Probabilistic Assessment of Vehicle–pedestrian Collision Risk at a Crosswalk Using the Monte Carlo Method

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Abstract: *Assessing the risk of collisions between vehicles and pedestrians at crosswalks requires approaches that account for the uncertainty inherent in real traffic environments and human behavior. In this study, the Monte Carlo method is applied to perform a probabilistic assessment of vehicle–pedestrian collision risk under predefined ranges of key parameters, including vehicle speed, driver reaction time, and the tire–road friction coefficient. The simulation model is implemented in the MATLAB environment using a large number of iterations, ensuring statistical stability of the results. The analysis shows that the probability of collision is highly sensitive to the initial distance at the moment of hazard perception and reveals the existence of a transition zone between safe and critical conditions. The obtained results demonstrate the applicability of the Monte Carlo method as a tool for quantitative risk assessment and for supporting engineering and expert analyses in the field of road traffic safety.*

Keywords: *Monte Carlo method, traffic safety, vehicle–pedestrian collision, probabilistic analysis, driver reaction time*

1. INTRODUCTION

Road traffic accidents involving pedestrians represent a significant problem in traffic safety, particularly in crosswalk areas, where increased attention is expected from both drivers and pedestrians. Despite regulatory measures and imposed speed limits, the risk of collisions in such zones remains considerable and is strongly influenced by various factors related to road user behavior and traffic environment conditions. Traditional approaches to traffic accident analysis are often based on deterministic models that employ fixed values for key parameters such as vehicle speed, driver reaction time, and tire–road friction coefficient. These models allow the calculation of threshold values and the assessment of stopping feasibility in a given scenario; however, they do not sufficiently account for the inherent uncertainty of real traffic situations. In practice, these parameters vary over wide ranges, and their combined effect on the outcome cannot be adequately described using single deterministic values [1–4].

Probabilistic methods provide a more comprehensive description of risk by enabling the modeling of multiple possible scenarios and the estimation of the likelihood of undesirable events. Among these methods, the Monte Carlo approach is widely used in problems where analytical solutions are difficult or impossible and where multiple influencing factors must be considered. By repeatedly generating random realizations of input parameters, the method allows quantitative risk assessment and the identification of critical regions in which small changes in conditions may lead to different outcomes [8–9].

The objective of the present study is to apply the Monte Carlo method to assess the probability of a collision between a vehicle and a pedestrian at a crosswalk under specified ranges of key kinematic and operational parameters. Using a simulation-based approach, the influence of vehicle speed, driver reaction time, and tire–road friction on collision avoidance is analyzed. The obtained results provide not only a quantitative evaluation of collision risk but also a visualization of the transition zone between safe and hazardous behavior, which is of practical value for expert analyses and assessments of traffic accident scenarios [13].

2. METHODOLOGY

DESCRIPTION OF THE STUDY SCENARIO

The study considers a pedestrian crossing scenario at a crosswalk, where a vehicle approaches the crossing area with a given initial speed. The moment of hazard perception by the driver is defined as the beginning of the reaction process (Fig. 1).

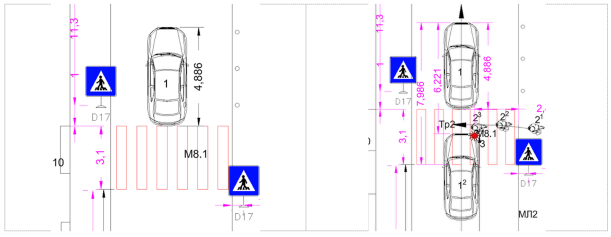


Fig. 1. Geometry of the analyzed scenario and definition of the initial distance to the potential collision point

The distance between the vehicle and the potential collision point at this moment is taken as the initial distance of the analysis and is treated as a fixed parameter for the considered scenario.

Pedestrian: three possible walking speeds are considered – slow walking (4.5 km/h), normal walking (5.6 km/h), and fast walking (7.9 km/h);

Vehicle: speed range 36–47.5 km/h, vehicle length 4.886 m, positioned transversely to the crosswalk, with the rear end located at the edge of the crosswalk;

Driver: reaction time in the range 0.6–1.0 s; Friction coefficient: 0.55–0.7;

Distance at hazard perception: 2.47 m from pedestrian entry to the collision point;

Method: Monte Carlo simulation with 50,000 iterations, where each iteration evaluates collision occurrence (yes/no); a higher number of iterations leads to more stable results.

Pedestrian motion is assumed to be uniform, with speed values corresponding to realistic walking conditions. The focus of the study is on the vehicle's ability to stop before reaching the collision point, evaluating whether the stopping distance exceeds the available distance.

KINEMATIC BRAKING MODEL

The vehicle stopping process is modeled as the sum of the distance traveled during the driver's reaction time and the effective braking distance under constant deceleration. The total stopping distance s_{stop} is defined as:

$$s_{\text{stop}} = vt_r + \frac{v^2}{2\mu g} \tag{1}$$

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where: where

v is the initial vehicle speed,
t_r is the driver reaction time,
μ is the tire–road friction coefficient,
g is the gravitational acceleration.

A collision is assumed to occur when the condition

$$s_{\text{stop}} \geq d \tag{2}$$

is satisfied, where d is the initial distance to the potential collision point.

The main input parameters of the model are treated as random variables describing the uncertainty of real traffic conditions and human behavior. Uniform distributions within predefined ranges are used, allowing the investigation of the full spectrum of possible values without assuming a most probable value.

Vehicle speed, driver reaction time, and friction coefficient are generated as independent random variables. This approach enables analysis of their combined effect on collision avoidance while accounting for their simultaneous variation.

The collision probability is estimated using the Monte Carlo method [10–12], where each iteration generates a unique realization of the input parameters and checks the collision condition. The procedure is repeated a large number of times to ensure statistical robustness. The collision probability P_c calculated as:

$$P_c = \frac{1}{N} \sum_{i=1}^{N} I_i \tag{3}$$

where N is the number of simulation iterations and I_i is an indicator function equal to 1 if a collision occurs and 0 otherwise. Sensitivity analysis is performed to assess the influence of individual parameters on collision probability, based on conditional distributions and visualization of results in the parameter space. This allows identification of transition regions where small parameter variations lead to significant changes in outcome.

The simulation algorithm is implemented in MATLAB. The source code is provided in Appendix A.

3. RESULTS

3.1. Overall collision probability

Based on Monte Carlo simulations with 50,000 iterations, an estimate of the collision probability between a vehicle and a pedestrian under the considered conditions is obtained. For the specified parameter ranges and fixed initial distance, the probability of collision is approximately 84%. The obtained value remains stable with increasing iteration numbers, confirming the statistical reliability of the results.

3.2. Relationship between vehicle speed and collision probability

The results show a clear relationship between initial vehicle speed and collision probability. The dependence of collision probability on vehicle speed is presented in Fig. 2, based on grouping simulation scenarios into speed intervals.

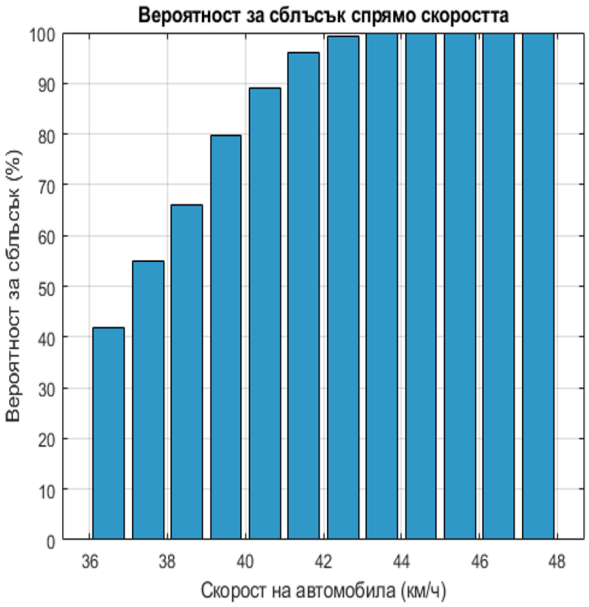


Fig. 2. Collision probability as a function of vehicle speed

At lower speeds, the probability of collision avoidance is significantly higher, whereas increasing speed leads to a higher proportion of scenarios in which the stopping distance exceeds the available distance. The relationship exhibits a gradual transition between predominantly safe scenarios and those dominated by collision risk.

3.3. Distribution of scenarios in the parameter space

To visualize the results, the distribution of individual simulation scenarios in the parameter space is analyzed. The distribution of scenarios in terms of vehicle speed and driver reaction time is shown in Fig. 3.

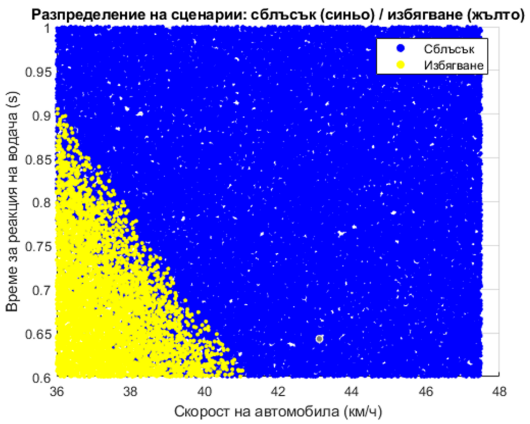


Fig. 3. Distribution of simulation scenarios as a function of vehicle speed and driver reaction time

The scatter plots show a clear distinction between scenarios resulting in collision and those in which collision is avoided. At the same time, a transition zone is identified, characterized by overlap between the two scenario types. Within this zone, small changes in vehicle speed or reaction time lead to different outcomes. This observation is valid across the entire analyzed range of friction coefficients.

3.4. Sensitivity analysis of input parameters

The simulation results indicate different levels of sensitivity of collision probability to individual input parameters. The largest variation in outcome is observed with changes in the initial distance at hazard perception, while variations in the friction coefficient have a more limited influence within the analyzed range. To summarize the influence of the main input parameters on collision probability, a sensitivity analysis table is provided (Table 1).

The data in Table 1 confirm that vehicle speed and driver reaction time have comparable effects on collision probability, with their combined increase leading to a significant rise in risk. These relationships are also evident in the graphical representations of the results.

Table 1. Sensitivity analysis of collision probability

Parameter	Influence on collision probability
Distance at hazard perception	Highest
Driver reaction time	Moderate
Vehicle speed	Moderate
Friction coefficient	Minimal

3.5. Summary of results

The conducted simulation analysis enables quantitative estimation of collision probability and reveals characteristic patterns related to the main input parameters. The obtained results provide a basis for subsequent discussion and interpretation of the influencing factors and the applicability of the adopted probabilistic approach.

4. DISCUSSION

The results of the Monte Carlo simulation confirm the importance of probabilistic approaches for assessing vehicle–pedestrian collision risk at crosswalks. Unlike deterministic models, which yield a single outcome for fixed input values, the applied approach allows consideration of the full range of possible scenarios and estimation of collision probability under realistic parameter variability [2]. A particularly important finding is the identification of a transition zone between safe and critical conditions, clearly visualized through the distribution of simulation scenarios. The existence of this zone indicates that for certain combinations of vehicle speed and driver reaction time, the outcome is highly sensitive to small parameter changes. This explains why real-world traffic situations with apparently similar conditions may result either in collision avoidance or in an accident [7]. Sensitivity analysis shows that the initial distance at hazard perception has the dominant influence on collision probability. From a kinematic perspective, this is expected, as the available distance determines the feasibility of effective braking [15]. Vehicle speed and driver reaction time have comparable effects, and their combined increase leads to a substantial rise in risk. Within the analyzed ranges, the friction coefficient has a more limited influence due to its relatively narrow variation and the dominant role of kinematic parameters. It should be noted that the presented model includes several simplifying assumptions. Vehicle motion is treated in a one-dimensional framework, and driver and pedestrian behavior are described using a limited number of parameters. Factors such as evasive maneuvers, variations in braking effort, or dynamic changes in pedestrian behavior are not considered. Nevertheless, the model is suitable for comparative analysis and risk assessment in well-defined scenarios. In this context, the Monte Carlo method proves to be an effective tool for quantitative analysis of traffic risks, enabling a shift from single-case threshold assessments to probabilistic descriptions of system behavior. The results can serve as a foundation for future model extensions, including the introduction of additional random parameters and the analysis of more complex interaction scenarios.

5. CONCLUSIONS

In this study, a probabilistic approach for assessing vehicle–pedestrian collision risk at a crosswalk is presented using the Monte Carlo method. The developed simulation model enables quantitative evaluation of the influence of key parameters related to vehicle motion and driver response while accounting for the uncertainty inherent in real traffic environments.

The results demonstrate that collision risk cannot be adequately assessed using single deterministic parameter values, as transition regions exist in which small parameter variations lead to substantial changes in outcome. This confirms the necessity of probabilistic methods when analyzing traffic situations involving vulnerable road users.

The proposed approach can be further developed by extending the model to include additional parameters, such as variability in pedestrian behavior, different braking regimes, and a broader range of road conditions. A promising direction for future research is the incorporation of correlated random variables to better capture dependencies between vehicle speed, driver reaction time, and road surface conditions.

Further development of the model would allow its application to different crosswalk configurations and the evaluation of the effectiveness of traffic safety measures. In this sense, the Monte Carlo method provides a robust foundation for future studies aimed at more objective and quantitatively grounded assessment of risk in road traffic systems.

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A. MATLAB CODE FOR COLLISION PROBABILITY ESTIMATION

Listing 1: Monte Carlo simulation for collision probability estimation

```
N = 50000;
v_kmh = 36 + (47.5 - 36) * rand(N,1);
t_react = 0.5 + (1.0 - 0.5) * rand(N,1);
mu = 0.55 + (0.7 - 0.55) * rand(N,1);
distance = 2.47;
s_stop = v_kmh/3.6 .* t_react +
(v_kmh/3.6).^2 ./ (2 * mu * 9.81);
collision = s_stop >= distance;
P_collision = mean(collision) * 100;
```