A Preliminary Effort to Develop a Framework of Distance Decay Functions for New Urban Active Mobility

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Abstract. Sustainable mobility in urban areas has made a giant leap forward with the widespread diffusion of muscular bike, e-bike and e-scooter in the last years. There is therefore the need to provide new modelling tools for urban transport planners in order to manage the increase of these new transport users as far as the safety issues are concerned. Following a risk-based approach to urban road safety, evaluating the road network exposure to the new active modes (especially cycling ones), implies the use of suitable Distance Decay Functions (DDFs) that can be easily implemented in a travel demand prediction model. In this paper, a new methodology to develop DDFs is proposed. The method has been calibrated and applied to a dataset of over 90 Italian cities where land use and terrain data have been collected and regressed in order to evaluate a combined model taking into account modal split and trip distance**.** It is believed that the use of this method may help urban road designers and city planners in identifying critical traffic scenarios induced by new active mobility and in studying suitable countermeasures to improve traffic safety.

Keywords: Sustainable Mobility · Impedance Function · Modal Split · e-Bike

1 Introduction

Although cycling is one of the most used mode of transport, according to the existing international literature on cycling mode choice and route choice modelling, cycling users follow some specific rules than other users not do [1].

In the last years, according to several national and European sources [2, 3], bikes sales are increased, and this can be addressed to the lower cost for transportation for road users [4]. The most frequent factors that encouraged cycling are physical health and fitness (38%), contribution to environmental sustainability (14%), economy (13%) and

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time saving (10%), and the antagonist factors are perceived crash risk (17%), adverse weather conditions (17%) and lack of safety (16%) [5].

Cycling and in general bike commuting have huge health benefits, such as a 16% increase in VO_{2max} (maximum oxygen consumption) and a 15% increase in HDL cholesterol [6] and improve also the cardiorespiratory system by 30% in low fitness adults [7]: the thresholds for cardiorespiratory fitness improvements is reached for approximately for 170 (women) and 250 (men) min/week at moderate intensity [8]. According to Matthews et al. [9] a daily cycling activity leads to a 20% risk reduction of all-cause mortality with an activity of less than 60 min, and with 100 min to a 30% (among women): a moderate cycling activity reduces also the risk of colon cancer of 20% and 45% for respectively 90 min and 2h cycling for women and men [10].

Often cycling is described as a way to reduce the congestion in urban areas for several reason, from environmental to safety aspects. But recently the desire to introduce cycling demand analysis in traffic plan and design has become very strong. Assessing the cycling demand is not easy and this type of analysis are also in an early stage because the variables that play a fundamental role are several but also difficult to retrieve somehow. As it is possible to read in the works of Maldonado-Hinarejos et al. [11], two approaches are often used to assess the cycling demand, and in particular references are made to: aggregate level method and discrete choice model.

The concept of finding an accurate form of the cycling travel choice models is strictly connected with the accessibility, which reflect the personal ability to reach a destination [12]: this is a crucial aspect to bear in mind because it is correlated with cycling (but also walking) behaviors [36–40]. In general, the distance (but also other land variables, such as slope and the energy expenditure) between home/office and a transport terminal is one on the major barrier to the promotion of active mobility [13, 14] and if this distance is very high or not very accessible in term of land characteristics, the use of motorized mean of transport is encouraged [15]: according to Pucher et al.[16], half of the trip made with private vehicle shorter than 5 km could be replaced by cycling trips.

In this paper, the role of the cycle lane equipment (that is related with safety issues), slope and travel distances characteristics during cycling activity will be explored. A model that give information on bike share by comparing data among 90 Italian cities is proposed and several Distance Decay Functions (DDFs) are obtained in order to assess the modal split to new and sustainable mode of transport.

2 Framework of the Methodology

2.1 Description of the Methodology

The aim of this paper is to find a correlation among the main explanatory variables that affect the choice to cycle. To better understand the reason behind this choice, the main step is to identify an optimal sample size for each class of population. For this purpose, (see Fig. 1), a flow chart of the proposed methodology is reported here below, in order to highlight the main step of the procedure and to simplify the total understanding of the method proposed.

Going to sample design, the layout of the procedure can be split into two main steps: development of a travel choice model at municipal level, on one hand, and the development of a calibrated distance probability density function for each investigated travel mode.

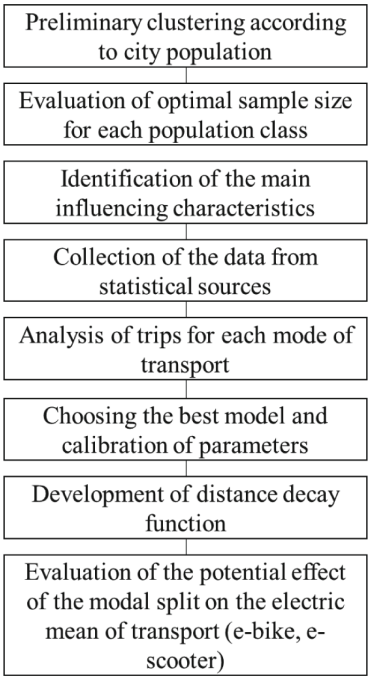

Fig. 1. Flow chart of the proposed methodology [41].

2.2 Travel Choice Model: Identification of the Explanatory Variables

Travel mode choice models allow to study how many transport users will move in a certain area of interest. The bike demand follows rules that other modes do not and so is essential to study which characteristics or which determinants influence in a positive or a negative way bike commuting [17], very different from car and public transport use [18]. People that use bike for recreational matter have other motivation than people that use bike for commuting and these characteristics are proposed here. In the monolithic study of Heinen et al. (2009) [1], the authors give a systematic review on the current scientific literature in this field. They divided the main determinants into five groups:

1. Built environment.
2. Natural environment
3. Socio-economic factors
4. Psychological Factors

5. Cost Aspects.

Travel behaviors are very influenced by built environment and several investigations have been carried out in order to discover these relationships. A fundamental role, that is common also to other mode of transport, is played by the trip distance between the origin and the destination [19]. In a study on cycling behaviors in 17 countries across the whole world [20], the authors show that the distance distribution is unrelated to the diffusion in a particular country of the cycling phenomena and there is a high likelihood that a bicycle-related trip is shorter than 5 km.

It essential also to recognize that the cycling demand is also influenced by the surrounding landscape, hilliness and weather. Heinen et al. [1] state that hilliness and landscape are rarely considered in mode choice model. According to Parking et al.[21], hilliness is expected to have a very predominant role in the proportion of users that cycle to work.

Among the socio-economic factors, it is possible to find household characteristics, age, gender, income, car and bicycle ownership, employment status [18] that are strictly related. Several studies highlight that men cycle more than women [22, 23], and women who bicycle are more likely to bicycle by choice [24].

Psychological factors are also introduced in mode choice studies in recent years, and references are made to the Theory of Planned Behaviors [1, 25]. Personal attitude, perceived social norms and habits influence commuters' decisions to use bike as a mode of transport.

Travel time and related costs, safety and efforts influence the most cycling than other mode of transport [1]. Muñoz et al. [26], show that with an increasing sidewalk width, total length of bike lane, and proportion of protected bike lane, users are more likely to use active transportation mode.

As a matter of fact, for each single trip it is possible to associate a generalized cost, affected by the length of trips, the travel time, the internal and external cost of movement. In a heterogeneous territory, such as Italy, all these aspects may affect the different choices that road users make. In order to highlight these characteristics, a careful experimental design has to be carried out and urban areas must be selected in a way they will represent the whole territory and the population's behaviors in modal choice at national level.

2.3 Collection of the Data and Disaggregation Process

In order to collect adequate data on commuting for several mode of transport, references are made to the Italian Census [27], that store freely downloadable commuting data. The main problem with this type of data is that they are organized in an "aggregate" form. As a matter of fact, if c is a homogeneous group of people that makes a trip, with these type of data it is impossible to retrieve information on the exact movement of a single individual, but only the transportation mode used and the interval time in which every class of movement c is in. Although other important information are not available in these type of data, for each mode of transport, a common value of operational speed is chosen in order to calculate the distance of the movements of single c homogeneous group of individuals (it is essential to highlight that Italian Census data do not give the

exact duration of the trip, but a specific range of time in which the trip of the specific group is completed).

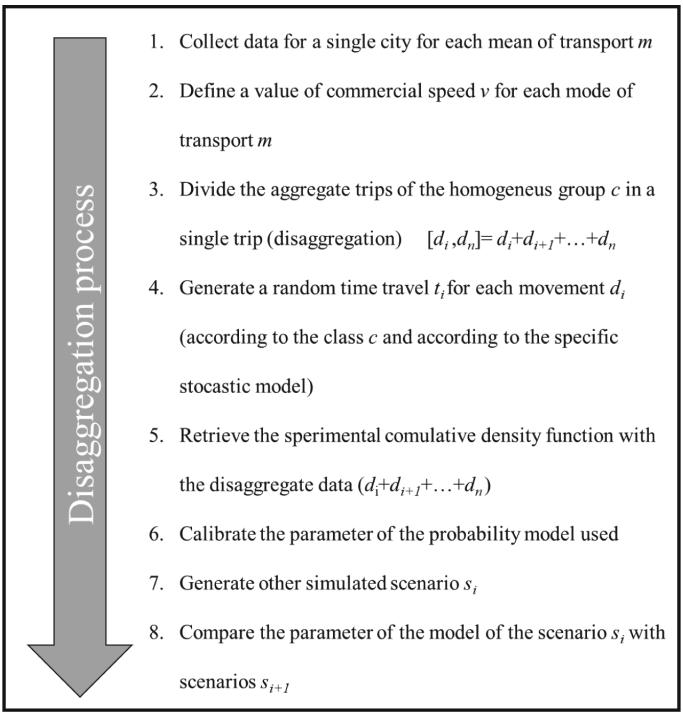

Fig. 2. Disaggregation process: the main steps [41].

The main drawback is that this way to proceed is a simplification of the reality because the assumption that a group of individuals make a movement with the same amount of time is a rough hypothesis: each individual will complete a single trip according to some specific factors and/or conditions that will influence his own travel time with a determinate mode of transport. In order to use data in a more useful and also realistic way, a "disaggregation" process is proposed, that consists in assigning a random time for each movement in the single homogeneous group, to replicate the human behaviours that will be translated in a different travel time for each single individual analysed: the "disaggregation process" allows to move from a global to a particular point of view (see Fig. 2).

2.4 Analysis of the Movements and Development of Distance Decay Functions

As discussed previously, the "disaggregation" process allows to elaborate in a more realistic and punctual way the aggregated data, available for several mode of transport (pedestrian, bike, motorbike, car passenger, car driver, train, public transport). After applying the "disaggregation" procedure for each mode of transport analysed (not only

for bike but also the for other ones, since there is the need to assess the relationship among them), a set of probability density distribution of trip length is obtained by means of an Erlang model, expressed as follows (1):

$$f_{\mathrm{d}}(\mathrm{d}) = \frac{\lambda e^{-\lambda \mathrm{d}} (\lambda \mathrm{d})^{k-1}}{(k-1)!} \tag{1}$$

Where:

- d is the distance [km];
- k is the shape parameter (mainly expressed as a natural number);
- λ is the rate parameter.

By comparing the cumulative probability function, according to the Erlang model proposed and the experimental one, obtained by disaggregating the available data with the aforementioned process, the two parameter of the model can be estimated (2):

$$F_{\mathrm{d}}(\mathrm{d}) = 1 - e^{-\lambda \mathrm{d}} \sum_{n=0}^{k-1} \frac{(\lambda \mathrm{d})^n}{n!} \tag{2}$$

Where:

- d is the distance [km];
- k is the shape parameter;
- λ is the rate parameter.

The best value of k (a natural number) and λ are evaluated after the calibration phase. Once the value of k is defined and a corresponding λ is evaluated, a new value of k is defined and a new λ is evaluated: this process will stop until the best agreement in terms of Pearson coefficient between the values of experimental cumulative probability distribution function and the values of the cumulative probability distribution of the Erlang model expressed is reached.

3 Case Study

3.1 Experimental Design and Travel Choice Models

According to the aforementioned technical literature reported in the Sect. 2.2, land use variables (such as cycle lane equipment), socio-economic variables (car insurance, average income, and parking fee) and terrain-related variables (such as the elevation gain, expressed as the maximum difference between the elevation of a randomly sampled set of points within an defined study area or also slope parameter) can greatly affect the transport modal choice. It is therefore necessary to collect relevant data in order to develop sound statistical models allowing to evaluate the proportion of trips for each transport mode.

As a preliminary step of this procedure, 90 cities from different regions across Italy are selected: the philosophy behind this process is to highlight the differences in terms of different descriptor that could influence commuting behaviours. Within the sampling design process, it is essential to guarantee that cities have different main characteristics

such as different altitude, different terrain characteristics, mean income, car insurance, cycle lanes, parking fee, area of the municipality and of the city centre and number of inhabitants. These main characteristics may have strong influence on bike-commuting uses: some of them could facilitate the use of the bikes, other may not encourage the travel-to-work or travel-to-study trips. In the Table 1, the main characteristics collected are reported and arranged for each territorial unit (North, Centre, and South Italy) and for three selected population range values within small and middle-size Italian cities (namely, <10′000 inhabitants, between 10′000 and 50′000 inhabitants and between 50′000 and 100′000 inhabitants). It is important also to highlight that the Italian territory is not very uniform in terms of terrain characteristic, socio-economic descriptors such as work occupancy and average income, due to some historical and cultural matters that are difficult to evaluate.

Table 1. Mean Values of the Attributes in Cycling choice model at Municipal level [41].

City Size	0-10000 Inhabitants			10000-50000 Inhabitants			50000-100000 Inhabitants		
Mean Value	North	Centre	South	North	Centre	South	North	Centre	South
Car Insurance [Euro]	292	357	364	290	351	363.	299	353	330
Parking Fee [Euro]	0.93	-	1.25	1.21	1.01	0.89	1.27	1.01	1.15
Income [Euro]	19992	16145	14503	21872	18815	17469	21326	21009	18164
Cycle lane Equipment [m/inhab]	0.022	0	0	0.012	0.004	0	32.59	21.12	8.48
Elevation Gain [m]	177	83	89	55	157	76	55	53	134
Bike Proportion [%]	2.43	0.46	0.71	5.15	1.99	1.15	10.45	5.11	1.05

As it was seen, several studies tend to summarize and classify in specific determinants the reason why a movement is made with bike or using another mode of transport. In this study particular attention is paied to cycle lane equipment and slope parameter that are not very addressed in the current scientific literature review.

Generally speaking, cycle lanes are specific infrastructure dedicated to the cycling flows, but they interact with motorized traffic within a wider transport supply system. According to the European Guideline PRESTO [28], cycle infrastructures need five main requirements: they must be safe, direct, cohesive, attractive, comfortable, but, among them, the author highlight that safety is "undeniably the basic requirement and must to be overriding concern". Rietveld et al. [29] found that safety constitutes a component in the generalized cost (defined by some authors [30] as resistance) and it explains also the amount of cycling proportion in municipalities: for these reasons Cycle Lane Equipment is considered in this study as a vital factor in forecasting cycling demand at national level.

As discussed before, the topography of the territory influences the reason why to cycle or not for commuting purpose, but it is less likely to influences recreational cyclists' attitudes. As it plays a fundamental role, hilliness and the effect of slope on cycling demand need to be studied in greater depth. According to Meeder et al.[31], few studies account for topography in travel choice model. With these strong scientific evidences, a Travel Choice Model is here proposed by collecting the information required for the three class of dimensionality:

$$BS = a * CLE + b * e^{-c*s} \tag{3}$$

Where:

- *BS* is the Bike Share;
- *CLE* is cycle lane equipment;
- *s* is the value of the slope parameter;
- *a,b,c* are the estimated parameter of the model (as can be seen in Table 2).

Table 2. Estimated parameters of the three models and main statistics.

City Size (no. Inhabitants)	Variable	Value	Std. Error	t-ratio	Prob(t)	Adj-R^2
0-10000	a	8.437784	8.098035	1.041955	0.30667	0.55
	b	5.01E-02	9.27E-03	5.401254	0.00001	
	c	64.59339	18.05094	3.578395	0.00133	
10000-50000	a	134.173	23.8274	5.631037	0.00001	0.62
	b	5.63E-02	1.22E-02	4.598703	0.00009	
	c	56.25408	24.24962	2.319792	0.02815	
50000-100000	a	91.12659	30.23564	3.01388	0.00555	0.51
	b	0.124859	3.39E-02	3.687348	0.00101	
	c	38.78388	19.27888	2.011729	0.05433	

It is also essential to highlight that for the model for a city size between 50′000 and 100′000 inhabitants, the max value of the slope parameter is considered (in agreement

with some technical evidence [32]), while for the other size class the mean value of the slope parameter has been used. As it possible to see in Fig. 3, a graphical output of the model is proposed.

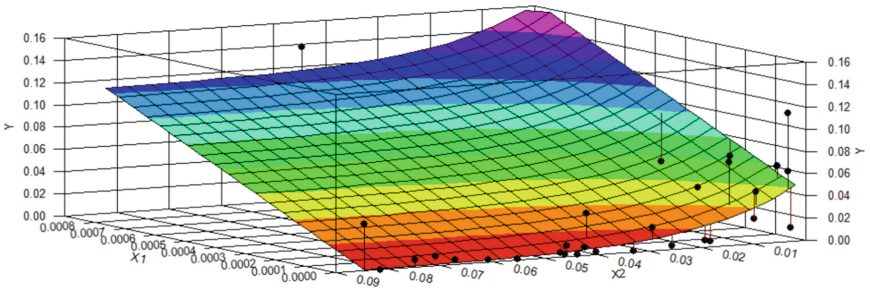

Fig. 3. Graphical output of the model for a city size between 10′000 and 50′000 inhabitants, where *Y* is *BS*, *X1* is *CLE* and *X2* is *s*.

3.2 Development of Distance Decay Functions

The methodology above described is applied on a real case study (a city in Northern Italy has been chosen falling within the size range 50 k to 100 k number of inhabitants). It is essential to remember that the "disaggregation" process (by simulating different scenarios starting from a random generation by a uniform random variable of the travel time) is also tested.

In order to understand how reliable and accurate is this procedure, 10 different scenarios are generated and a benchmark among them is made: as it possible to see in Table 3, the dispersion coefficient is used as main metric to compare the 10 different simulated scenarios, providing so good results, yielding an error related to a simulated scenario of about 1%. As a graphical mode of comparison (see Fig. 4), an experimental cumulative probability function and a cumulative function according to the Erlang model is shown. A fairly good agreement between experimental and theoretical cumulative distribution can be highlighte confirming the statements before.

The fitting criterion used, within an optimisation process to calibrate the parameters of the described Erlang model, is based on the evaluation of the Pearson coefficient, assessed by comparing the cumulated probability generated by the disaggregation process (in this study a uniform random variable is used) and the cumulated probability of the Erlang model. Given a defined value of k, the best λ is estimated when the maximum value of the correlation Pearson coefficient is obtained for different mode of transport. In Fig. 5, several density probability functions are shown: the main information given is how the probability to use a defined mode of transport, *m*, for a specific trip's length range will be. This modal split model is essential to evaluate traffic flows on the road network, within a Travel Demand Prediction Model (TDPM).

By combining the information of the density probability function with the number of trip that have a common distance, seven Distance Decay Functions, DDF (for each

Table 3. Simulation of different scenarios after the disaggregation process: comparison of different value of λ and dispersion coefficient (DC) calculated [41].

s_i	k	λ	E[λ]	σ[λ]	*DC[λ]*	*DC%[λ]*
1	2	0.670598				
2	2	0.673344				
3	2	0.671799				
4	2	0.683659				
5	2	0.676874	0.675645	0.00552	0.00817	0.816995
6	2	0.672633				
7	2	0.676854				
8	2	0.670984				
9	2	0.671923				
10	2	0.687781				

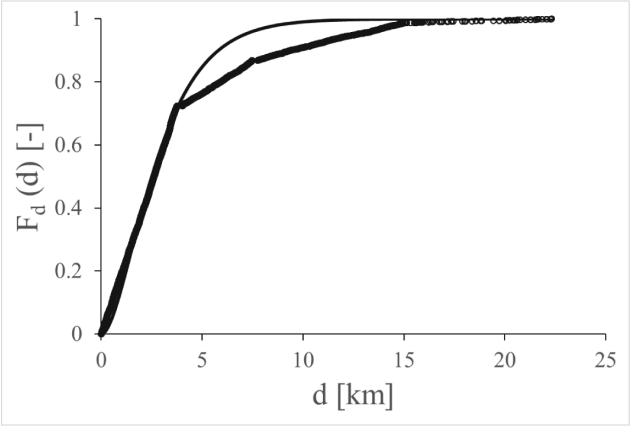

Fig. 4. Comparison between an experimental cumulative probability function and a cumulative function according to the Erlang (the transport mode selected is "Bike") [41].

mode of transport), can be obtained. In Fig. 6, for a defined distance range, the modal proportion among the different mode of transport is shown and, in turn, the corresponding amount of trips that are carried out.

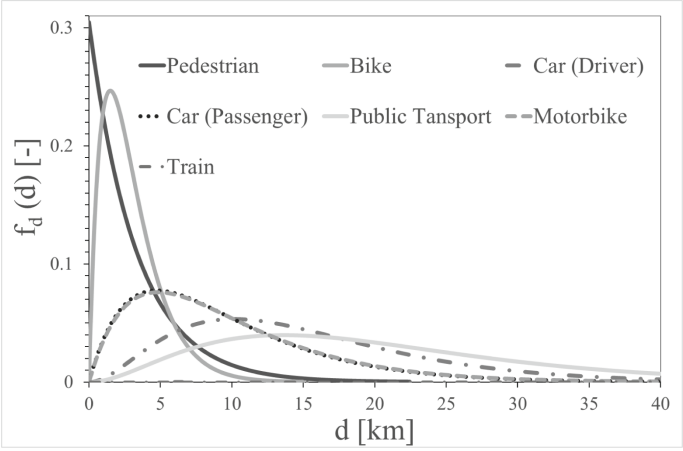

Fig. 5. Erlang density probability functions for the selected mean of transport: "Pedestrian", "Bike", "Car (Driver)", "Car (Passenger)", "Public Transport", "Motorbike", "Train" [41].

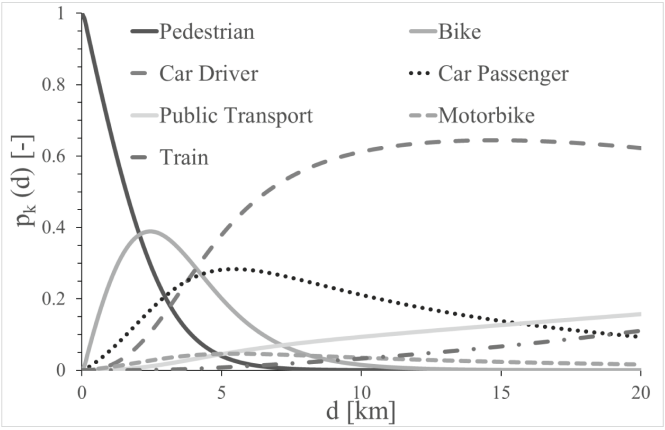

Fig. 6. Distance Decay Functions for the selected mean of transports: "Pedestrian", "Bike", "Car (Driver)", "Car (Passenger)", "Public Transport", "Motorbike", "Train" [41].

3.3 An Application to Assess the Modal Split to e-bike

A potential aspect of a DDFs framework is that it is possible to assess the modal split behaviours after the adoption of alternative mode of transport. One particular effect that can be studied is the modal split to electric mode of transport, and in the present case, the e-bike. As it was highlighted in the current scientific literature review, physical activity is similar for e-bikers and cyclists that use a conventional bike [33], but the main difference is that e-bikes trips are faster than c-bike trips [34] and that could impact the length of the trip that an user is willing to do.

After the adoption of e-bike, as it is been studied by Sun et al. [35], car users will use the new mode of transport and the amount of this modal split depends on the length

of the trip. Although no studies has been performed in the Italian context, given also the difficulty to create a relationship by which assessing how the modal split will be, such type of information could be derived in a very simple and effective way within a DDFs framework. Combining the information of the aforementioned work [35] on the percentage of the modal split according to a specific trip length with the information retrieved by the DDFs here developed for a specific case study, new DDFs are calibrated for the all mode of transport. With this methodology, new relationships among the mode of transport on a defined trip distance are obtained: in Fig. 7, an example of modified DDF framework taking into account the modal split from car to e-bike is provided.

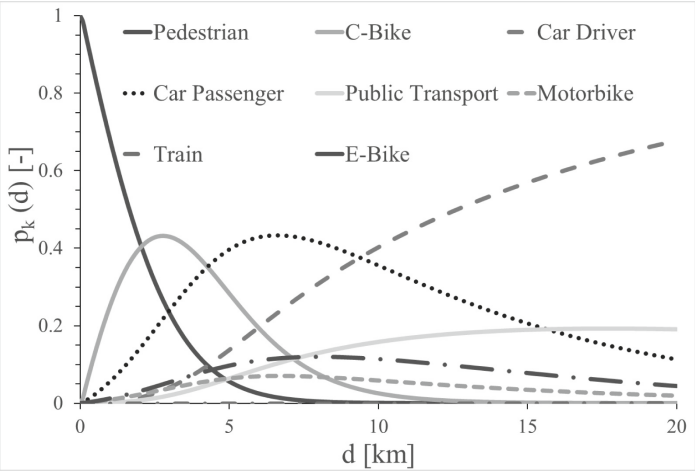

Fig. 7. Distance Decay Functions for the selected mean of transports after the modal split from "Car" to "E-Bike": "Pedestrian", "C-Bike", "Car (Driver)", "Car (Passenger)", "Public Transport", "Motorbike", "Train", "E-Bike" [41].

4 Conclusions

Travel mode choice models allow to study how many transport users will move in a certain area of interest and it is essential to study which characteristics or which determinants influence in a positive or a negative way bike commuting [16]. People that use bike for recreational matter have motivation other than people using bike for commuting and these latter characteristics are proposed here in this paper. After the collection of several data regarding the main characteristic that may influence bike share (with a specific focus on Cycle Lane Equipment and slope characteristics), three demand models are obtained. Within this context, also several DDFs for a specific case study are retrieved for different mode of transport and finally, using this tool, an example on how use these functions is proposed in order to evaluate modal split from cars to e-bike.

According to the scientific literature, it seems that some terrain-related variables such as slope may affect travel mode choice behaviour as far as urban commuting on bike is

concerned. However, several cities in Italy are located on Alps and Apennines, so users have to spend a lot of energy and resources in order to make even a simple movement of few meters. Therefore, in these cities, the elevate value of the slope parameter may play an impeding role compared with those cities with low or null elevation gain. However, it has to be underlined that, other than this aspect that is more related to the field of "energetic" issues, the presence of cycle lane could influence the modal choice, based on a principle of perceived and quantifiable safety [30]: users will follow a route if they feel themselves in a safety condition and so cycle lane equipment play a fundamental role in commuting choices. In addition, it has to be acknowledged that municipal size, expressed in terms of population, may also play a critical role on travel model choice behaviour at municipal level since city's size may affect the traffic scenario and the transport supply model operating in a specific analysis area.

Following these premises, after collecting several data from different national databases on 90 Italian cities of different dimensions, three Travel Choice Models are obtained and calibrated for each city size class. Within these models, two main aspect are highlighted: the terrain related variables, such as slope, that have not enough investigated in the current scientific literature, and the cycle lane equipment may influence the decision to cycle for commuting purpose. For a specific case study, several DDFs are also proposed and the modal split to new mode of transport has been assessed. This methodology, with some limitation (for instance, due to the low numerosity of the city studied, the need of a validation for the three models and a lack of Italian data on the modal split), could be an useful tool for city managers and road designers to improve, for instance, safety level on specific corridors, promote new sustainable infrastructure where the demand it is expected to be higher and also to gain more information to tackle accessibility issues related to sustainable mobility within a urban context. As future development a validation on a new dataset of cities is needed in order to assess the efficiency and efficacy of the methodology and, as a future research step, the aim is to explore the influences of safety and energy expenditure parameters on cycling Travel Choice Models.

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