A Risk-Based Pedestrian Crossing Decision Model for Traffic Simulation in African Urban Traffic

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Abstract. Traffic jams are a particularly difficult global problem. They cause considerable economic losses. These losses are particularly significant for large cities in developing countries such as Dakar. Hence the need to optimize urban traffic by studying the impact of the various factors determining traffic flow.

Traffic simulators are an inexpensive way of studying and improving traffic flow. However, most existing simulators are adapted to the traffic context of cities in developed countries, for which they were primarily created. Their use in African cities such as Dakar would be ineffective if they were not adapted to the local context, where pedestrian crosswalks are almost non-existent.

In this work, we propose a pedestrian decision model for crossing the road in illegal locations. We demonstrate its effectiveness through three simulation scenarios using SUMO, an open-source, microscopic, and very popular traffic simulation package designed to handle large networks.

Keywords: Traffic Simulation · Pedestrian Crossing · Behavior Modeling

1 Introduction

The growing urbanization of the world's major cities poses enormous challenges for transport systems. A significant proportion of the economic losses is directly linked to poorly performing transport systems, which causes numerous traffic jams on the roads [4,18]. This loss is particularly significant for large cities in developing countries such as Dakar, where it is estimated to 235 billion West African CFA francs[1]. Hence the need to optimize urban traffic by studying the impact of the various factors determining traffic flow. For instance, Bhardwaj *et al.* find that Nairobi, the capital of Kenya, experiences three times the mean jam time per road segment as compared to São Paulo and New York City [3]. They assert that chaotic driving patterns and traffic mismanagement in the developing

[1] https://shorturl.at/eqELS.

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world cities lead to tighter traffic curves, more intense jams and overall lower road capacity utilization, which explains their observed data. Thus they conclude that the problem of traffic congestion in developing countries cannot be solved entirely by building new infrastructure, but also requires smart management of existing road infrastructure.

Since experimenting traffic on a real environment is not practical, computer simulation is widely used to study the flow of traffic at least since 1955 [16]. Indeed the use of numerical simulations enables the benchmarking of several scenarios for organizing transport systems at lower cost, and provides a clear view of the impact of any future road or other development. Thus many urban traffic simulators have been designed and proposed [8,15].

Through the years they have evolved to use better simulation paradigms, better models and eventually cover whole traffic networks instead of specific locations [19]. However, it should be noted that they are almost all designed for the highly organized transport systems of developed countries which have different operating modes compared to cities in developing countries. Examples include reserved lanes for two-wheelers or buses, the presence of crosswalks and traffic lights at most intersections.

As a result, the use of traffic simulators primarily made for developed countries in a less regulated context proves less effective, unless adapted [17]. Some authors have already tackled the issue of adapting simulators to the urban traffic context of several cities. Most have focused on modeling driving styles that can vary from one country to another [17]. Fewer have focused on pedestrian behavior and the factors determining road crossing decisions [9,10]. Moreover they focus on modeling pedestrian behavior at signalized crossings or regularized crosswalks [9] and thus do not consider the behavior of pedestrians crossing a road at a location other than a designated crossing. In addition they use a gap acceptance model that represents how a pedestrian decides when to cross a road, based on the frequency and speed of approaching vehicles, while considering the spacing between them. The aim of this work is to develop a pedestrian model more suited to cities lacking organization and crosswalks. In this context, several factors contribute to the pedestrian crossing decision. Our model takes into account most of the decision factors cited in the literature, including age, gender, impatience, speed and distance of approaching vehicles. We demonstrate the effectiveness of our model by simulating it with real traffic data collected in Dakar. The sequel of this paper is organized as follows. In Sect. 2, we present a brief review on related works on pedestrian crossing decision models. Section 3 details our pedestrian crossing decision model based on risk-taking relative to sociodemographic factors and pedestrian waiting time, on the one hand, and traffic conditions, on the other. We address also the integration of the model with a popular traffic simulator we used. Then in Sect. 4, we expose the simulation scenarios we ran with our model and discuss the results we obtained. Three scenarios are considered in this section. Finally, in Sect. 5 we conclude the paper.

2 Literature Review

As cities continue to grow, increasingly complex, high-performance transportation systems are being developed. Computer simulation is therefore widely used in research into urban traffic modeling, planning and transport system development.

Traffic simulation models are generally classified according to their field of application: microscopic, mesoscopic or macroscopic modeling. Macroscopic models are models of traffic in a continuous flow, mesoscopic models consider individual vehicles, while microscopic models capture the behavior of vehicles and drivers in detail. The latter can take into account a vehicle's interactions with other vehicles and pedestrians, its lane changes, its reaction to incidents and its load-dependent behavior. As a result, microscopic models are better suited to simulating pedestrian behavior models, as they enable a very fine simulation of traffic [8,15].

As we said in our introduction, most microscopic simulators use a simple decision model for pedestrians at crosswalks. The behavior of pedestrians crossing a road at a location other than regular crosswalks is not well taking into account: a pedestrian wishing to cross the street at an uncontrolled intersection can only do so if its expected time slot for using the intersection does not interfere with that of an approaching vehicle [1,9].

Recent research has thus been carried out to improve this behavior by integrating more realistic decision models that consider additional factors motivating the decision of pedestrians to cross at red lights or in areas without regular crosswalks [1,5,10,12].

In [10], Garrido *et al.* used Unity3D to create an external 3D representation of a running simulation, they are able to create and control pedestrians. This also opened the possibility to use virtual reality immersed subjects to participate in the simulation, but it is limited to manage only a few number of pedestrians. Amini *et al.* used a game theoretic approach to model pedestrian road crossings [1]. A safety level is embedded into their model to evaluate the collision risk depending on a wide range of factors such as pedestrians' group size and density, number of vehicles approaching the crossing, and approaching lane for both pedestrians and vehicle.

Lawrence *et al.* utilize a simpler model based on a gap acceptance model that represents how a pedestrian decides when to cross a road, based on the frequency and speed of approaching vehicles, while considering the spacing between them [12]. Therefore their gap acceptance model allows the pedestrians to choose to cross all lanes in one go, when safe to do so, known as *Double Gap* or *one stage crossing*. Cai *et al.* propose to use machine learning to optimize and improve pedestrian crossing predictions in intelligent transportation systems, where the crossing process is vital to pedestrian crossing behavior [5]. They applied OpenCV image recognition and machine learning methods to analyze the mechanisms of pedestrian crossing behaviors. However they do not consider pedestrians' gender and age category in their work.

Like [5], our proposal uses machine learning to take decision but it differs from all these cited works in the fact that we consider sociodemographic factors (e.g., gender and age) in addition to pedestrians' group influence and traffic state. This is the greatest difference between our work and theirs.

3 A Risk-Based Pedestrian Crossing Decision Model

Like many cities in developing countries, Dakar lacks regular crosswalks on several streets, particularly in its suburbs. As a result, crossing the carriageway is a big risk for pedestrians, who have to decide on the right timing to start crossing. In the literature, a number of studies have focused on the factors influencing pedestrians' decisions. It goes without saying that pedestrians base their decision to cross on the risk of collision, given their speed and that of vehicles. For instance, this is the basis of the current model implements into SUMO, an open source, microscopic and very popular traffic simulation package [9]. This model is not adapted to African urban traffic where the lack of crosswalks leads pedestrians who do not want to wait longer to take more risks.

Moreover the literature shows that age and gender are the two individual factors that primarily determine the degree of risk-taking by pedestrians, in addition to the length of time they spend waiting at the roadside [11]. Added to this is the influence of other pedestrians during the crossing [13]. Pedestrians tend to join those crossing if they are not far away. In this way, they take few risks by taking advantage of the slower speed of cars to avoid pedestrians.

This work want to consider all these factors to build an efficient decision model. Therefore, our contribution consist in three items: i) collection data about pedestrian crossing decision in real traffic for our learning process, ii) designing and evaluating a risk-based crossing model by using machine learning algorithms and iii) simulating urban traffic with the model and evaluating its efficiency.

3.1 Data Collection

To build our risk-based decision model which takes more account of the pedestrian sociodemographic characteristics and pedestrian flow, we first collected pedestrian crossing data using video camera as illustrated in Fig. 1 where one can see a group of pedestrians illegally crossing the road on one of Dakar's main avenues.

We collected nearly ten hours of video over three days at peak traffic times. In a second step, we analyze the videos and manually build a structured dataset with the following information:

- the pedestrian gender (man or woman)
- the pedestrian age category (visually estimated among: young, adult, senior)
- the pedestrian waited time (in seconds)
- fastest vehicle speed to arrive (calculated from the videos, in m/s)
- the distance of the vehicle (estimated from the videos, in meters)

Fig. 1. Illegal pedestrian crossings.

– the number of pedestrians who are currently crossing the road
– and the pedestrian decision to cross or not the road

Table 1 shows a sample of 1850 rows we prepared for our machine learning phase.

Table 1. A sample of the dataset

Gender	Age	Waiting	Car Speed	Car Distance	Crossing Ped.	Decision
woman	adult	2	10	50	0	crossing
man	adult	1	17	25	0	waiting
man	young	4	5	37	0	crossing

3.2 Modeling Pedestrian Crossing via the Risk of Accidents

Once the data was collected, we compared the performance of eight machine learning models: logistic regression (LR), support vector machines (SVM), k-nearest neighbors (KNN), naive Bayes (NB), decision trees (DT), random forests (RF), gradient boosting (GB) and multilayer perceptrons (MLP).

We have splitted the dataset into training and testing data (75% and 25% respectively). We then tested the performance of each of the machine learning models ten times, renewing the training and test data each time. The Table 2 shows their average accuracies over all experiments.

From our testing, SVM models appear better than the rest in predicting pedestrian crossing probabilities. We used it for pedestrian crossing prediction in our traffic simulations.

Table 2. Average accuracies of the machine learning models

LR	SVM	KNN	NB	DT	RF	GB	MLP
90.33%	91.67%	83.33%	75%	58.33%	66.67%	75%	85.67%

3.3 Simulation of Urban Mobility (SUMO)

For our simulation, we decide to use Eclipse SUMO [14]. The reason is that SUMO is an open source, highly portable, microscopic and continuous multi-modal traffic simulation package designed to handle large networks. It is widely used [10]. SUMO allows modeling of inter-modal traffic systems - including road vehicles, public transport and pedestrians. Despite its popularity, it was only in 2014 that SUMO included pedestrian modeling in its package. Its model, called stripping model, allows a pedestrian wishing to cross the street at an uncontrolled intersection to only do so if its estimates it has enough time to cross the road without the arrival of coming vehicles [9].

SUMO offers several tools which automate core tasks for designing a road network, creating a simulation data and making traffic simulations. Therefore it allows network imports from GIS platforms like OpenStreetMap, the visualization of simulations and the calculation of many output data like CO2 emission or lost time on a road. To end, SUMO can integrate custom models and provides various APIs to remotely control the simulation.

Along these APIs, we cite the Traffic Control Interface (TRACI) which leverages the use of external application in combination with SUMO in order to manipulate the simulation states and variables in real time and so enables the control of vehicles and pedestrians through its interface. We used TRACI to control the pedestrian crossing decisions in our simulation.

Figure 2 presents the architecture of our simulation. In one side, we have SUMO core functionalities which run the traffic simulation. SUMO integrates also the TraCI server which uses TCP communication. The latter combines our risk-based decision model with the TraCI client API via Python scripts.

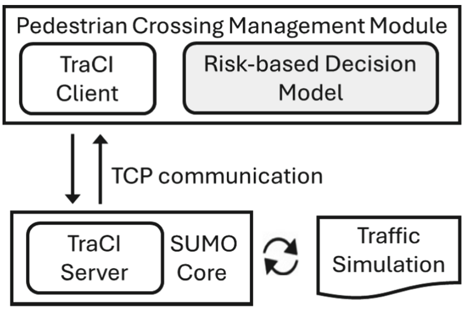


Fig. 2. Simulation architecture.

4 Experimentation

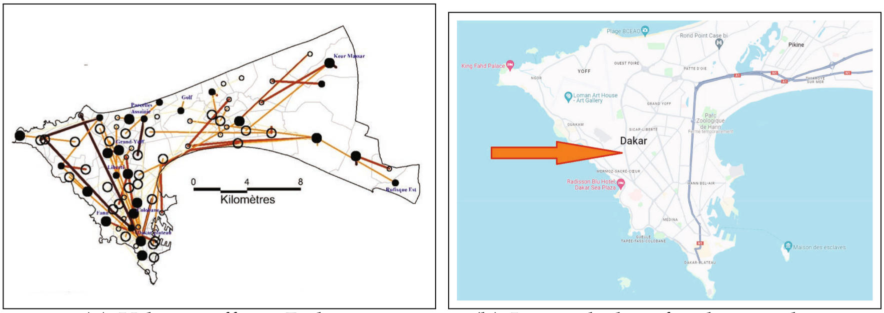
In order to demonstrate the suitability of our decision model to the traffic context of cities such as Dakar, we carried out a series of simulations and compared the performance of our model with that currently implemented in the SUMO simulator.

In this section, we first describe the configuration of our simulation and then present the results we obtained and their analysis.

4.1 Simulation Setup

Road Network. For our study, we chose a section of one of the heavily used highway of Dakar, called the VDN (Voie de Dégagement Nord). The configuration of Dakar makes this highway often busy. Indeed, the suburbs are located to the north and northeast of the peninsula, while economic activity is mainly concentrated to the south, with the administrative center and Dakar port. Figure 3(a), taken from the work of [6], illustrates the bimodal nature of the region.

The section corresponds to the part of VDN highway covering the west side of Keur Gorgui quarter, as highlighted in Fig. 3(b).



(a) Urban traffic at Dakar (b) Located place for the simulation

Fig. 3. Dakar region and urban mobility.

As the city is economically very dynamic, many employees work there and take public transport to go working. Out of laziness or ignorance, many of them do not cross the road at the crosswalk under the autobridge. They prefer to illegally cross the road at the stop where they are. Figure 4 shows in green the position of the crosswalk to be used by pedestrians, in orange the area most used by pedestrians to illegally cross the freeway, and in red the stretch of road directly impacted by these illegal crossings. In the following, we will refer to this road stretch by *Edge 1*.

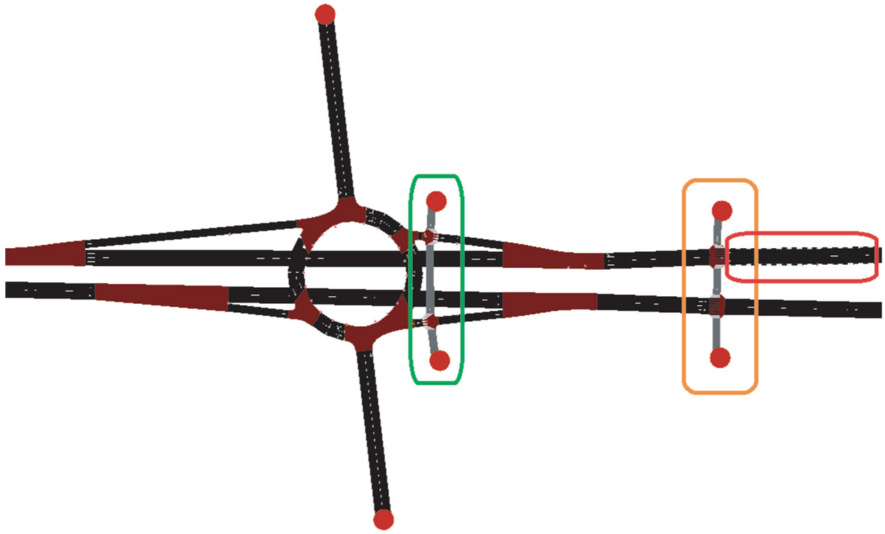


Fig. 4. Studied road network section.

Traffic Data. We used data from the Dakar urban master plan by 2035 [7]. Chapter 12 of this report deals with the project to improve junctions on the VDN highway. This chapter alone provides sufficient information on the current traffic. In particular, it includes statistics on the daily number of vehicles at normal hours at the junction. Similarly, on page 252 of the same document, traffic evolution forecasts are drawn up for the year 2035[2].

On the basis of all these data and the breakdown of the Senegalese vehicle fleet as established in chapter 13 of ANSD report on the economic and social situation in Senegal from 2017 to 2018, published in July 2020 [2], we estimated a number of vehicles to consider during our experimental time slot corresponding to the peak hour between 8am and 9am.

Finally, we validated the reliability of our values by comparing them with traffic survey data collected in July 2016 by students of the graduate school of applied economics (ESEA) as part of a project with the Dakar urban transport executive board (CETUD). As a reminder, the main goal of the survey was to collect data on the frequency of public transport vehicles and their occupancy rate on certain Dakar roads [6]. The local types of vehicle targeted were *Dakar Dem Dikk* buses, *Tata* minibuses and *Ndiaga Ndiaye* and *Car Rapide* vans. Private vehicles and cabs were not included. Over 160 surveyors were stationed in different parts of Dakar department for a week. Their task was to fill in a form collecting information on several observation variables, including the time of passage of the target vehicle, its type and its occupancy level.

2 https://pdudakar.sec.gouv.sn/PDU-Dakar-et-environs-a-l-horizon-2034.html.

Three Simulation Scenarios. We carried out three simulation scenarios. In the first scenario (sim1), we assume that all pedestrians take the regular crosswalk dedicated to crossing the road. They have the right of way when crossing. In the next two scenarios, two-thirds of pedestrians illegally cross the road. In the first case, we use the simulator's default decision model (sim2), and in the second, our proposed model (sim3) is used.

4.2 Results and Discussion

It follows from all our results that traffic is slowest on *Edge 1*, as shown in Fig. 5. The time lost on this section represents 92% of the time taken by the bulk of the traffic using the autobridge. This lost time is greatly due to illegal pedestrian crossings.

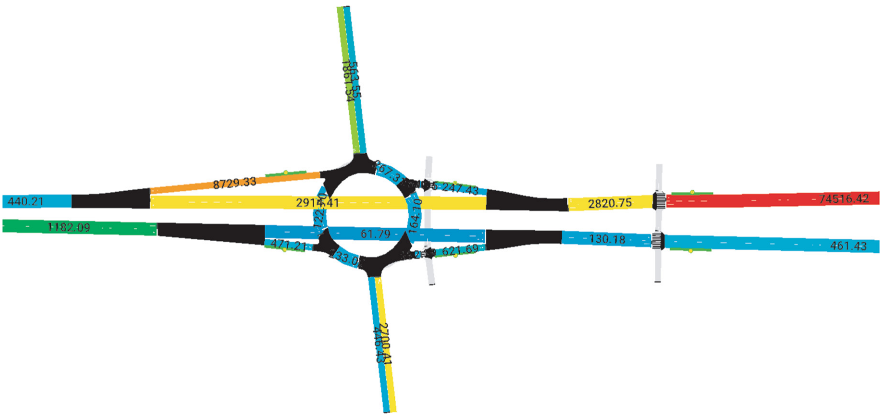


Fig. 5. Average time lost on different sections of the road.

Table 3 details the results of the three simulation scenarios on the impact of pedestrian crossings on the traffic. For each scenario, the table reports the number of vehicles having completed their travels, their average travel time and the average time that they lost during slowdowns. The first row shows data for the traffic on the overall network, while the second row shows data only on *Edge 1* where their are illegal pedestrian crossings. It is easy to see that cars waste more time in their travels with the second scenario (sim2). Fewer and fewer cars reach the end of their path. The third scenario (sim3) wastes less time with our decision model.

Table 4 gives the average waiting time for pedestrians at the illegal crossing position in *Edge 1* before deciding to engage. It also shows the number of vehicles' emergency braking on this road section. One can see that the average time with our decision model is five times lower than the one with the basic SUMO simulator model. With the latter, some pedestrians may indeed wait several

Table 3. Simulation output data on vehicles

Road Section	Nb Arrived Vehicles			Travel Time (s)			Time Loss (s)		
	sim1	sim2	sim3	sim1	sim2	sim3	sim1	sim2	sim3
Global road	3690	3397	3648	57.24	64.39	58.46	26.8	34.65	27.83
Edge 1	1870	1570	1835	52.63	75.21	47.01	39	61.52	40.12

Table 4. Simulation output data on pedestrian waiting time and vehicle emergency braking

Waiting Time (s)			Emergency Braking		
sim1	sim2	sim3	sim1	sim2	sim3
1.69	46.85	8.54	114	90	117

minutes for a safe slot, while they do not necessarily take advantage of the momentum of other pedestrians crossing the road.

Our model is more consistent with reality. Indeed, as studied by Zafri *et al.* in [20], pedestrians did not want to wait more than 20 to 30 s to cross the road in case of waiting. They find that the waiting time of the pedestrians varied with intersection control type, gender, age, minimum gap, waiting location, and vehicle flow. The average time of 46.85 s seems so too exaggerated. For the first scenario (sim1), the average waiting time is less than one second, since in this scenario pedestrians use the legal crosswalk and therefore have priority over vehicles.

A second element confirming the effectiveness of our decision model is the increase in emergency braking on *Edge 1* compared with the simulator's base model. In the latter, pedestrians prefer to wait as long as necessary to cross safely, whereas our model seeks to reproduce the logic of many pedestrians, based on the fact that drivers will see them from a distance and reduce their speed to avoid them.

5 Conclusion

In this paper, we presented a road crossing decision model for pedestrians based on risk judgment. The model is specifically designed for African urban traffic, as we collected data from a busy economic activity location in Dakar. We explained how we integrated our model into SUMO using the TRACI API.

We then carried out three urban traffic simulation scenarios. The results highlight the effectiveness of the model compared to the native SUMO model.

As part of our future work, we aim to collect more data on pedestrian behaviors when crossing the road illegally at different locations, at different times of the day and in different weather conditions, in order to improve and to generalize our decision model. Second, we intend to study a larger portion of Dakar's road network, which will allow us to truly understand the impact of multiple pedestrians crossing a road in dispersed locations.

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