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Original Research Paper

Calibration and validation of a simulation model for predicting pedestrian fatalities at unsignalized crosswalks by means of statistical traffic data

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HIGHLIGHTS

- A model accounting for collisions on unsignalized crosswalks is presented.
- The simulation model is calibrated and validated using experimental data.
- Realistic traffic conditions were used to test the model accuracy.

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ABSTRACT

This work presents a simulation model for unsignalized crosswalks which takes into account collisions between vehicles and pedestrians, thus allowing to assess the estimated yearly pedestrian fatality. In particular, we focus on a method to calibrate such a model combining measurable crosswalk characteristics, such as maximum speed limit or drivers' compliance, with statistical data for past accidents obtained from local municipality. In order to perform simulations under realistic conditions, we constructed a one-week scenario where pedestrian and vehicle traffic vary using specific patterns each hour of the week. The constructed traffic profile is based on openly available data and the suitability for the scenario considered (a crosswalk in Milan, Italy) is investigated showing that cultural/lifestyle elements determine the variation of weekly traffic. Simulations using the constructed one-week scenario were used to obtain the only non-measurable parameter which account for pedestrians' and drivers' distraction. In addition, we also focused on the presence of elderly pedestrians which have different physiological characteristics compared to adults or children and are becoming an important part of the population in several countries around the globe. The simulation model presented here and the method suggested for calibration may be employed in different contexts, thus allowing to build an important tool to be used not only for transportation efficiency/optimization but also for safety analysis.

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1. Introduction

Crosswalks are ubiquitous urban structures found in every city around the globe. In particular, unsignalized crosswalks are a very popular method to allow pedestrians crossing the street in a safer environment compared to the dangerous jaywalk which would occur when crosswalks are not provided. The low costs for installation and the very low technical requirements make them a very flexible solution to improve pedestrian mobility in urban areas. Signalized crosswalks making use of traffic lights are much more expensive and are usually preferred in particularly dangerous areas (e.g., low visibility) or when vehicular and pedestrian traffic volumes are high, making it difficult to reach a spontaneous negotiation between both road users.

While the physical difference between signalized and unsignalized crosswalks only lies in the presence of light signals, the mechanisms observed during the crossing event are much different, since, in the case of signalized crosswalks, the negotiation is entrusted into the light switching system. In unsignalized crosswalks, pedestrians and drivers need to reach a sort of mutual agreement to avoid collisions and crossing the relative section without unnecessary delays.

Collisions resulting from misunderstandings or distractions are particularly dangerous for pedestrians who cannot rely on the active safety technology offered by cars. This is also confirmed by statistical data showing that pedestrian fatalities in the U.K. account for 25% of the total traffic victims (Department for Transport, 2015), with the proportion for Italy lying at 17% (Istituto Nazionale di Statistica (ISTAT), 2016b) and the one for the U.S. at 14% (U.S. Department of Transportation, 2015). In developing countries, percentages of pedestrian fatalities are much higher, with India having an average value of 40% and large cities like Mumbai or New Delhi having pedestrians as the biggest proportion of traffic victims (Peden et al., 2004).

In addition, traffic statistics show that pedestrian fatalities are stable or even slightly on the rise also in countries where the overall number of victims by road accidents is declining (Department for Transport, 2015; U.S. Department of Transportation, 2015). Some studies suggest that the fairly constant number of pedestrian fatalities can be explained with an increase in the elderly population (Asher et al., 2012; Department for Transport, 2015), which has been regarded as the most vulnerable group of pedestrians (Al-Ghamdi, 2002; Prato et al., 2012).

Although in modern vehicles, several systems are being introduced to detect the presence of pedestrians and limit the consequences in case of collisions, it is unclear when and to which extent the diffusion of such systems will help improving pedestrian safety.

With this said, crosswalks do not only represent an important aspect in relation to pedestrian safety but also play an important role on traffic flows for both vehicles and pedestrians. However, most of the literature focused on either safety or efficiency, considering both aspects rather separately.

Experimental investigations have been performed to understand how drivers and pedestrians determine their actions (Sun et al., 2015; Várhelyi, 1998) and what are the most important elements influencing crossing speed (Goh et al., 2012; Marisamynathan and Perumal, 2014) and risk-taking (Evans and Norman, 1998; Hamed, 2001) by pedestrians. Over the years, several measures have been defined to judge the criticality of interactions among road users (either car-car or pedestrian-car) at the microscopic level, like the time-to-collision (TTC), the post-encroachment time (PET), the time advantage and the time gap (Laureshyn et al., 2010). In a more macroscopic scale (both in terms of time and space), there have also been attempts to identify dangerous areas for pedestrians using statistical methods. This type of approach resulted in the definition of different measures for "pedestrian exposure" (Lam et al., 2014; Yao et al., 2015).

Theoretical studies mostly focused on traffic flows to investigate what are the best cycles for traffic lights and under which conditions signalized crosswalks can help reducing waiting times for both drivers and pedestrians.

Early simulation models considered only very simple aspects and both vehicles and pedestrians were modeled uniformly as particle-like systems (Helbing et al., 2005) or mathematical distributions (Griffiths, 1981). The improvement in performance of modern computers allowed to develop even more complex simulation models which treat drivers and pedestrians as single entities with specific characteristics such as walking speed, reaction time or accepted time gaps for crossing (Crociani and Vizzari, 2014; Feliciani et al., 2017; Zeng et al., 2014).

Experimental knowledge and computational capabilities have contributed in making simulation models the more and more accurate and validation has also been possible using pedestrian trajectories (Liu et al., 2017; Zeng et al., 2014, 2017) or delays for both drivers and pedestrians (Bandini et al., 2017; Feliciani et al., 2017). Simulation models have therefore become an important tool for traffic engineers to optimize cycle of traffic lights and determine, for example, when a signalized crosswalk can turn its light off and allow pedestrians and vehicles to negotiate by themselves crossing actions. Also, simulation models can help city planners

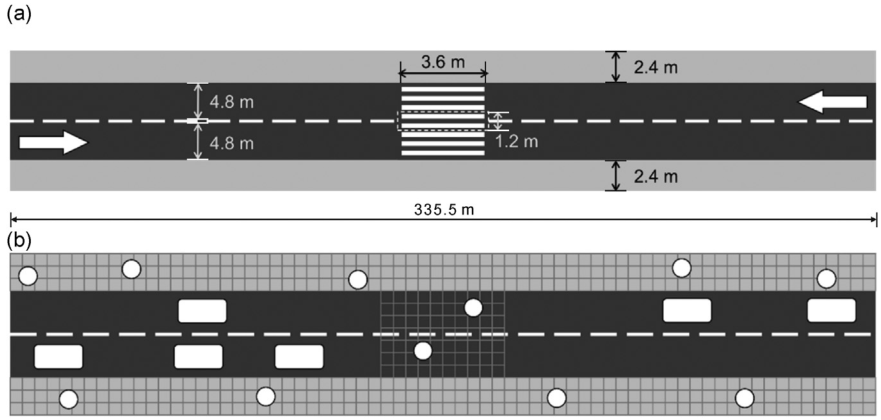

Fig. 1 – Simulation model size and computational grid. (a) Size and dimensions. (b) Computational grid.

understanding in which location crosswalks are necessary and what are the expected delays for the different road users.

In short, efficient planning has made the use of simulation models easier and, since computational performance is continuously on the rise, it is possible to consider increasingly wider areas, with whole city simulations becoming possible in the near future.

With this said, safety issues are still not directly accounted for in simulation models. Although recently some researchers (Chen et al., 2017; Killi and Vedagiri, 2014) started using measures relative to pedestrian/vehicle interaction criticality (PET in particular) to evaluate simulation models by comparing numerical results with experimental data, collisions are not specifically accounted in such approaches, thus limiting their range of application.

In our previous study (Feliciani et al., 2019), we presented a method to analyze pedestrian safety in unsignalized crosswalks by computing fatalities occurring over long periods of time. However, we were not able to calibrate the simulation model which returned unrealistically high number of fatalities. While our focus was set on qualitative aspects to understand, for example, how traffic flows relate with pedestrian safety, the inaccurate quantitative results precluded an application of such a model to real situations.

In this study, we aim at developing a method to calibrate and validate our simulation model by determining parameters using statistical data. This work is organized as follows: section 2 describes the simulation model. The one-week scenario considered in simulations is presented in section 3. Results are given and discussed in section 4 and conclusions are presented in section 5.

2. Simulation model

The simulation model presented here is based on a previous work which did not account for collisions (or accidents in general), but focused on delays for road users caused by the presence of the crosswalk. In this section, we will focus on aspects related to vehicle-pedestrian interaction, which is a central topic of this work, while providing only essential information on the dynamics used for vehicles and pedestrians. Readers interested in details on those aspects are addressed to Feliciani et al. (2017) for more information.

2.1. *Geometry and general layout*

The crosswalk considered in this work is modeled by taking as reference an unsignalized crosswalk from Via Padova in Milan (Italy), which has been the focus of an experimental study (Gorrini et al., 2016, 2018) investigating decision-making of drivers and pedestrians. Size and dimensions of the modeled crosswalk are given in Fig. 1(a). Although the crosswalk considered did not have a midblock, we considered appropriate to add a "virtual" midblock to allow pedestrians stopping in the middle of the road to model a behavior often observed in reality. The road considered has two lanes with vehicles running in opposite directions. In all simulations we assumed (as observed in reality) that the proportion of vehicles (and pedestrians) from both directions is equal.

Vehicle dynamics is computed using a continuous model (some details are given later), thus not requiring a specific computational grid, but pedestrians move in a discrete space which is presented in Fig. 1(b) illustratively. Pedestrians are randomly generated on one of the four corners and, in order to cross the street, are assigned a random destination on the opposite side. Both pedestrian and vehicle environments intersect in the crosswalk which is where interactions and eventually accidents occur.

At this stage, we should mention a first limitation of this model, which will have an influence on further discussions: shortcuts often made by pedestrians when crossing the road are not accounted and vehicles move perfectly straight without being allowed to steer within or outside their lanes. Our previous analysis on delays created by the presence of crosswalk showed that, despite this limitation, results are still fairly accurate, but some special considerations are required (Feliciani et al., 2017).

2.2. *Vehicle and pedestrian dynamics*

Both vehicle and pedestrian dynamics are computed based on models well established in the literature. Nonetheless, we found necessary to make some modifications to account for the very different moving speeds of both road users. In particular, to properly account for vehicle-pedestrian collisions (or crashes), cars are required to move in steps which are smaller than the crosswalk itself. Typical vehicular models assume a time step equal or similar to the reaction time of drivers, usually 1 s. At a speed of 50 km/h, a car travels almost 14 m in one second, thus easily going from one side to the other of the crosswalk in a single time step.

Early vehicular models were constrained by computational power, thus requiring relatively large time steps. Since this is no more a major concern, small time steps can be employed also allowing to consider the reaction time as a distribution rather than a constant value. To allow the use of small time steps, a modified version of the Gipps model (Gipps, 1981; Krauss et al., 1997) has been employed. The reasons for selecting the Gipps model are that it is a well-known and widely used simulation model, it is simple and computationally fast, it allows to consider vehicles' state and their interactions and, with proper modifications, it fits well into the discrete pedestrian environment.

The Gipps model is based on the assumption that drivers take one time step to act, thus effectively accounting for the reaction time when time steps are chosen accordingly. Among the several variables and parameters making up the Gipps model, there is the gap g which accounts for the distance from the proceeding vehicle. In the modified Gipps model employed for crosswalk simulation a "shorter" gap $\tilde{g}$ is used.

$$\tilde{g} = g - t_r v_{car} \tag{1}$$

where g is the original "real" gap, t_r is the reaction time (specific for a given driver), and v_{car} is the speed of the car.

In other words, the "real" gap is made shorter by accounting for the distance traveled during the reaction time. The only requirement when using such a modification is that the time step needs to be much smaller than the reaction time.

Although one may argue that the modification proposed here may not be the most elegant approach when the model by Gipps is considered in its original formulation, in Feliciani et al. (2017), we showed that the modified model converges to the original one for small time steps. We also showed that a time step of 0.1 s already allows to smoothly compute vehicular dynamics and reproduce the empirical fundamental diagram of vehicular traffic. In short, while probably not the most rigorous approach, it still allows to obtain accurate results and keep the model simple, thus reducing computational time.

The dynamics of pedestrians is based on the cellular automata (CA) floor field model (Burstedde et al., 2001; Feliciani et al., 2017). Pedestrian environment is divided into cells where only one pedestrian at a time is allowed. Pedestrians are guided to their destination by the so-called static floor field which decreases as pedestrians get close to the destination. In the approach considered here, the Moore neighborhood is used: pedestrians are allowed to move to any neighboring cell (side or corner) assuming the target cell is not already occupied. Target cells are chosen using the previously mentioned static floor field. To avoid conflicts, when multiple pedestrians attempt to move to the same cell, positions are reserved first and only one pedestrian is randomly chosen in case of conflicts.

Similarly to cars, also for pedestrians, some special algorithms are used to account for typical characteristics of crosswalks. In particular, we want to consider the presence of elderly people given their increased vulnerability compared to adults and young pedestrians. One of the most distinguishing characteristics of elderly pedestrians lies in their lower walking speed and longer reaction time. This requires the ability to consider different walking speeds which is usually not accounted for in normal Floor Field models.

Time steps for simulation are constrained by the vehicular model and fixed at 0.1 s. As already proposed in Weng et al. (2006), it is possible to achieve a desired walking speed by moving a pedestrian every time that $r < \mu$, with $r = [0, 1]$ being a random number and μ defined as the "update probability" given by

$$\mu = v_{ped} \frac{t_s}{s} \tag{2}$$

where v_{ped} is the (desired) pedestrian speed, t_s is the time step, and s is the side length of the cells used for the pedestrian environment.

Mesh size for the pedestrian model has been set at 0.4 m according to Weidmann (1993) and an extensive literature (Burstedde et al., 2001; Fang et al., 2003; Feliciani and Nishinari, 2016; Yamamoto et al., 2007) showing that this size is sufficient and adequate to reproduce most crowd phenomena occurring in reality (the fundamental diagram to start with), also including people moving with different walking velocities (Weng et al., 2006).

With this said, we also need to acknowledge that although this approach allows to get desired average speeds over long distances, fluctuations can be quite large. In this regard, it should be also reminded that under equal conditions in terms of static floor field, corner cells may be chosen with the same probability of side cells although center-to-center distance for corner movements is $\sqrt{2} - 1$ larger, thus resulting in a higher momentary speed.

To stabilize the speed, a simple algorithm (Fig. 2) is applied. The average moving speed (v_{avg}) is computed over a number of time steps according to

$$v_{avg} = \frac{d_{tot} s}{N_{avg} t_s} \tag{3}$$

where d_{tot} is the total distance (in cells) traveled over N_{avg} time steps (diagonal motion counts as $\sqrt{2}$).

As given in Fig. 2, if v_{avg} is within tolerated values, a position update is performed as described earlier. When speed is below the acceptance margin, a movement is forced. On the other side, when v_{avg} exceeds the tolerated value, a pedestrian is forced to stop.

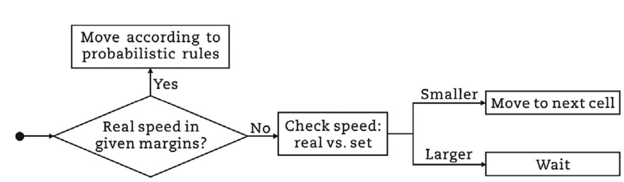

Fig. 2 – Algorithm used to account for different pedestrian speeds.

This approach allowed to consider different velocity distributions for adults and elderly people. In addition, we also tried to model the changes in speed observed in the different phases reported during the crossing action, such as approaching, appraising and crossing (Gorrini et al., 2016, 2018), but we found that, despite the applied algorithm allows to reduce velocity fluctuations, quick changes in speed cannot be modeled accurately.

2.3. *Vehicle-pedestrian interaction*

Having discussed how vehicles and pedestrians are modeled individually, we now wish to discuss the way in which they interact. In particular, it is important to understand under which circumstances vehicles decide to break when approaching the crosswalk and how pedestrians decide to cross or not.

When cars are created, different properties are assigned according to numerical values provided within the simulation parameters. For instance, the previously discussed reaction time is assigned individually based on an experimental distribution. In addition, each driver may be compliant or not and may also be distracted.

In this regard, an important point needs to be discussed here: there is a subtle but relevant difference between non-compliant and distracted drivers. Non-compliant drivers do not break when a pedestrian is on the curbside waiting to cross, but will always break when a pedestrian is already crossing. In other words, they "signalize" to pedestrians their intention not to stop by keeping the same speed. On the other side, distracted drivers do not look at all at the street and will not break also when a pedestrian is on the crosswalk.

For each time step and for each vehicle, the decision-making algorithm presented in Fig. 3 is used to judge whether the driver should break or not. We should remind here that Fig. 3 refers only to the crosswalk; cars adjust their speed in accordance to the distance from the previous vehicle by using rules contained within the Gipps model.

In the decision-making algorithm for vehicles, first of all, one should determine if the vehicle is approaching to the crosswalk or not and if the driver is compliant. Next, we determine if a pedestrian is on the curbside (waiting to cross) and if there is enough space to break. If a car is approaching, the driver compliant and there is enough space to give way to a waiting pedestrian, then the car will slow down and stop. Exception to this are distracted drivers which will not attempt to break. To keep vehicle dynamics simple, we assume that distracted drivers are still able to see other cars and their distraction is only relative to pedestrians on the crosswalk (we are not interested in car-car crashes).

Decision-making algorithm for pedestrians is presented in Fig. 4. It is important to say that vehicles' positions are updated before pedestrians (Fig. 5). In this sense, pedestrians have an advantage in terms of safety since they are able to predict drivers' behavior.

Pedestrians start their crossing action when on the curbside, so we can neglect other pedestrians in this description. On the curbside, pedestrians evaluate if an approaching car in the nearest lane is able to stop and, if so, move to the crosswalk. As already presented above, in this model we consider a "virtual" midblock where a pedestrian may stop in the middle of the street. Pedestrians on the midblock perform the same decision-making process as curbside pedestrians but consider the opposite lane (or the nearest one, which they are attempting to cross).

Also in the case of pedestrians, distracted ones are generated according to a given parameter. Distracted pedestrians basically skip the safety check and cross the street even when cars are too close and too fast to stop.

2.4. *Assessment of pedestrian fatalities*

The overall simulation loop is summarized in Fig. 5. At first, cars and pedestrians are generated if required. Vehicle environment is cyclic, so cars need only to be generated at the beginning of each simulation, but pedestrians disappear once they reach their destination, so they are continually generated. Later, vehicles' and pedestrians' position and speed are updated. Finally, eventual collisions are detected and time step statistics are generated.

In the simulation model, a collision (or a crash to use a different word) is counted when the area of a vehicle is overlapping a cell occupied by a pedestrian. Since both vehicles and pedestrians keep moving after a collision, we avoid multiple counts by assuming that a pedestrian can have an accident only once (under very unfavorable circumstances a distracted pedestrian may collide with vehicles on both lanes).

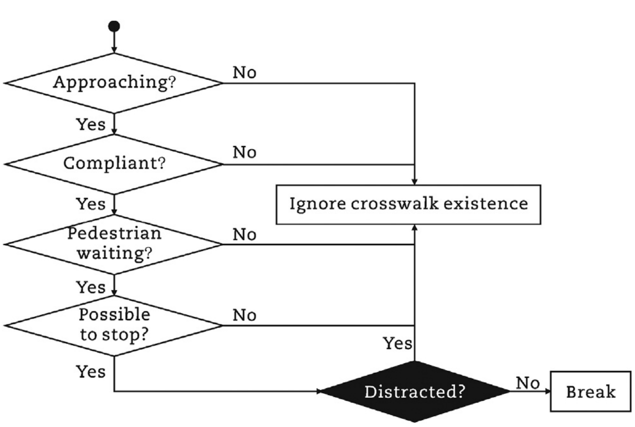

Fig. 3 — Decision-making algorithm determining drivers' decision to break or not.

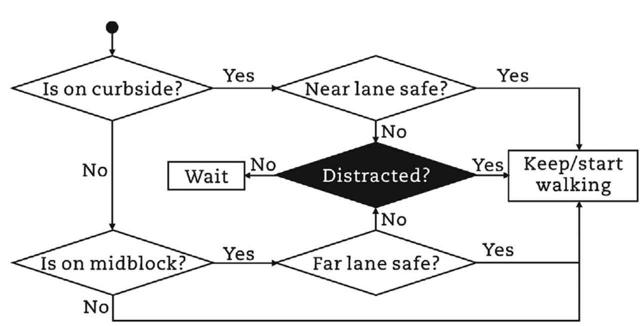

Fig. 4 — Decision-making algorithm determining pedestrians' decision to cross or not.

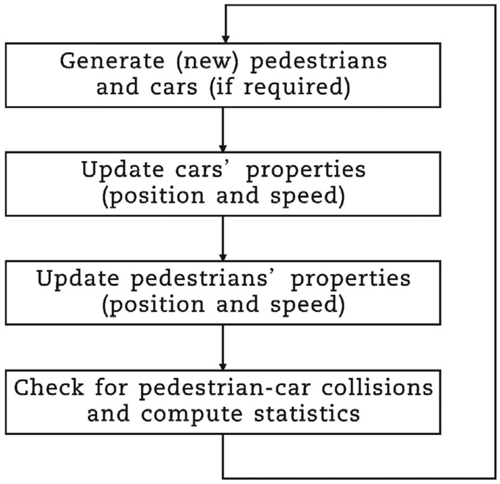

Fig. 5 – Overall simulation loop including routines for vehicles, pedestrians and collision detection.

Frequency of collisions is surely a relevant aspect in determining the safety of a crosswalk, but the speed at which those collisions occur is also very important. Based on statistical data relative to traffic accidents involving pedestrians collected by Ashton and Mackay (1979) in the 1970's, Davis (2001) estimated that fatality risk (p) (death within 30 d of the accident) can be calculated according to Eq. (4).

$$p = 1 - \frac{e^{a-bv}}{1+e^{a-bv}} \tag{4}$$

where v is the collision speed and a, b are empirical parameters. Those parameters change depending on the age of the pedestrian involved in the accident, with numerical values used in this study given in Table 1. The different curves obtained by plotting Eq. (4) using parameters contained in Table 1 are presented in Fig. 6.

As Fig. 6 clearly shows, elderly people have a higher probability of getting deadly injured compared to adults and children. Not only the curve for elderly people starts growing from a lower speed, but also the steepness is higher compared to younger generations. While elderly people will almost certainly pass away for collisions occurring at 60 km/h (risk of fatality is higher than 90%), adults and children are more likely to survive (surviving probability is more than 70% for both). From the graphs of Fig. 6 it can be also concluded that while a speed of 50 km/h (which is a typical limit for urban areas) is safe for adults and children, the same speed is likely to be fatal for elderly people. This shows again the importance of considering a diverse population also including elderly people in simulations.

Finally, we ought to add a few words on the general method used to count collisions (crashes). While we are aware that the above definition for collision may be overly simplistic, we need to remind that the goal of this study is not to investigate the microscopic dynamics of traffic accidents to replicate in details how crashes occur, but rather study the influence of macroscopic variables such as speed limit or traffic flow on large time scales using a large number of simulations. We also want to check whether such a minimalistic approach still allows to obtain some qualitatively realistic results which replicate phenomena from real-life observations.

Table 1 – Parameters employed in Eq. (4) for the calculation of the pedestrian fatality risk based on the age group (Richards, 2010).

Parameter	Child	Adult	Elderly people
a	8.85	8.87	9.73
b (h/km)	0.12	0.13	0.20

2.5. *Relevant simulation parameters*

To conclude the description of the simulation model we wish to add a few words on the parameters used in calculations, which are summarized in Table 2.

Most of the numerical values are based on the observation reported in (Gorrini et al., 2016, 2018) and are specific for the crosswalk of Via Padova which constitutes the scenario for this study. In particular, speed limit and non-compliant drivers' ratio were directly known or obtained by observation. Parameters which are not specific for the scenario considered and are more related with human behavior have been obtained from literature. This applies to drivers' reaction time (Jurecki et al., 2012; Mehmood and Easa, 2009; Taoka, 1989) and the pedestrians' acceleration and deceleration (Zebala et al., 2012) (used when changing speed of pedestrians during the different crossing phases).

3. Considered scenario and weekly traffic evolution

As already discussed above, some of the model parameters are directly quantifiable through observation or by searching through the literature, but others are much more difficult to obtain using conventional methods. In particular, the ratio accounting for distracted people is one of the most important parameters quantifying the number of accidents occurring over the crosswalk. While there are studies showing that the proportion of distracted pedestrians account for about 2%–3% of the crossing population (Hatfield and Murphy, 2007), we should remind that a direct use of those data in the frame of

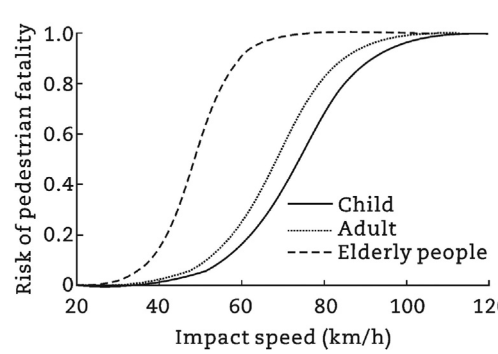

Fig. 6 – Probability of pedestrian fatality depending on collision speed and age group (Richards, 2010).

Table 2 – Numerical values for parameters used in the simulation model.

Parameter	Value
General constant	
Time step (s)	0.1
Pedestrian cell size (m)	0.4
Pedestrian dynamics	
Adult speed (mean) (m/s)	1.30
Adult speed (variance) (m/s)	0.20
Elderly people speed (mean) (m/s)	1.05
Elderly people speed (variance) (m/s)	0.20
Acceleration (m/s^2)	0.30
Deceleration (m/s^2)	0.50
Vehicle (driver) dynamics	
Car length (m)	4.5
Car width (m)	1.8
Minimum gap (m)	1.0
Reaction time (mean) (s)	1.1
Reaction time (variance) (s)	0.2
Maximum speed (limit) (km/h)	50
Non-compliant drivers' ratio	0.5 (50%)
Maximum breaking (m/s^2)	9.0
Maximum acceleration (m/s^2)	2.0

the proposed simulation model is not possible. The reasons preventing a direct use of experimentally measured levels of distractions are listed as follows.

- Levels of distraction are difficult to be quantified empirically. A pedestrian not watching at the street may be considered as distracted, but, in most of the cases, he/she will still be able to listen to sounds (especially warning ones), thus allowing him/her to judge if a car is approaching or not. Similarly, a person watching at his/her phone while approaching or walking through the crosswalk may notice approaching cars out of the corner of the eyes.
- The simulation model does not account for emergency maneuvers, such as a sudden steering. In reality, people are able to suddenly stop or move back if they spot an approaching car at the last moment. Similarly, cars will perform an emergency break and try to deviate to avoid striking a pedestrian. As a consequence, the ratio of distracted people used in the model is a very conservative measure compared to reality.
- Generally, most of parameters used in the model are quite conservative and the combination of them leads to a very conservative scenario in terms of collisions if an empirical value for distraction is used. Therefore, by adjusting that parameter it is possible to correct the conservativeness encompassed in most of the other parameters.

From the discussion above it can be concluded that to estimate the parameter relating to the ratio of distracted people, an alternative method is required compared to the other parameters directly measured. A common practice in modeling and simulation is to compare the results with experimental data and vary the parameters until a satisfactory agreement is reached (a method usually defined as calibration). Since the number of collisions (and related fatalities) is the principal result of our simulation model, statistics in this regard are necessary.

According to the statistical data from the municipality of Milan, 18 accidents involving pedestrians were reported on Via Padova in 2016 (Istituto Nazionale di Statistica (ISTAT), 2016a) and 6 of them were related to unsignalized crosswalks. In counting the number of accidents occurring on unsignalized crosswalks, each event had to be judged on a case-by-case basis because sometimes reports were partially contradictory on the location of the accident. For example, in some cases a "rectilinear section" was given to indicate the type of infrastructure, but under "circumstance" was stated that the pedestrian was crossing on an unsignalized crosswalk, which would require a classification of the facility as "crosswalk without traffic lights". In Table 3, data are sorted based on the occurrence during the week. Actual day of the event is provided in the dataset but is not given here to protect the privacy of victims and drivers. When vehicle type and driver age are not given, it is because the driver escaped from the accident scene.

Table 3 presents the single accident events which have been counted in order to obtain the necessary statistics to calibrate the model. Since the simulation model does not consider visibility and/or road conditions, we used all accident records to allow replicating the situation represented by the collected data. However, we are aware that, as more sophisticated models will become available, road conditions and darkness will have to be considered in a special manner when calibrating the model.

As for the vehicle type, we believe cars and trucks can be considered in the same way since very large trucks are not allowed into central Milan and small trucks have breaking and steering performances similar to cars. Table 3 also shows that elderly pedestrians are indeed among the most vulnerable road users. While the sample number provided here is very small, data relative to the whole city of Milan confirmed that

Table 3 – Accidents with injured pedestrians in Via Padova (only considering the main straight section) in 2016.

Event		Driving conditions		Vehicle	Age	
Weekday	Approximate time	Road	Weather		Driver	Pedestrian
Monday	13:00	Dry	Clear	Car	18–29	65+
Wednesday	17:00	Dry	Clear	Car	30–44	45–54
Friday	9:00	Dry	Clear	Truck	65+	45–54
Saturday	16:00	Wet	Raining	Truck	45–54	65+
Sunday	23:00	Dry	Clear	N/A	N/A	30–44
Sunday	23:00	Wet	Raining	N/A	N/A	30–44/0–5

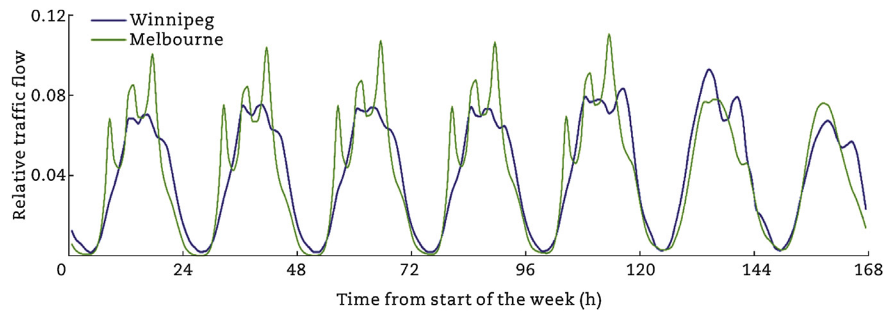

Fig. 7 – Pedestrian traffic variation over a typical week in different cities (week starts from Monday).

elderlies belong to the age group with the highest number of fatalities.

In our analysis, only the main rectilinear section of Via Padova stretching from street number 1 to 345 and consisting of intersections and crossroads is considered here. The following part (from street number 346 and later on) contains a number of roundabouts and bridges and, as a consequence, reasons for pedestrians' accidents are more difficult to guess. The 4.1 km straight section of Via Padova contains 40 crosswalks, so we can assume that an average of 0.15 accidents per year (6 accidents occurred in 2016) occur on a given crosswalk.

Along with the data relative to the number of accidents, the variation of traffic over a typical week is also required to calibrate and validate the model. Unfortunately, that kind of data are not available for the case of Via Padova and in general data relative to the weekly variation of pedestrian traffic are quite rare as sensors detecting pedestrians are still relatively expensive. Also, to get realistic estimation of traffic variations over a typical week, a long-time data collection on multiple locations is necessary for both pedestrians and vehicles and such an approach was not possible for the case of Via Padova.

We therefore decided to create a realistic scenario representing the evolution of vehicular traffic and crossing pedestrians over a typical week based on available data from a similar environment. As we will see later, the selection of the reference location to construct the scenario for our simulation

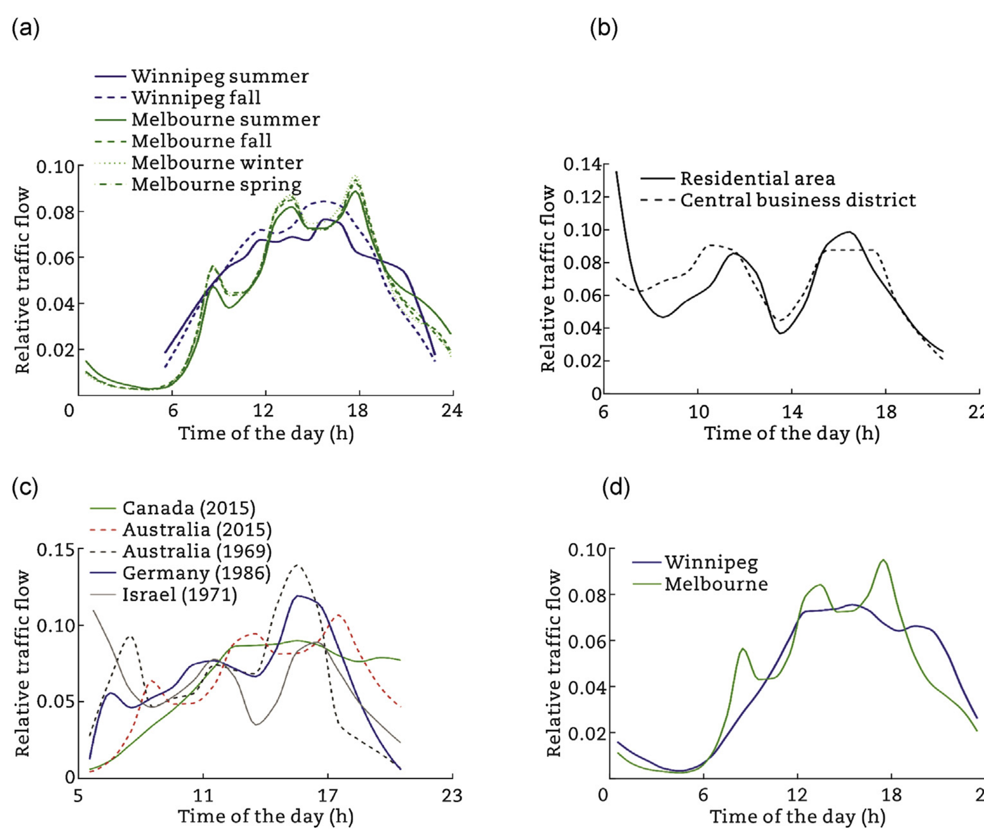

Fig. 8 – Different aspects of pedestrian traffic variation over a single day. (a) Seasonal variation (City of Melbourne, 2018a; Poapst, 2015). (b) Neighborhood relationship (Hocherman et al., 1988). (c) Cultural effects (City of Melbourne, 2018a; Hocherman et al., 1988). (d) Scenarios considered (City of Melbourne, 2018a; Glasgow, 2016).

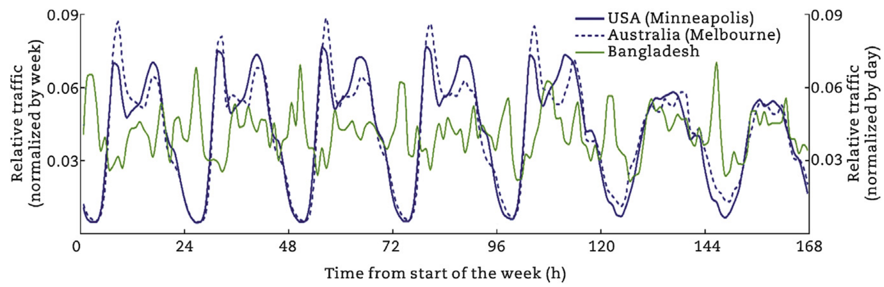

Fig. 9 – Relative vehicular traffic over one week (City of Melbourne, 2018b; Minnesota Department of Transportation, 2018; Siddiquee and Hoque, 2017).

plays an important role and this section will be devoted in explaining what are the criteria for this selection and try to assess how reliable is the scenario constructed.

At first, the pedestrian traffic relative to the frequency of crossing pedestrians will be considered. Later, the vehicular traffic representing the number of vehicles transiting over the crosswalk is discussed.

3.1. *Pedestrian traffic*

Pedestrian traffic flow is affected by a variety of factors, but not all of them have the same impact in determining variations. Fig. 7 shows the relative pedestrian traffic flow in two different cities. In Fig. 7, data for Winnipeg (Canada) are relative to a commercial area on Corydon Avenue between Cockburn Street and Stafford Street (sensors were located in 4 locations) (Glasgow, 2016). Data for Melbourne are relative to a vast area roughly corresponding to the central business district (CBD). More than 40 sensors are considered in this case (City of Melbourne, 2018a). Data for both Winnipeg and Melbourne were obtained by analyzing one year of pedestrian traffic around 2015.

The relative traffic flow is a measure defining the number of people passing on multiple locations normalized using the average number of counts in a single day. To obtain such kind of data very long observation periods are required, usually one or several years. In both cases, pedestrian counts were collected every hour on several locations within the city for a period of one year. As it can be seen from Fig. 7, there are several differences among both datasets. One of the main reasons explaining those differences lies in the type of area considered. In the case of Winnipeg, a mostly commercial and leisure neighborhood is surveyed and therefore people tend to walk around from late morning to late evening. Also, commercial areas tend to be comparatively busy over the weekends. On the other side, data for Melbourne are relative to a work/business related area and peaks are clearly recognizable for the morning and the evening rush and during the lunch break. Also, in the case of business areas the pedestrian traffic is generally lower in the weekend.

Although data for a full week are relatively rare in the literature, it is easier to find average day variations. Fig. 8 presents several aspects related to the change of relative pedestrian traffic over a typical day (considering the whole week). In Fig. 8(a), data for Melbourne are relative to 2015 and those for Winnipeg (sensors' locations are different from Fig. 7) are relative to 2012. In Fig. 8(b), both graphs refer to Urban areas in Israel. Data for Melbourne (Australia) in Fig. 8(c, d) are derived from the one-week graph of Fig. 7. Winnipeg data in Fig. 8(d) are also derived from the corresponding graph of Fig. 7.

As shown in Fig. 8(a), seasonal changes are relatively small and are mostly limited to a reduction of traffic at noon and an increase in the evening during summer. The changes are larger in Winnipeg, where a commercial and leisure area has been considered. Business areas are less prone to seasonal variations with pedestrian traffic in central Melbourne being fairly constant throughout the year.

Fig. 8(b) presents a comparison of the pedestrian traffic volume between residential and business areas in urban Israel (several locations are considered for both neighborhoods). As it can be seen, both curves are similar with a first peak at late morning and a second one in the late afternoon. However, a comparison with the graphs of Fig. 8(a) already shows that difference among countries with different cultures can be quite large.

This observation is confirmed by checking the graphs of Fig. 8(c) which compares pedestrian traffic in four different countries. Clearly, customs have a strong influence in determining peaks and traffic dynamics. While countries with European/western lifestyle show some similarities, especially when it comes to the morning and evening peaks, Israel has a different behavior in relation to pedestrian traffic, although all data are relative to urban areas. Interestingly, changes in lifestyle and customs may also contribute to modify traffic dynamics over the long term, as the case of Australia shows when data from 1969 are compared to that of 2015 (a time span of almost half a century).

To conclude, we can affirm that in choosing a reference scenario for pedestrian traffic, cultural aspects are the most important and, consequently, a city with similar lifestyles to Milan will have to be chosen to create a realistic profile.

3.2. *Vehicular traffic*

In the case of vehicular traffic, transit data are quite easy to retrieve as a number of municipalities employ automatic counters to estimate levels of congestion in different locations within the city to assess the eventuality of infrastructural improvements. However, most of the counters are installed on highways and, in general, data are limited to 24 h counts which are not useful for the aim of this research.

Fig. 9 presents a comparison between three different datasets relative to USA (central Minneapolis), Australia (central Melbourne) and Bangladesh (Jamuna multi-purpose Bridge). In Fig. 9, data for Minneapolis (USA) and Melbourne (Australia) are normalized over the average daily traffic volume (without distinction by weekday). In the case of Bangladesh (Jamuna multi-purpose Bridge), average traffic volumes are taken for each weekday. Data for USA are relative to the whole year of 2017, data of the whole 2015 are used for Australia and data for Bangladesh were collected during 13 weeks from 1999 to 2002. In the latter case traffic volume is normalized using the total count for each day of the week and therefore a different scale is used in the visualization. Similarly to the case of pedestrian traffic, it can be seen that when cultural contexts are not much different, vehicular traffic tend to show similar profiles over the week. The case of Bangladesh proves that very different contexts can generate a very different traffic profile. In the specific, data for Bangladesh are relative to the Jamuna multi-purpose bridge, an important road connecting the north and the south of the country which is mostly used at night by trucks moving goods around the country.

The remarks on cultural and local aspects on traffic behavior are further confirmed by Fig. 10, in which a dataset representing vehicular traffic in southeast Michigan (obtained from 13 permanent counting stations) and one relative to a “typical scenario” in Botswana are added. In Fig. 10, data for southeast Michigan (USA) or generally the greater Detroit are relative to a period from 2009 through 2012 (Batterman et al., 2015). Data for Botswana are possibly relative to an urban area, although details are unclear (Ministry of Works and Transport, Roads Department, 2004). As it can be seen, USA and Australian data are very similar in spite of the different geographical location. In particular, a very close similarity is found between the curve for Melbourne and Minneapolis, which could be related to the fact that both datasets are relative to locations close to the city center (data for southeast Michigan consider a wider area around the City of Detroit). Again, when quite different cultural backgrounds are considered, here Bangladesh and Botswana, the curves tend to have a different shape which reflects different customs and lifestyles.

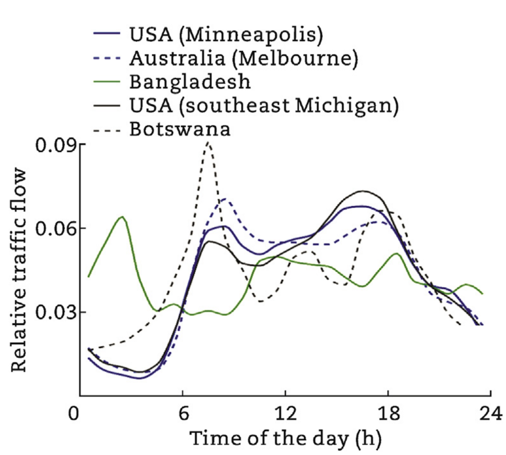

Fig. 10 – Relative daily vehicular traffic.

3.3. *Selected scenario*

In light of the above considerations we concluded that the dataset for Melbourne could represent the general weekly traffic behavior in Milan with sufficient accuracy. One of the authors of this study also lived in both Melbourne and Milan and confirmed that both cities have relatively similar lifestyles.

With this said, it is important to remark that datasets considered so far all consisted of relative traffic flows, but absolute levels are required to generate simulation inputs. On this scope, few steps are necessary and are described in Fig. 11. In Fig. 11, data from Melbourne relative to 2015 have been used to create the weekly traffic profile and measurements from Via Padova (relative to the same year) have been used to quantify traffic volumes. Vertical line in Fig. 11(b) corresponds to the time interval used for quantification.

Fig. 11(a) shows the weekly relative traffic for vehicles and pedestrians obtained from the several sensors located in central Melbourne. This is the scenario that will be used to generate vehicle density and pedestrian crossing frequency used in the simulation. To obtain those curves, measurements from Via Padova are used. The observation (Gorrini et al., 2016, 2018) has been performed on a Friday between 10:45 to 12:00, thus corresponding to hour 108 when considering the whole week. The measured values of 16.30 veh/km/lane and 5.52 ped/min have been used to create the graphs presented in Fig. 11(b), where the vertical line indicates the moment used as reference interval. The same values were also used to validate the model not accounting for accidents by using delays for pedestrians and drivers (Feliciani et al., 2017).

To allow an efficient implementation into the simulation model without losing in computational accuracy we divided each curve of Fig. 11(b) into 20 levels creating two distinct profiles for vehicles and pedestrians, each with a resolution of one hour as shown in Fig. 11(c, d). Using both information it is possible to create a list of simulation conditions considering the corresponding level of traffic as shown in Table 4. A single week simulation considering the changes in traffic flow is therefore computed by simulating the different conditions for the corresponding time. Please note that Table 4 is not complete and is only intended for explicative purposes. By considering 20 levels for each agent (vehicle and pedestrian) in total 79 conditions are obtained.

4. Simulation results, calibration and discussion

In this section, we will present the results from simulation and compare them with experimental data. At first, we will study the effect of different parameters on the final outcome of simulations, both considering the number of collisions and the resulting fatalities. Later, we will consider the traffic flow profile presented above and calibrate the model using statistical data for traffic accidents.

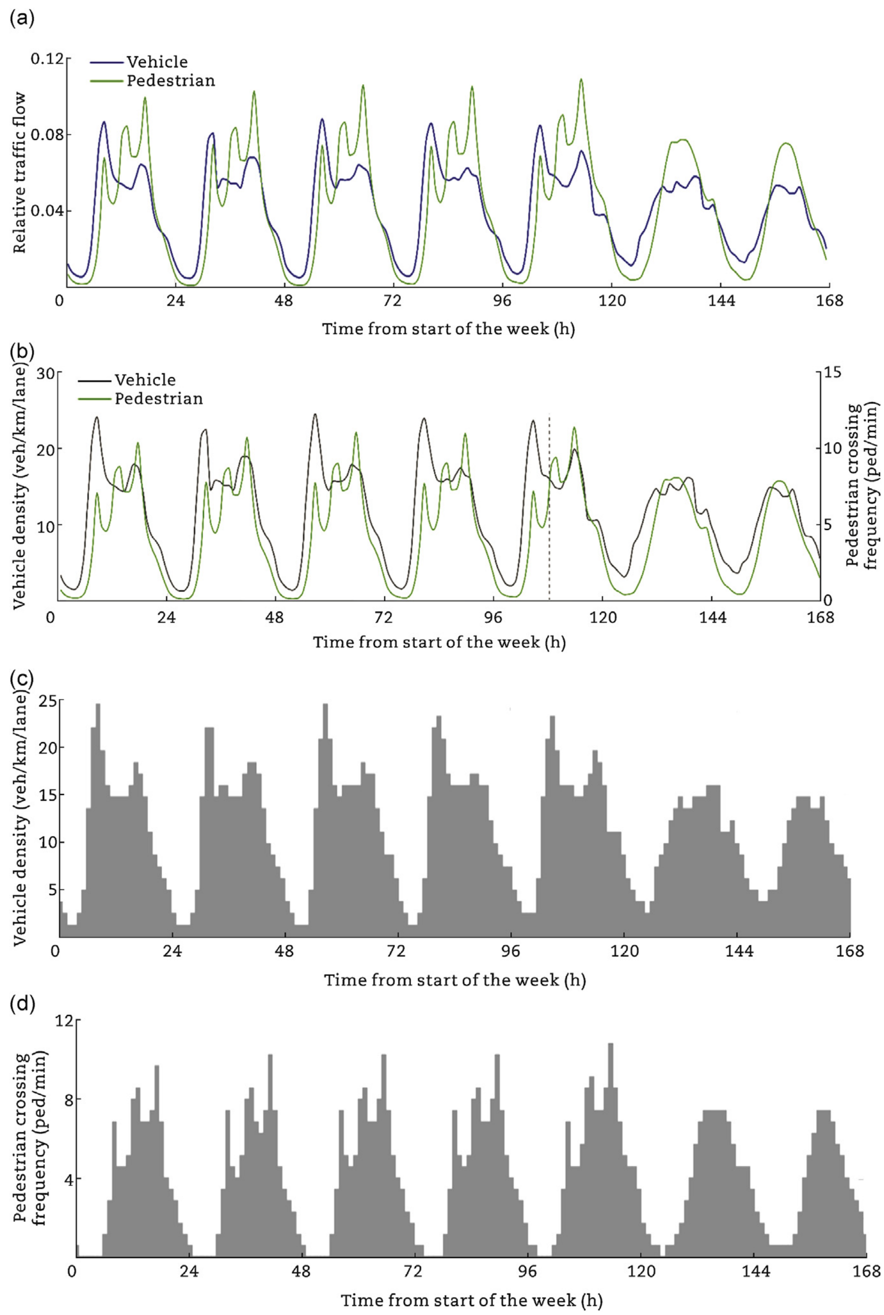

Fig. 11 — Method employed to create traffic volumes used as simulation input. (a) Relative traffic profile for pedestrians and vehicles used as scenario. (b) Vehicle density and pedestrian crossing frequency created from reference data. (c) Input data for simulation obtained by using hourly vehicle density. (d) Input data for simulation obtained by using hourly pedestrian crossing frequency.

4.1. *Parameters' variation and influence on pedestrian fatality*

This first part will be devoted in understanding how traffic flow and levels of distraction affect the number of collisions (accidents in more general terms) and fatalities. This step is an important milestone before calibrating the model, because by comparing qualitative simulation results with experimental studies from the literature and reports on traffic safety, it is possible to get an idea of the model's accuracy and its capability to correctly reproduce macroscopic dynamics of accidents occurring on unsignalized crosswalks. Also, it is important to understand the qualitative effects of different variables and parameters to grasp the relevance that a parameter's change may have on the final outcome.

To understand qualitative aspects of the model, we performed several simulations by varying only one variable at a time. Reference values used in simulations are given in Table

Table 4 – Conditions considered in simulation and simulated time for each condition (one week is presented here).

Vehicle density (veh/km/lane)	Pedestrian crossing frequency (ped/min)	Simulated time (h)
1.31	0.09	10
2.54	0.09	9
3.76	0.66	9
14.77	7.50	6
⋮	⋮	⋮
23.33	6.93	1
23.33	7.50	1
24.56	6.93	1
24.56	7.50	1

5. Traffic conditions were selected in order to be similar to the reference time-point previously considered to create the weekly traffic scenario (Friday morning around 11 AM). Distraction for pedestrians and drivers is based on experimental observations (Hatfield and Murphy, 2007), but, as we will see later, much lower values are required to obtain realistic results. Nonetheless, a high number of collisions was also required to get enough data for a statistically relevant analysis (several centuries of simulated time would be required to have enough collisions under realistic conditions), so an overly high parameter for distraction helps in this initial qualitative analysis.

In each case, we varied a single parameter stepwise by keeping the others constant. Simulations were performed using constant conditions for 20 d (480 h) and statistics for collisions and fatalities were collected. Three population compositions were chosen: only adults, adults and elderly pedestrians in equal number and elderly pedestrians only.

To compute the total number of casualties among pedestrians in a given time period, we summed up the risk of pedestrian fatality relative to each collision obtained using Eq. (4). To make an example, we can assume that if 10 (low speed) collisions with a fatality risk of 0.1 occur in one year, one person would get killed in that year (the remaining 9 would survive). This reasoning obviously holds true only for large numbers and long time periods, but generally fits well with the approach employed in our study.

Fig. 12 presents the results obtained by varying traffic conditions. A first observation concerns the frequency of fatalities. Values range from a few casualties per week to almost one every hour; both values are clearly well above real conditions where deadly collisions happen much more rarely. But, since the model is not yet calibrated, we will consider only qualitative aspects.

Table 5 – Reference values used in the simulations to investigate the influence of different parameters.

Type	Parameter	Value
Traffic condition	Vehicle density (veh/km/lane)	15.0
	Pedestrian flow (ped/min)	5.0
Distraction	Distracted pedestrian	0.025
	Distracted driver	0.025

Note: When the proportion of distracted drivers/pedestrians was varied, distraction for the other road user was set at 0.

In this regard, it is remarkable to notice that the curve describing pedestrian fatalities in relation with vehicle density does not have a monotonic shape. While the curve relating to pedestrians reaches a plateau for high levels of traffic, the one for vehicles peaks at around 30 veh/km/lane. In the case of pedestrians, the plateau can be explained by considering that when there is a large number of pedestrians crossing the street, it is more likely that distracted pedestrians will jump into the crosswalk when cars are already at still to give way to other pedestrians. In this way, distracted pedestrians are “rescued” by the large crowd which keeps cars at still by continuously crossing.

To understand the shape for the case of vehicles from Fig. 12(a), we will take a further step by considering the frequency of collisions and the speed at which they are occurring separately, as provided in Fig. 13. Clearly, the frequency of collisions increases with the density of cars. However, as the density of cars increases, congestion occurs and cars have to slow down. This results in a reduction of collision speed, which ultimately has an effect on the fatality rate. We can conclude that collisions are more frequent when traffic is dense, but they will likely result in light injuries mostly not life-threatening.

Unfortunately, the authors have no data and are not aware of studies taking into account crashes which resulted in no injuries. As traffic statistics largely relies on reports from police and insurance companies, crashes without physical or material damages are not listed. Everyday experience by the authors nonetheless indicates that crashes without consequences do occur, but, in many cases, people simply exchange their contact details without reporting it to police or insurance companies.

In this context, we may conclude that urban solutions which aim at making the traffic denser and slower, such as the “shared-space” concept may help improving pedestrian safety. In fact, it has been reported that after the town of Drachten (Netherlands) employed the “shared-space” design in 2002, the number of accidents fell from 8.3 per year between 1992 and 2002 to an average of one in 2005; this despite an increase in traffic volumes (Senthilingam, 2014). Similar results were reported for the city of Auckland (New Zealand) (Karndacharuk et al., 2014; Senthilingam, 2014). While behind the success of shared spaces, there is also an important psychological component (mostly related with a shared responsibility) which cannot be denied (Schulz, 2006), even traffic dynamics almost certainly plays a relevant role.

Next, we wish to consider how distraction of both drivers and pedestrians affect fatalities in crossing pedestrians. To understand the relevance of each road user separately, distraction was set to zero for the counterpart when each variable was changed (i.e., drivers' distraction was set to zero when distraction for pedestrians was varied). Results relative to both road users are presented in Fig. 14.

A first look on the very high number of fatality rates suggests that distraction parameters well below the minimum considered until now will have to be used when calibrating the model.

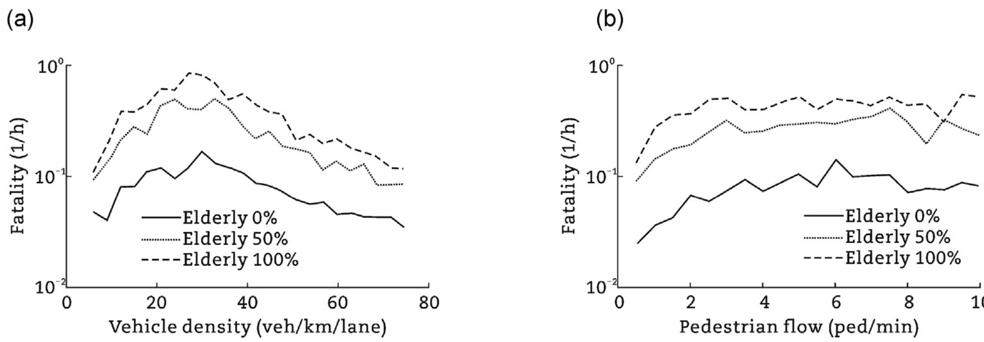

Fig. 12 – Relationship between levels of vehicular and pedestrian traffic and pedestrian fatalities. (a) Vehicle density. (b) Pedestrian flow.

More generally, curves for both road users show similar profiles although absolute values are different. In the specific, distracted drivers are about 3 times more dangerous compared to distracted pedestrians. Although pedestrians are always the victim, this result suggests that prevention should focus on drivers to improve traffic safety more efficiently.

Before going into quantitative aspects and perform the calibration, we want to add a few remarks on the presence of elderly people. In all the scenarios considered so far, crowds with a large elderly population always had highest fatality rates. This is however only a consequence of the different values used in Eq. (4) and we did not find the lower walking speed relevant to determine frequency of collisions. Results may change if different values of distraction are used for each age group, but this would make the model unnecessarily complex and difficult to calibrate and validate.

4.2. Model calibration and critical assessment

Having discussed qualitative aspects, we now finally wish to calibrate the model by finding the correct values for distraction. It is important to remind here that, in reality, accidents happen on average once every decade for a given crosswalk (especially referring to the case of Via Padova), so, in order to have a sufficient amount of data for a statistically relevant analysis, a time window of several years would have to be simulated. While the model is quite simple and a single year may be simulated in a few hours of calculation, we want to limit unnecessarily long computational efforts. In particular, to make calculations easier we may employ a single parameter for distraction, same among drivers and pedestrians. But, to ensure that this is a correct assumption, we want to check the combined effect of both levels of distraction.

Fig. 15 presents the number of collisions occurring during one month of continuous traffic assuming different combinations of distraction for drivers and pedestrians. In Fig. 15, traffic conditions given in Table 5 are used and 30 d (720 h) of continuous traffic are simulated for each point. As it can be seen, there is a nearly linear relationship between distraction and number of collisions for both road users. Also, the steepness in regard to collision frequency seems similar among both road users, thus confirming that using a common parameter may be a viable and correct alternative.

Having reduced the number of scenarios to investigate, we can now move toward the final calibration and consider very long simulation time. For calibration purposes we wish to consider a logarithmic variation for distraction (now equal among drivers and pedestrians) and 6 values ranging from 10^{-7} to 10^{-2} were consequently considered. For each case, 10 or 20 years of realistic traffic conditions were simulated using the approach described in the previous section by varying both vehicular and pedestrian traffic flows over one week. An elderly population of one quarter of the total has been used to fit empirical conditions observed for the scenario of Via Padova. To obtain the results presented in Fig. 16 (with numerical values provided in Table 6), a total time of almost 3 d was necessary using a machine equipped with a quad-core 3.50 GHz processor (simulations were performed in parallel using all 8 logical processors available). The model is

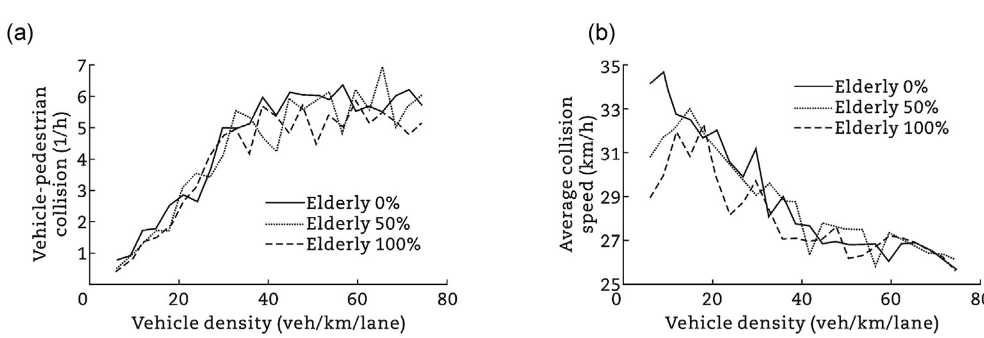

Fig. 13 – Details for collisions. (a) Collision frequency. (b) Collision speed.

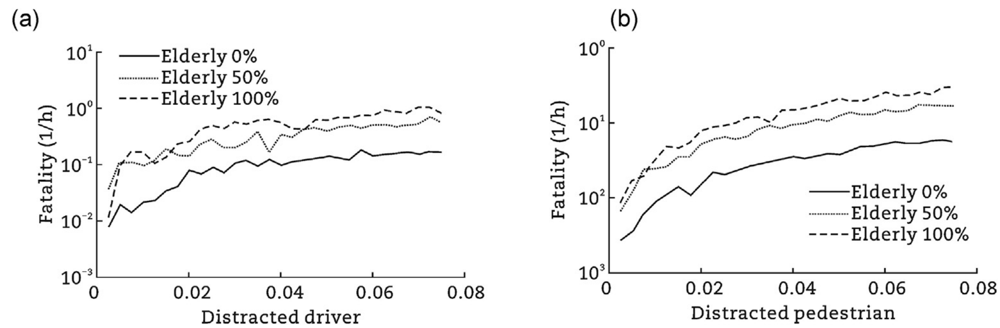

Fig. 14 – Relationship between the proportion of distracted road users and pedestrian fatalities. (a) Drivers' distraction. (b) Pedestrians' distraction.

calibrated considering the experimental value of 0.15 accidents (collisions) per year per crosswalk. Traffic flows are varied according to the one-week scenario presented earlier.

When results are plotted on a double logarithmic scale (Fig. 16(a)), a line is shown as connecting the different points relative to the collision rate (and the same possibly holds true for the fatality rate considering the low statistics at low levels of distraction). A linear fitting on the logarithmic values returns a R^2 of 0.99949, clearly indicating a good fit. In other words, it is possible to calibrate the model using the logarithmic values of both distraction and collision rate. Given the experimental value of 0.15 accidents (collisions) per year per crosswalk, a distraction parameter of $10^{-6.125}$ is obtained. In the calibration process, results for a distraction of 10^{-7} have been omitted, but the result is still important to show that collisions did not occur for the simulated time of 20 years. Considering the several uncertainties involved in the calibration process, we can conclude that values between 10^{-7} and 10^{-6} can be considered acceptable for distraction in our model.

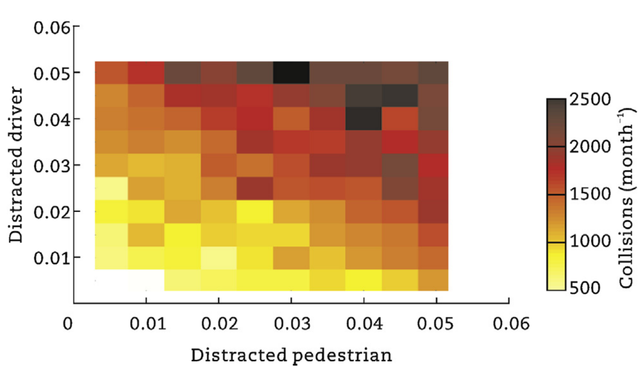

Fig. 15 – Number of collisions resulting from the combined distraction among drivers and pedestrians.

Besides the importance relative to calibration purposes, Fig. 16(a) also provides additional information in regard to the behavior of our model. In particular, it is remarkable to notice that there is a linear relationship between distraction and collision rate (the slope in the logarithmic fit for collision rate returns 1.009 ± 0.0420, indicating an almost perfectly linear relationship). This is important, because a linear relationship means that the qualitative aspects previously discussed would not change when a realistic value for distraction is used. In other words, we can expect the same qualitative results for Fig. 12 by using the calibrated value for distraction, only the scale would change.

When the collision speed is considered (Fig. 16(b)), it is seen that speed decreases when the distraction parameter is reduced. This can be explained by considering that for high levels of distractions, many cars do not have to stop and therefore the general speed of the vehicles is increased. However, as the single logarithmic scale shows, the change in collision speed is relatively low and only large variations of the distraction parameter can influence it.

Finally, using the results from the various simulations, we can check when most of the accidents did happen. On this scope, we need to use again a quite large distraction

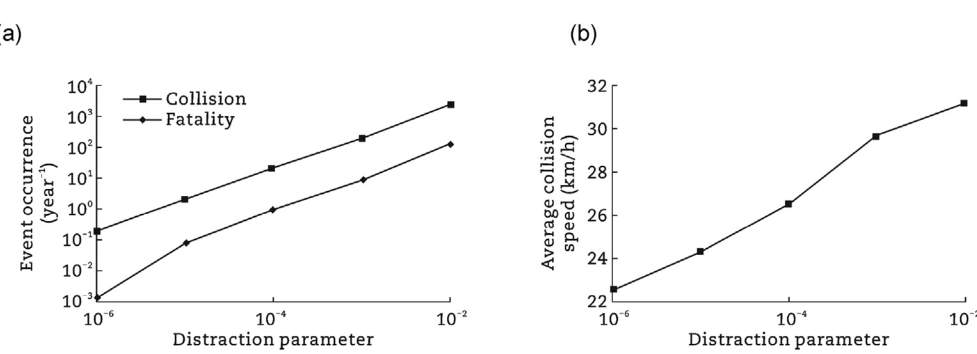

Fig. 16 – Results for yearly collisions and fatalities by simulating 10 or 20 years of realistic traffic conditions. (a) Collisions and fatalities per year. (b) Collision speed.

Table 6 – Calibration results obtained by simulating several years of realistic traffic conditions and varying the distraction parameter.

Distraction	10^{-7}	10^{-6}	10^{-5}	10^{-4}	10^{-3}	10^{-2}
Simulated time (year)	20	20	20	10	10	10
Collision ($year^{-1}$)	0.00	0.20	2.10	21.60	185.40	2354.10
Fatality ($year^{-1}$)	0.00000	0.00141	0.07860	0.90400	8.68000	134.72000
Average collision speed (km/h)	N/A	22.53	24.33	26.53	29.69	31.14

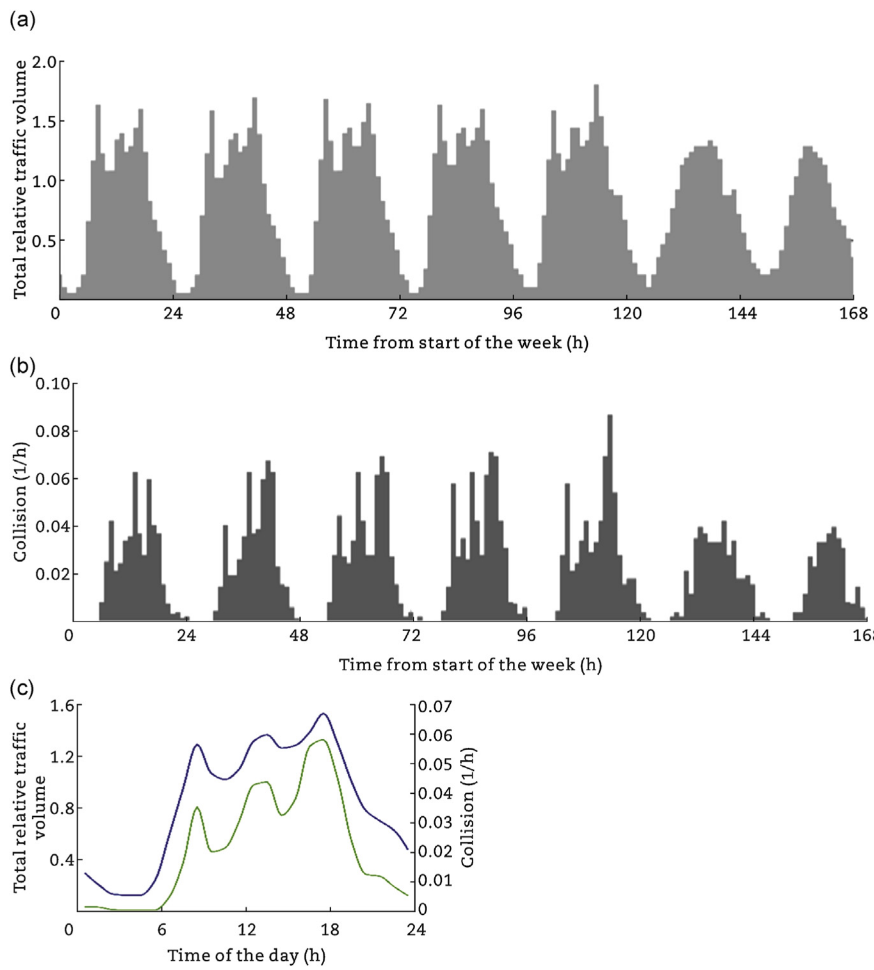

Fig. 17 – Distribution of collision rate considering the combined traffic volume for a distraction value of 10^{-3}. (a) Total relative traffic volume over one week. (b) Collisions over one week. (c) Collisions over one day (traffic volume is given in blue, collision in green).

parameter, as the calibrated value generates too few collisions to allow this type of analysis (however we know now that a very similar result may be obtained in which only the scale would be different). Fig. 17(a, b) presents a comparison between the combined relative traffic (the sum of the relative traffic for pedestrians and drivers discussed earlier in introducing the scenario) and the collision rate in different moments of the week, with the average daily dynamics is given in Fig. 17(c) (in Fig. 17(c) blue is used for the total relative traffic volume and green for the collision rate). Since simulations are performed in a grouped fashion using a tabulated input, it is not possible to know exactly when collisions happened but we know which traffic combination was the most dangerous. From the weekly dynamics it is seen that, in general, collisions are more frequent when traffic is intense. However, when the daily visualization is considered, some more subtle details appear. While traffic flow (blue line) tends to be high from 8 to 18, with 3 distinct peaks, the collisions frequency (green line) also has 3 distinct peaks, but the late ones appear to be proportionally higher. Interestingly, by computing the average time and its variance relative to the reported accidents for Via Padova in 2016 (data are relative to the accidents of Table 3), it is found that the time period between 11:18 and 22:22 had the highest number of collisions. The same time interval accounts for around three quarters (77.96%) of the total collisions occurring in simulation.

Although the number of accidents from Via Padova may not be sufficiently high to statistically show that evening hours are the most dangerous, a recent survey (Egger et al., 2018) made in Switzerland on a 6 years period (2011–2017) found that the highest number of pedestrian accidents countrywide happened between 17:00 and 18:00, with Wednesday being the weekday with most fatalities. Although the similarities between simulation and experimental data may only be a coincidence (the model does not account yet for specific aspects such as lighting conditions and weather, thus making such a comparison very arguable), it could be also seen as a possible way of validation.

5. Conclusions

In this work, we presented a simulation model for unsignalized crosswalks (i.e., zebra crossings without traffic light systems, characterized by the right-of-way of pedestrians) which has the particularity of considering collisions between vehicles and pedestrians. Dynamics for both road users is based on specific models well-known in the literature, while the decision-making algorithms (referring to actions on the crosswalk) have been developed based on empirical findings. To account for collisions, we assumed that a given portion of drivers and pedestrians is distracted and do not pay attention to the road. Collision speed is also computed and is used to estimate the fatality probability for different age groups based on equations from the literature.

In particular, a lot of attention has been given on the calibration process, necessary to gain realistic estimates for the parameters accounting for distraction. In this regard, we showed that literature values relating with distraction among road users cannot be used and much lower figures need to be employed in simulations. On the overall, the proposed calibration approach consists in building up a realistic scenario containing vehicular and pedestrian traffic over one week. Later, simulations over long periods of time (10 or more years) are carried out replicating the one-week traffic conditions. Finally, statistics for accidents are compared with data collected by local authorities. In addition, we showed that even when on-site measurements for the weekly traffic are not available, cities/regions with comparable culture and lifestyle could be used as reference.

In order to investigate the dynamics of the model, very large values for distraction had to be used, resulting in an unrealistically high number of collisions. However, we also showed that the distraction parameter has a linear relationship with the frequency of collisions, thus making it reasonable to consider overly-high values of distraction to investigate qualitative aspects and later scale down results when quantitatively accurate estimates are sought.

Simulation results showed that pedestrian fatalities are strongly influenced by collision speed. In this regard, we also found that vehicle speed could be adjusted using indirect methods, such as by creating a dense, slow traffic typically occurring in shared-space areas.

While the simulation model presented here may still need several improvements considering, for example, the changes in visibility and related driving behavior at night or during rainy days, we also showed that it is possible to consider pedestrian safety (and not only traffic efficiency) when designing urban areas. In this sense, we also provided hints to show that even a simple model, but still based on empirical evidence and sufficiently calibrated, allows to estimate collisions and fatalities on large time scales. With this said, we remind that this study does not aim at presenting a model reproducing accident dynamics in detail, but should be rather seen as a guideline presenting the several steps and challenges which would have to be overcome by researchers wishing to adapt their model to account for pedestrian safety.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

Acknowledgments

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