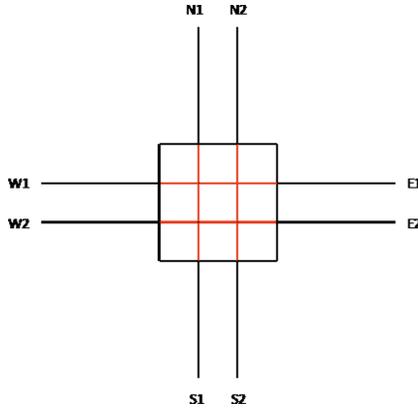


Fig. 1. Road network used in the experiments. Red lines represent the control zone.

4.4 Results

Table 1 shows a summary of the results of the experiments. For each strategy we present the number of vehicles (out of a total 3108 vehicles) that did not enter the control zone due to access limitations, the total amount of NO_x (mg) emitted by vehicles in the control zone, the average transportation time per parcel and the average time per trip. We also included the results without access limitations.

We confirmed that applying control strategies the amount of pollution emitted by vehicles in the control zone was reduced about 33%. All strategies obtain similar results following different approaches as described in Sect. 4.2. This is due to the fact that they all use the same low and high thresholds (θ_L, θ_H) of allowed pollution. The different

Table 1. Simulation results.

Strategy	#vehicles no access control zone	NOx emitted control zone	Time per parcel (s)	Avg. trip time (s)
No control	15/0.5%	12439311	1359	1359
Baseline	1077/34.7%	8061291	1501	1501
VE	627/20.2%	8002710	1455	1457
VEP	553/17.8%	7959436	1436	1445
RRE	301/9.7%	8100536	1389	1391
RREP	242/7.8%	8088261	1374	1379

strategies achieve this goal by limiting access to more or less vehicles. Besides the access limitations, vehicles may select to bypass the city because of traffic congestions. This is the case for example for the 15 cars with the “no control” strategy that did not enter the control zone.

As expected, the *baseline* strategy restricts the access to more vehicles than the others, since it randomly chooses which ones are granted access. *VE* and *VEP*, obtain similar results granting access to much more vehicles than *baseline*. These strategies’ approach is to reduce the same percentage of vehicles as *baseline* but they select the less contaminant vehicles. The effect is that less contaminants are released, thus pollution is reduced and, consequently, more vehicles are allowed to enter the control zone. *RRE* and *RREP* are the strategies that allow more vehicles to enter the control zone. Their approach is to allow access to less contaminant vehicles that jointly add up a percentage of expected emissions. That is, they restrict access to a few but high contaminant vehicles (e.g. trucks represent 80% of total emissions in our experiments).

Average trip times are in line with the rate of vehicles that could/could not access the control zone. Strategies that took into account the number of packages benefited of slightly lower travel times per package as compared to just considering emissions. However, the differences are rather small.

Figure 2 shows the evolution of NO_x pollution (*p*) in the control zone over time. We present the results after a “warm up” period of about 1000 s. The curve for the no control strategy escapes the graph at time 4400 s reaching a maximum value higher than 5·10⁶, so we opt for not showing that part and keep the other curves visible.

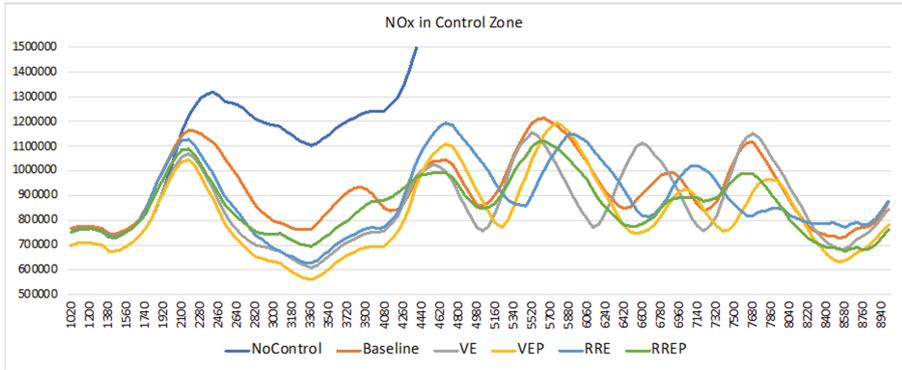


Fig. 2. Evolution of pollution (NO_x) in control zone through the simulation time (seconds)

As it is shown in Fig. 2, all control strategies help to limit the level of NO_x emissions and there is no clear difference among the different strategies in that sense. The strategies start limiting the access when the threshold value of 800.000 is reached and close the access at 1.000.000. As it can be noted, triggering limitations does not have an immediate effect on reducing *p* and the limitations have to be set for more time in order to reduce *p* under the lower threshold of 800.000. In fact, even if the control zone is closed at all, *p* may still increase because of the vehicles that are already in the control zone. The effect is that *p*, may pass the upper threshold (here 1.000.000) on several occasions. This

also produces the effect of p to oscillate roughly between 800.000 and 1.200.000. The oscillation will only occur if the demand is high and would produce too many emissions if no control strategy is used. This happens in the experiment from about 4000 s.

5 Conclusions

The demand for using the transportation infrastructure has increased tremendously in the last years, especially in highly dense urban areas. In this paper, we have argued that the use of infrastructure elements should be regulated and prioritized with the aim of fostering global utility. In particular, we present a general assignment model that assigns limited traffic resources to the traffic activities (trips) that have a higher utility from the point of view of the society. Here utility is considered to have two components: i) cost (e.g. emissions), and ii) social “importance” of the transportation activity.

We have instantiated the model for the case of last-mile delivery in a city with an access restricted area. We present a control system that dynamically determines the access limitation level for the control zone based on the current measures of environmental pollution. Furthermore, the system employs a prioritization strategy that determines which vehicles (trips) can enter the area and which ones need to bypass it. We have proposed different strategies: i) all trips have the same priority, ii) low-emission cars have higher priority, and iii) priority depends on the “importance” of the trips and on the emissions of the cars. In the latter case, “importance” is measured in terms of packages a vehicle is delivering.

We have carried out several experiments with the traffic simulation tool SUMO to analyse the performance of our proposal with different strategies. As a conclusion we can determine that the general idea of dynamically limiting the access to a restricted area allows to maintain the environmental pollution in this area below given limits. Furthermore, a prioritization of access based on emissions and/or “importance” of a trip improves the utility of the system and allows to accomplish in an efficient way more of the important transportation tasks under the given pollution limits.

Given the prioritization methods, less important tasks or the use of vehicles with more emissions will imply more restrictions and limitations of movement. As a side effect, users may tend to acquire more environmentally friendly vehicles and may try to combine different transportation tasks in a single movement. In this way, they could benefit from higher priorities in the use of the infrastructure.

With regard to future lines of research, the proposed methods and strategies are still at an early stage of research. We plan to specify the general model for prioritized access in more detail. Furthermore, with regard to the access limitation for an area, we want to analyse more sophisticated methods for specifying the access levels using gradient minimization models. Another line of research is the definition of “importance” of different types of trips, probably using semantic technologies.

Acknowledgments. This work has been partially supported by the Spanish Ministry of Science, Innovation and Universities, co-funded by EU FEDER Funds, through project grants InEDGEMobility RTI2018–095390-B-C31/32/33 (MCIU/AEI/FEDER, UE) and by the Regional Government of Madrid (grant PEJD-2019-PRE/TIC-16575), cofunded by EU ESF Funds.

References

1. Botsman, R.: Defining the sharing economy: what is collaborative consumption-and what isn't? fastcoexist.com. available at <http://www.fastcoexist.com/3046119/defining-the-sharing-economywhat-is-collaborative-consumption-and-what-isnt> (2015)
2. Namazi, E., Li, J., Lu, C.: Intelligent intersection management systems considering autonomous vehicles: a systematic literature review. *IEEE Access* **7**, 91946–91965 (2019)
3. Dresner, K., Stone, P.A.: Multiagent approach to autonomous intersection management. *J. Artif. Intell. Res.* **31**, 591–656 (2008)
4. Vasirani, M., Ossowski, S.: A market-inspired approach for intersection management in urban road traffic networks. *J. Artif. Intell. Res.* **43**, 621–659 (2012)
5. Vergés, J.T.: Analysis and Simulation of Traffic Management Actions for Traffic Emission Reduction. TU, Berlin (2013)
6. Lemos, L.L., Pasin, M.: Intersection control in transportation networks: opportunities to minimize air pollution emissions. In: *IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)* (2016)
7. Mascia, M., et al.: Impact of traffic management on black carbon emissions: a microsimulation study. *Netw. Spat. Econ.* **17**, 269–291 (2017)
8. Kamishetty, S., Vadlamannati, S., Paruchuri, P.: Towards a better management of urban traffic pollution using a Pareto max flow approach. *Transportation Research Part D: Transport and Environment*, **79**, 102194 (2020)
9. Artuñedo, A., del Toro, R.M., Haber, R.E.: Consensus-based cooperative control based on pollution sensing and traffic information for urban traffic networks. *Sensors* **17**(5), 953 (2017)
10. Alvarez Lopez, P., et al.: Microscopic traffic simulation using SUMO. In: *21st IEEE International Conference on Intelligent Transportation Systems, Maui, USA*, pp. 2575–2582 (2018)