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A Dynamic Link-based Eco-indicator for supporting equitable traffic management strategies

Carlos Sampaio^a, Jorge M. Bandeira^{a,*}, Eloisa Macedo^a, Mariana Vilaça^a, Claudio Guarnaccia^b, Bernard Friedrich^c, Hélder Relvas^d, Sandra Rafael^d, Vera Rodrigues^d, Margarida C. Coelho^a

^aUniversity of Aveiro, Centre for Mechanical Technology and Automation (TEMA), Department of Mechanical Engineering, Campus Universitario de Santiago, 3810-193 Aveiro, Portugal

^b University of Salerno, Department of Civil Engineering, via Giovanni Paolo II 132, Fisciano, Italy

^cTechnische Universität Braunschweig, Institute of Transportation and Urban Engineering, Hermann-Blenk-Straße 42, 38114 Braunschweig, Germany

^dUniversity of Aveiro, Centre for Environmental and Marine Studies (CESAM), Department of Environment and Planning, Campus Universitario de Santiago, 3810-193 Aveiro, Portugal

Abstract

This paper presents a methodology for building a link-based eco-indicator which includes different impacts of road traffic. The proposed traffic management tool can be updated in real-time through multiple information sources and translated into a cost factor to be straightforwardly applied into eco-routing algorithms and/or intelligent road pricing systems. The link-based eco-indicator has been tested in several urban and rural links of heterogeneous characteristics during peak and off-peak hours. It has been shown that both dynamic adjustment factors related to online background concentrations and/or citizen's activity may lead to different sustainable traffic management strategies. When evaluating and comparing costs of a single link-based eco-based indicator with National Average (without taking in account people exposure) and a Vulnerability Factor (VF), the total costs using VF increase 158%. In the origin-destination routing problem performed using the distance and travel time as criteria, the costs (for off-peak hours) using VF factor are 80% and 15% higher, respectively. The results achieved in this paper highlight the importance of taking into account vulnerability of people exposure when implementing eco traffic management measures.

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Keywords: eco-indicator; vulnerablity analysis; externalities assessment; origin-destination routing; GIS.

* Corresponding author: Jorge M. Bandeira

E-mail address: jorgebandeira@ua.pt

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1. Introduction

The key objective of the European Union's (EU) transport policy is to promote an efficient, safe, secure and environmentally friendly mobility. For this purpose, the EU has created a framework to encourage Member States to use taxation and infrastructure charging in the most effective and fair manner to foster the 'user pays' and 'polluter pays' principles (EC, 2011; Transport & Environment, 2017). In this context, and given the increasing connectivity of vehicles, it is crucial to develop innovative methodologies allowing a dynamic evaluation of the costs associated with crossing a certain road segment by a specific vehicle type. Such systems for assessment of externalities should be flexible and able to be integrated into intelligent navigation systems algorithms or smart pricing schemes.

The assignment of traffic with environmental objectives has been studied since the last decade of the 20th century (Tzeng and Chen, 1993). Since then, several studies have shown choosing an eco-friendly route may lead to considerable reductions in traffic emissions and fuel consumption of a given journey (Bandeira et al., 2014; Frey et al., 2008; Wu et al., 2014). However, population exposure to pollutants and noise are key factors that have been neglected in the literature, but can significantly contribute to decrease or increase actual estimated damages of choosing a certain route. Few studies addressed air quality levels and the exposed population in optimization algorithms (Zhang et al. 2010, Kickhöfer and Kern, 2015; Rodriguez-Roman and Ritchie, 2015). Focusing on a link level, Kang et al. (2011) presented a link-based emission model to estimate the quantities of emissions produced by vehicles passing through each road segment, and Long et al. (2018) formulated a link-based traffic assignment model to minimize system emissions, but potential exposure of population to traffic-related externalities were not considered. Regarding the complexity of transportation network which involves many objectives (minimizing time, cost, energy, environmental concerns and increasing safety) it seems that multi-criteria analysis can be the best option to evaluate the best path in the routing network. Hazmat routing approach can be used in origin-destination problems consisting in the optimization of routes taken in account not only the costs but also the consequences that may happen due to an accident mainly in vulnerable spots like schools and hospitals, for the transportation of hazardous material (Dadkar et al., 2010).

The main objective of this paper is to present a methodology for building a link-based eco-indicator, which can be updated in real-time through a set of information sources and translated into a cost factor that can be straightforwardly applied into optimization problems. A case study in a Portuguese medium-sized city is used to test the proposed methodology.

2. Methodology

2.1. Traffic and emissions assessment

The proposed eco-indicator has the ability to adapt to different traffic monitoring systems. In a microscopic approach, we simulate existence of Floating Car Data (FCD) based on onboard sensors capable of predicting driving cycles using Global Navigation Satellite Systems (GNSS). The macroscopic approach is based in average speed (e.g., loop detectors, video, Bluetooth sensors). For this purpose, two types of emissions models (VSP – Vehicle Specific Power (Coelho et al., 2009) and COPERT (Emisia, 2016)) are used. COPERT is an average speed-based emissions model widely used in Europe and it is easily adapted to the data available in terms of local fleet distribution, being this average speed based emission models commonly used in eco-routing systems (Guo et al., 2012).

GNSS data and flow data (based on video cameras) were obtained from previous research studies conducted in the city of Aveiro, Portugal (Tafidis et al., 2018; Teixeira et al., 2017) for the main links of the network. Due to the lack of flow traffic monitoring data in all links of the study area, data of a macroscopic traffic model previously calibrated and validated was used (Bandeira et al., 2011). The main objective is to simulate the impacts of applying the eco-indicator for a representative vehicle, assuming reasonable situations of traffic demand, urban activity, air quality and acoustic condition in the study area.

The case study consists in an origin-destination routing problem in the city of Aveiro, Portugal. The network comprises 488 links, 47 km, 367 nodes and has high levels of heterogeneity in the roads type, traffic conditions and resident's density. The data collection methods, models used and data needed is described in table 1.

| Data collection method | Parameters | Model | Impacts | Vulnerability |
|--------------------------------------|-----------------------------|-----------------|-------------|--------------------|
| GNSS | Speed second by second | VSP | Emissions | - |
| | | VSP/EMEP/URBAIR | Air quality | - |
| Eg. Video, Bluetooth, loop detectors | Traffic flow, average speed | COPERT | Emissions | - |
| | | CNOSSOS-EU | Noise | - |
| Statistical country data (INE, 2011) | Residents per block | - | - | Population exposed |
| Local station | Meteorological data | URBAIR | Air quality | - |

Table 1 - Data collection methods, models used and data needed for each impact and vulnerability.

2.2. Noise modeling

For noise assessment, the CNOSSOS-EU model suggested by the European Commission (Kephalopulos et al., 2012) was used. The basic concept is to evaluate the source power level of the traffic, assumed to be a line source, composed by several point sources moving on the road, each of them including the rolling and the propulsion sources. The propagation at the receiver is calculated assuming confident percentages of "favorable" and "homogeneous" conditions and including possible reflections and diffractions. A comparison of CNOSSOS-EU model performances with respect to other predictive models results and with field measurements, in different case studies and conditions, can be found in Guarnaccia et al. (2018).

2.3. Determination of link-based emission and noise damage costs

The determination of the costs of externalities associated with crossing a particular link by a specific vehicle is based on the methodology described in Korzhenevych et al. (2014). A novelty in the present work is that the costs of crossing a given link are adjusted to local vulnerability factors associated to each zone and potential exposed population.

• Local pollutant emissions

An adjustment factor for representing link-based vulnerably risk was developed to reflect the variability of citizens' exposure to the harmful effects of traffic in a given road network links. The population density among the adjacent blocks of each link can be determined through specific data (socioeconomic spatial data, counts, videotaping); or through online data such as artificial vision systems, crowdsourcing information, etc. In this case, we used only historical data to estimate population density at block scale (INE, 2011). An automatic platform based on video image recognition (determination of the number of pedestrians and vehicles) and radiofrequency (cell phone density) is being calibrated to predict urban activity patterns in real-time.

According to Korzhenevych et al. (2014), determination of air quality damage costs is provided for each EU Member State, and it is based on average socioeconomic data and population exposure numbers per country (Table 2). The mean value of population density for urban areas is 1500 inhab/km². In this context, an adjustment factor related to local vulnerability was introduced for each block of the study area to reflect more closely the local demographic characteristics (Vulnerability Factor). At the end, the adjustment factor for assessing a link-based vulnerably risk takes into account the average value of adjacent blocks (see Fig. 1 a)).

Simultaneously, the marginal impact per unit of pollution emitted may be adjusted according to background concentrations. For instance, if background concentrations are significantly below the legal pollution limits, the impact cost can be lower. On the other hand, if air quality indexes are near a threshold alert, the managing authority may want to increase the cost to minimize the risk of exceedances to legal limits. Thus, both adjustment factors will tune the costs of traffic-related environmental externalities for a link-based level instead of current approaches based on country-level impacts.

• Air quality estimation Concentration adjustment factor

The NO_x concentration fields at the urban scale (city of Aveiro) were simulated by applying the air quality model URBan AIR (URBAIR) for a week study period (in an hourly basis). URBAIR is a second-generation Gaussian model, that requires as main inputs data meteorological and emissions information. More details related to the model setup can be found on Borrego et al. (2016). Figure 1 b) illustrates the response of URBAIR for a peak traffic conditions (8-9 a.m.) on the 6th of June 2013, showing that the dynamics of traffic (and related emissions) and atmospheric conditions are preponderant to the magnitude and location of the NO_x hot-spots. Typically, concentration in the network never exceeds the value of 200 μ g NO_x/m³ (Fig. 1 b)), so the concentration adjustment factor related to background concentration (cf) will always be 1 for this case study.

| | 0 | | 1 0 | 1 2 |
|-------------------|-----------|-------|---------------------------|----------------------------|
| External costs | EUR | Noise | COSTS | COSTS |
| | (EUR/ton) | (dB) | (EUR/Year.person exposed) | (EUR /person exposed hour) |
| CO ₂ | 90 | 51 | 6 | 0,000685 |
| NO _x | 1947 | 55 | 29 | 0,003311 |
| NMVOC | 1048 | 60 | 56 | 0,006393 |
| PM _{2.5} | 196335 | 65 | 84 | 0,009589 |
| | | 70 | 113 | 0,0129 |
| | | 75 | 187 | 0,021347 |
| | | | | |

Table 2 - National Average values for transport externalities damage costs data base provided by Korzhenevych et al. (2014).

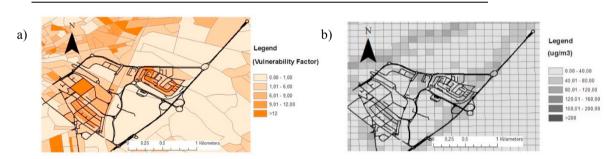


Fig. 1. a) Link-based vulnerably risk adjustment factor. b) NOx concentration grid.

• Noise costs

To estimate the damage costs of noise associated with a vehicle crossing a certain link, a methodology was designed to predict individual noise costs. The first step was to adapt annual costs for people exposed to noise from year values to an hourly basis, since traffic flow data is usually represented in vehicles per hour (vph). Then, a quadratic regression model to predict noise cost exposure (ENC) according to different levels of noise (Leq) was developed. Such model is given by Equation (1). For values of traffic noise below 51 dB, costs were considered negligible.

$$ENC = 2.108^{-5}L_{eq}^2 - 1.855^{-3}L_{eq} + 4.1077^{-2}.$$
(1)

Using the noise model CNOSSOS (Kephalopulos et al., 2012), different noise values for different flows and speeds (assuming a distance of 7.5 m) were estimated and the consequent impact in terms of exposure noise costs was estimated using Equation (2). A multiple regression was performed to evaluate whether noise-related costs can be predicted based on flow and speed. The tests were conducted using the statistical software SPSS (IBM Corp., 2016). Numerical results show, within a 95% confidence interval, that the independent variables flow (Q), speed (v) and speed squared (v^2) are able to explain almost 90% of the variability of the dependent variable noise costs per person exposed (NC). Moreover, the independent variables statistically significantly predict the noise costs (p-value<0.05),

and the obtained regression model yields a good fit of the data. The general form of such model can be given as follows:

$$NC = -6.615E^{-9}Q + 3.822E^{-7}v - 1.419E^{-9}v^2.$$
(2)

After determining NC, i.e., the noise emission cost of single exposed person produced by vehicle crossing a link with a certain flow Q (vph) and speed v (km/h), it is possible to adjust the link-based cost by multiplying NC with the total exposed population. For the sake of simplicity, in this work we will assume the sum of the resident population in the adjacent blocks as well as the number of students in the existing schools in the study area as the "exposed population". In addition, we consider the sensible receivers at a fixed distance of 7.5 m from the center of the road. Of course, people leaving far away from the road will be less disturbed, thus the approach is prudent but still consistent with the distance proposed by the handbook (Korzhenevych et al., 2014) in urban areas, i.e. 10 m, for bottom-up estimation of road noise costs. A more detailed and thin spatial analysis will be object for further analysis, in which the dependence from the distance can be included. In the absence of data, a factor of 21.4 (EUR/1000 people exposure) times link length (km) (Korzhenevych et al., 2014) may be used. Cross-validation of function (2) was performed with data from CNOSSOS-EU model and a R^2 of 0.796 was achieved (30% of data used for validation).

2.4. Building the link-based eco-indicator

The proposed link-based eco-indicator is designed to assess greenhouse gases costs (GHGc) emissions, air pollution costs (APc) and noise pollution damages (NPc), for different vehicle types, weighted by local indices of vulnerability and real-time environmental conditions. One of the main advantages of this approach is the reduction of the computational resources required for multi-objective route optimization, since the problem of dealing with complex nonlinear functions (one for each externality) is minimized in a first phase. The link-based eco-indicator (LBEI) can be given by (3).

LBEI = GHGc + APc + NPc,

where, $GHGc = E_{CO_2} \cdot ECf_{CO_2}$; $APc = \sum Ep_i \cdot ECfp_i \cdot \frac{\overline{Pd}}{1500} \cdot cf$; $NPc = NC \cdot pop$, with Epi is the emission (g) of pollutant i (NO_x, NMVOC, PM_{2.5}); ECfpi is the average national emissions damage cost factor for pollutant i (Table 2); Pd is the average population density in adjacent blocks; and cf is the concentration adjustment factor related to background concentration; pop is the estimated population in adjacent blocks.

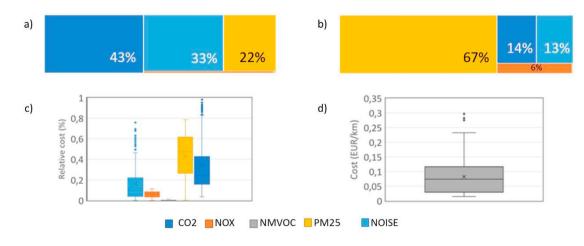


Fig. 2 - Example of link based eco-indicator. a) based on national average values b) weighted by local vulnerability factor. Box and whisker plots of c) relative costs and d) LBEI variations (links > 50 m).

(3)

3. Results

3.1. Link based eco-indicator

Figure 2 provides an example of a link based on an eco-indicator close to a school with a mean average speed (36 km/h) and a high number of people exposed.

When the LBEI is based on National Average (NA) damage cost values, the cost of CO_2 and noise accounts for 76% of the total link cost (with $PM_{2.5}$ representing 22%).

Regarding the link with Vulnerable Factor (VF), the influence of CO_2 and noise is 27%, while the $PM_{2,5}$ costs represent 67% of the total link costs.

3.2. Application of LBEI

Dijkstra's algorithm was used to find the shortest route to evaluate the performance of the link-based eco-indicator, in peak and off-peak periods with different routing criteria/costs (distance; travel time; eco-indicator with VF and eco-indicator with National Average (NA) values). The solution (routes) given by the Network Analyst tool from ArcGIS® software (Esri, 2015), for peak and off-peak periods, are the same, although the values are higher for peak hours. Fig. 3 illustrates the result for off-peak hours. With the Eco-indicator with VF, the algorithm suggests a road of a low number of people exposed, while with NA, the algorithm does not account with people's exposure, suggesting a road segment with more people potentially exposed. Table 3 presents the obtained results. The estimated cost of the tax value through fuel consumption was also estimated to verify to what extent it is aligned with the environmental costs generated.

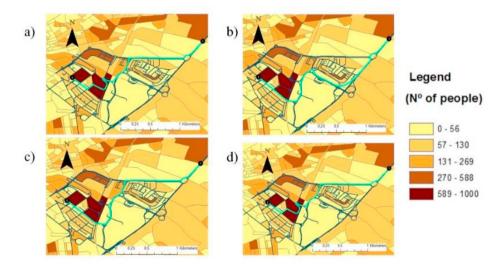


Fig. 3. Routing solutions using different criteria: a) Route optimization based on distance; b) Route optimization based on travel time; c) Route optimization based on Eco-indicator with VF; d) Route optimization based on Eco-indicator with NA.

In the off-peak period, routing with distance criteria (3.24 km) implies the largest amount of Environmental Costs with VF (EC-VF) (0.295€), while routing with the Eco-indicator with VF criteria (0.164€ EC-VF, 44% less than the costliest) yields the longest (3.56km, 10% longer than the shortest) and slowest (439.2s, 27% more time consuming than the fastest) route. Routing with distance criteria is also the cheapest option when VF is not considered. Routing based on travel time criteria yields a route with 0.189€ EC-VF, which is 15% higher than the route with less EC-VF. In this case study, routing with distance and Eco-indicator with NA criteria has the same results.

In the peak period, as stated above, the routes are the same, but, as expected, all the costs are higher. The distance is the same for all the routes, but the travel time increases an average of 13%, the EC-VF 46%, and the Environmental Costs with NA (EC-NA) 28%.

| | | | | | | Fuel |
|----------|-----------------------|----------|-------------|---------------------|---------------------|-------|
| | | Distance | Travel Time | Environmental Costs | Environmental Costs | Tax |
| Period | Routing criteria | (km) | (sec) | VF (€) | NA (€) | costs |
| | Distance | 3.24 | 378.0 | 0.295 | 0.166 | 0.19 |
| | Travel time | 3.31 | 345.6 | 0.189 | 0.167 | 0.19 |
| | Eco-indicator with VF | 3.56 | 439.2 | 0.164 | 0.184 | 0.21 |
| Off-peak | Eco-indicator NA | 3.24 | 378.0 | 0.295 | 0.166 | 0.19 |
| | Distance | 3.24 | 421.2 | 0.401 | 0.208 | 0.20 |
| | Travel time | 3.31 | 406.8 | 0.323 | 0.221 | 0.20 |
| | Eco-indicator with VF | 3.56 | 496.8 | 0.232 | 0.234 | 0.22 |
| Peak | Eco-indicator NA | 3.24 | 421.2 | 0.401 | 0.208 | 0.20 |

Table 3 - Results obtained in the origin-destination routing problem.

4. Discussion and conclusions

This paper presents a methodology for building a link-based eco-indicator that can be updated in real-time and translated into a cost factor to be used for routing optimization. To evaluate its performance, the proposed link-based eco-indicator is applied to a medium-sized city of Portugal, Aveiro.

For a single link relative costs, when the eco-indicator is based in NA values, the CO₂ (33%) and noise (43%) accounts for 76% of the total costs, with the PM_{2.5} representing only 22%. When analyzing the link with the eco-indicator based in VF, the weight of PM_{2.5} increases, representing 67% of total cost, while CO₂ and noise represent 27% of total cost. The cost of NMVOC in both situations is negligible, the relative cost of NO_x increases from 2% in a NA based link up to 6% in a VF based link. Considering the VF factor, the total cost of the link increases 158%, CO₂ cost remains the same and the NO_x, NMVOC and PM_{2.5} increase 695%, while noise costs decrease 16%, which in some links may be due to an overestimation of one or both approaches.

In off-peak period, considering a routing optimization with environmental concerns, the EC-VF is 44% lower than the shortest route and 13% lower than the fastest route. This route is also the costliest when taken into account the EC-NA. In fact, this result is quite relevant to conclude that it is important to consider people's exposure to the impacts, being the VF a representative factor of the impacts on population.

Comparing of the obtained results for peak and off-peak periods, the costs are higher in peak periods (+46%), although the route for the different criteria does not change, which can possibly be explained by the congestion in the network only happens in the links near the beginning and the end of the origin-destination routing problem. Taxes paid by drivers through the cost of fuel are curiously close to the EC-NA environmental costs, however they do not allow reflecting the variability of environmental costs taking into account local vulnerability. New taxation strategies for applying the polluter pays principle are necessary. Indeed, in an environment of increasing connectivity and automation, new navigation onboard algorithms may take these factors into account.

The procedure described in this paper is preliminary and is intended to be used for simplifying the calculation and for using a robust model such as CNOSSOS-EU, able to give valid predictions of noise, according to the variation of hourly traffic flow and mean speed. This work is a simple but innovative approach towards the development of a dynamic link based eco-indicator taking into account potential exposed people to traffic-related impacts. When comparing this approach to others such as Hazmat routing, it is more general and representative of people potential exposed because it takes in account people exposition and not only vulnerable hotspots. Future research involves updating and optimization of the people's exposure, through video image recognition and radiofrequency (cell phone density). This methodology could be applied in routing engines as part of a connected and automated Mobility environment.

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